Ratcheting, Competition, and the Diffusion of Technological Change: The Case of Televisions under an Energy Efficiency Program

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The study of the diffusion of innovation and technological change enjoys a long tradition in marketing and often places an emphasis on the role of consumer adoption. Complementing this process of diffusion are firms, which differentiate in the extent to which they provision technological change in their products. In markets with societal implications or externalities, policy is implemented to avoid the under provision of innovation. Firms have clear incentives to engage in strategic behavior in such markets because policymakers use market outcomes as a benchmark in designing regulation. This study examines a unique energy efficiency standard for television sets, under which future minimum efficiency standards are explicitly a function of current product offerings. The setting illustrates firms' dual incentives at work: Depending on the competitive environment, they have strategic incentives to both ratchet up, and ratchet down, the quality of their product offerings in order to influence future standards. These incentives affect the pace at which innovation reaches consumers. I develop and estimate a structural model of product entry and endogenous regulation to illustrate how such dynamic standards affect product release decisions, consumer purchases, and the competitive environment. My analysis provides evidence that firms are more likely to ratchet down quality when they have similar cost structures or when the market is concentrated.

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[*]The data used in this paper was provided by Hiroshi Ohashi. All errors are my own.

1 Introduction

The study of the diffusion of innovation and technological change enjoys a long tradition in marketing and economics. From the seminal work of Bass (1969) to more recent studies on the particular mechanisms that affect diffusion such as network effects and informational barriers, the empirical literature has emphasized the role of consumer adoption. Firms complement this process of diffusion by choosing the extent to which they provision technological change in their product offerings. As competitive forces lead firms to differentiate, some sell less innovative products than others.

In markets with strong societal implications or clear externalities due to safety, health, or environmental considerations, the diffusion of less innovative products may be deemed particularly undesirable, prompting policy intervention. The adoption of hybrid, alternative fuel, and electric vehicles, for instance, is driven by significant subsidies and standards. The FDA's list of approved drugs and food additives are frequently updated in response to developments in pharmaceutical and food research. The use of newer electronic health record systems spread rapidly among health care providers in the United States after the introduction of a series of subsidies and financial penalties.[1]

Product managers are not merely bound by such policies, however: they have the opportunity to shape them. Policymakers commonly consider the claims and actions of firms when designing regulation because firms have better knowledge about future technological advances. This information asymmetry motivates strategic behavior by firms, and in turn has important consequences for the pace at which innovation reaches consumers. This study focuses on an energy efficiency standard for television sets to analyze this behavior. As a subset of regulations, efficiency standards make an ideal point of departure, since the nature of the regulation is succinctly captured by one metric, the level of the minimum efficiency standard. Under efficiency standards, firms may engage in strategic behavior — such as manipulating the quality of their product offerings — in an attempt to ratchet up (or down) future standards. By developing a structural model of demand and supply that endogenizes product introduction and captures regulatory constraints, I assess how ratcheting policies[2] and competitive forces affect the diffusion of innovative products, consumer welfare, and competitive structure.

One aspect that makes ratcheting incentives especially interesting for empirical investigation is that economic theory is ambiguous as to whether these incentives encourage firms to increase or decrease product quality in competitive contexts. The well-known ratchet effect suggests that within firms, there is an in-

[1] On *automobiles*, a list of federal and state incentives for alternative fuels and advanced vehicles is available online (http://www.afdc.energy.gov/laws/state). For example, the website lists some 80 laws and incentives in place for the State of California. See Knittel (2011) for the role that CAFE standards play in affecting vehicle characteristics, including downsizing to meet standards. Sallee (2011) shows that the incidence of tax incentives for hybrid vehicles fell on consumers. A consumer who purchased a Toyota Prius in early 2006, for example, received \$3150 in tax credits. On *FDA standards*, see Cimons, Marlene "Seldane pulled for a safer allergy drug." *Los Angeles Times*. December 30, 1997. Seldane, an allergy drug, was disapproved after a safer drug Allegra was developed. The manufacturer of Seldane complied with the FDA and retracted Seldane only after two versions of the newer drug, which it also manufactures, were approved by the FDA. On *electronic health records*, see Rowland, Christopher "Hazards tied to medical records rush." *Boston Globe*. July 20, 2014. Since 2009, \$30 billion in government incentives have been provided to encourage medical professional to use electronic health records. Since 2015, hospitals that had yet to transition to new systems have been penalized through reduced Medicare reimbursements.

[2] Here, I call standards that are set following the ratchet principle as ratcheting policies. The "ratchet principle" refers to a central planner's tendency to use current performance in setting future goals (Weitzman, 1980).

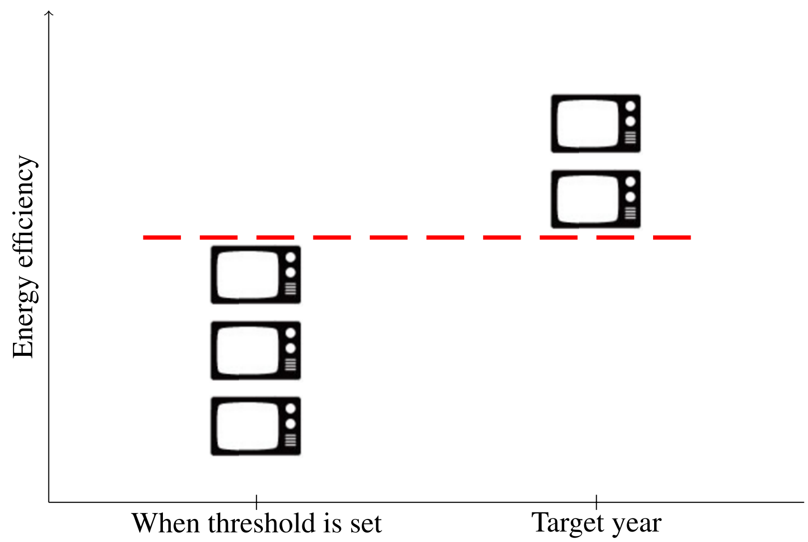

Figure 1: Stylized illustration of the regulation. Under the endogenous energy efficiency regulation, products sold during a future target year must be at least as energy efficient as the most efficient product being sold in the base year.

centive to keep product quality low in order to induce looser standards ("ratcheting down"). In competitive environments, however, the theoretical predictions are less clear. On the one hand, standards may encourage a firm to ratchet down even further, so that it can sell products with varying levels of quality post-regulation and differentiate its product offerings from those of its rivals. On the other hand, competition may cause firms to provision quality closer to the technological frontier, as firms attempt to subject its competitors to tighter regulation ("ratcheting up"). A key contribution of this paper is to employ a structural model that allows a better understanding of the relative importance of these forces on observed outcomes in the market for televisions sets. To the best of my knowledge, these forces have not been studied empirically thus far in competitive markets, despite an abundance of theoretical work in this area[3] and the prevalence of standards that elicit ratcheting behavior in practice.

Two features of the energy efficiency standard in the Japanese television market make this setting an ideal testbed. First, under this particular regime, the mapping of firms' product offerings onto the eventual level of the energy efficiency standard is explicitly a function of current product offerings. In general, *products sold during a future target year must be at least as energy efficient as the most efficient product being sold in the base year,* when the regulator sets the standard (Figure 1). In contrast to typical settings in which the standard-setting procedure is noisier,[4] in my empirical context I directly observe the critical

[3]This is a rich theoretical literature on the various incentives that exist when a firm realizes that a constraint or regulation in its competitive environment is endogenous. In the presence of a dominant player, the firm can use its asymmetric power to influence standards and increase the costs of its rival firms. The firm engages in raising rivals' costs, a form of non-price predation (Salop and Scheffman, 1983). Firms can engage in self-regulation, as well as advertise its voluntary behavior to preempt stricter regulation (Maxwell et al., 2000). Alternatively, firms can jointly engage in regulatory holdup by refusing to make investments that would be necessary for compliance with a standard (Gersbach and Glazer, 1999). For example, they can adjust investments in R&D and patenting to convince regulators of the lack of innovation (Hackett, 1995). Yet another option, if a predetermined schedule for setting regulations already exists, is for firms to release lower quality products to signal to the regulator its inability to abide by tighter regulation (ratcheting down) (Freixas et al., 1985). In Appendix 9.3, I discuss theory work that is related to minimum quality standards (MQS).

[4]Standards levels are commonly proposed and revised repeatedly before they are implemented. During this process the in-

actions that firms took in order to influence the standard. Second, the regulation is applied independently to different sub-markets based on screen size and other observable features. I can thus observe firm behavior around the time of standard-setting across regulatory sub-markets, which vary significantly in the number of active firms, product line length, costs of production, and demand.

In my model, firms have beliefs that are consistent with the endogenous standard-setting regime based on a set of simple heuristics. I use moment inequalities to partially identify firms' fixed-cost parameters, accounting for these dynamic beliefs. This helps to tease apart why firms might be ratcheting down in some product groups: for example, we can observe whether a firm is ratcheting down in anticipation of changes in future profits, or whether it is merely too costly for the firm to increase efficiency.

By evaluating a series of counterfactual simulations, I decompose strategic behavior along intra- and inter-firm incentives and identify the determinants of the diffusion of energy efficient products across regulatory sub-markets. Based on intuition from a simple model of competition that I develop, I find that concentrated markets, or those with firms facing similar costs, are likely to see more ratcheting down. When firms realize that their product releases may affect future regulatory standards, they trade off changes in short-term profits with the future stream of profits once the new standard is enforced. However, when many firms are subject to the same standard, an equilibrium with ratcheting down is less sustainable. This is particularly true when firms are heterogeneous, because advantageous firms are willing to further ratchet up.

While this study uses data from a specific empirical context, it nonetheless addresses a common, widespread phenomenon. Firms respond strategically to opportunities to influence regulatory standards in many settings by changing product offerings. In the seventies, the introduction of emissions controls for automobiles was repeatedly delayed, due to complaints from major automobile manufacturers, who claimed that the standards specified by the 1970 Clean Air Act could not be achieved (White, 1982, Yao, 1988). It "would simply not be possible," the manufacturers said, warning against a potential shutdown of the automobile industry that would do "irreparable damage to the American economy."[5] Yet, just two months after the Environmental Protection Agency conceded to extend emission deadlines, a major manufacturer announced that it would be able to implement technology that would allow them to meet the new standards. Automobile manufacturers

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terests of the involved firms, industry groups, and regulators are deliberated. For example, in setting appliance energy efficiency standards, the Department of Energy (DOE) goes through a four-phase process which typically takes three years to complete. ("Standard development and revision." U.S. Department of Energy., n.d. Web. 20 Mar. 2016. energy.gov/eere/buildings/standards-development-and-revision). This makes it challenging to understand firms' beliefs about how manipulating product offerings will affect the eventual levels of standards that are implemented. (The negotiations of U.S. appliance standards typically are a trade-off between more stringent standards and more time until the standards are enforced. Nevertheless, manufacturers have attempted to weaken standards as well [Nadel, 2002]).

In contrast, under the regulatory regime considered in this paper, deliberations are kept to a minimum, and the future standard levels are relatively clear. (Ministry of Economy, Trade and Industry. Top Runner Program, Developing the world's best energy-efficient appliances. 2010. 6-7.)

[5] The first quote is from a 1970 memorandum of the Automobile Manufacturers Association. The second quote is of Ford's executive vice president at the time. See Weisskopf, Michael. "Auto-pollution debate has ring of the past." *The Washington Post*. March 29, 1990.

In response to emission controls, automobile manufacturers were also accused of forming research joint ventures in an effort to retard development of emission control technology. The Department of Justice accused the three major manufacturers that they had "engaged in a combination and conspiracy to restrain competition in the development, manufacture, and installation of motor vehicle air pollution control equipment," including forming joint research ventures and agreeing to share patents. The Department of Justice and the three manufacturers eventually entered a consent decree. See Hackett (1995) and *United States v. Automobile Manufacturers Ass'n, 307 F. Supp. 617 (C.D. Cal. 1969).*

presumably already had the technology to meet the standards. But their lobbying efforts would not have been convincing had firms released products that met the standards they were lobbying against. The case is just one example of a general phenomenon: in product markets, the incentives to influence standards are likely to affect both the products that are introduced to the market and the timing of the introduction.

The study of regulatory constraints in marketing is by no means novel. There is a substantial literature on the implications of policies that regulate marketing variables. The study of highly regulated markets like the pharmaceutical industry (Branstetter et al. 2011, Coscelli and Shum 2004, Ellickson et al. 2001, Manchanda et al. 2005, Stremersch and Lemmens 2009) is commonly motivated by the premise that advertising, detailing, and pricing decisions are subject to regulations. Regulations on pricing (Daljord, 2014), information disclosure (Moorman et al., 2005), and advertising (Scheraga and Calfee, 1996) are also well understood. However, these studies typically assume exogeneity of the policy, despite the fact that regulators are commonly mandated to receive firms' feedback when developing standards.[6] Regulations for safety, health, or environmental considerations are ubiquitous, and the implications of accounting for firms' incentives when they realize that standards are endogenous may be substantial. My study will help understand the magnitude of firms' incentives in a large durable goods market.[7]

More generally, this study relates to a rich quantitative literature in marketing on the diffusion of new products and technologies. In early scholarship, beginning with Bass (1969),[8] demand was generally taken to be an exogenous process. Scholars later extended early models to take into account marketing variables such as pricing and advertising (Kalish, 1985) and intertemporal adoption by consumers (Horsky, 1990); yet others developed diffusion models with individual-level interpretations (Lattin and Roberts, 1988). More recently, the literature has focused on specific mechanisms of the diffusion process, such as the role of dynamic demand in durable goods (Conlon, 2010, Gordon, 2009, Gowrisankaran and Rysman, 2012, Melnikov, 2013, Nair, 2007), network effects (Ackerberg and Gowrisankaran 2006, Dubé et al. 2010, Ryan and Tucker 2012, Shriver 2015, Tucker 2008), and uncertainty and informational barriers (Bollinger, 2015). This literature is also closely tied to the empirical analysis of product introduction, positioning, and exit (Draganska et al. 2009, Eizenberg 2014, Hitsch 2006, Nosko 2010, Wollman 2014). I contribute to this body of work by studying the role of another mechanism — endogenous standards — that can affect product introduction and the diffusion of technology. This mechanism is particularly important for innovative markets. Because the most innovative markets generally tend to be more concentrated,[9] firms commonly realize that their current product offerings affect future regulatory standards.

Finally, this study serves as a cautionary tale for assessing the benefits of standards. The standards

[6]In the United States, the Administrative Procedures Act of 1946 requires regulators to give advance notice to interested parties when new regulations are drafted, and to allow them to give commentary to authorities (Lutz et al., 2000). See Lutz et al. (2000) and Stigler (1988) for more examples of firms' strategic behavior affecting regulatory policies.

[7]Ratcheting forces may arise for standards that are not regulations. For example, a major upscale supermarket chain, Whole Foods, only carries body care products that contain organic ingredients that meet the NSF/ANSI 305 Organic Personal Care Standard. Both Whole Foods and major organic product manufacturers were involved in designing the standard. The organic product manufacturers faced ratcheting incentives as they competed to sell products through a major distributor.

[8]Incidentally, one of the main examples examined in the seminal paper on the Bass Model was the diffusion of color televisions (Bass, 1969). See Peres et al. (2010) for a review of diffusion modeling in marketing.

[9]Schumpeter (1942) argued that a large firm operating in a concentrated industry is most effective at R&D. Cohen et al. (1989) summarize that the "majority of studies that examine the relationship between market concentration and R&D have found a positive relationship." The theoretical analysis in Sutton (1998) is motivated by this correlation.

considered in this study speak to the "diffusion" stage in Schumpeter's trilogy of technological change.[10] Because standards play an important role in influencing the final stage of this linkage, the effects of these regulations are of interest to policymakers. When evaluating these policies, however, the fact that firms respond strategically to dynamic regulation makes clear that a simple comparison of pre-regulatory firm behavior to post-regulatory firm behavior is not sufficient. Indeed, because the Japanese efficiency standards can introduce incentives to ratchet down, a short-term comparison is likely to overstate the benefits of the regulation. The United Nations Intergovernmental Panel on Climate Change suggests that the effectiveness of energy efficiency standards is debatable because demand side responses to the regulations, such as rebound effects,[11] are far from being fully understood (Edenhofer et al., 2014). In assessing the benefits of these standards, my research suggests the need for more careful investigation on supply side behavior as well.

The remainder of the paper is organized as follows. In the next section I describe the regulatory regime and the data. I also develop a simple model of endogenous standards in this section. Section 3 lays out an empirical model of the television market, and Section 4 describes estimation and identification. The results are described in Section 5, followed by the counterfactuals, in Section 6. Section 7 concludes.

2 The energy efficiency standard and data

Televisions are a nearly universal appliance in Japanese households. They accounted for roughly 10% of household electricity consumption, according to a 2009 survey by the Agency for Natural Resources and Energy. The introduction of more energy efficient, thin panel televisions became increasingly popular and affordable from the mid-2000s, gradually replacing conventional CRT televisions. Globally, the benefits from an energy efficiency program for televisions may be large. Park (2011) suggests that some 70 megatonnes of CO2 emissions can be reduced during 2012 through 2030 by encouraging adoption of more efficient televisions.[12]

It is also worth noting that studying firm behavior under energy efficiency standards in the Japanese television market is interesting in its own right, because the regulation may have intensified competition in an already competitive market. Manufacturers placed great pride in marketing these televisions, the "king of the living room." Anecdotally, firms believed that by having consumers purchase their brand of television sets, consumers would go on to purchase other appliances by the same manufacturer.[13] Nevertheless, today most Japanese electronics manufacturers have de facto exited from the television market. This study helps explain the extent to which environmental regulations added to the costs that these firms incurred to produce

[10]Firms' product line decisions are a key determinant of the pace of diffusion of new technologies, the final step in Schumpeter's trilogy of technological change. In Schumpeter suggests that the process of technological change involves three stages: invention (the generation of new ideas); innovation (development of new ideas into marketable products); and diffusion (adoption of products by agents) (Stoneman, 1987). I further comment on this linkage in the conclusion.

[11]When energy efficiency policies are successful, they induce more consumption of energy services because the price (of energy services) decreases (the "rebound effect"). For instance, one may drive more as a result of buying a more fuel efficient car. See Gillingham et al. (2016).

[12]Globally, televisions consume as much as 168 TWh, corresponding to 3 to 4% of global residential electricity consumption, and about 27 megatonnes of CO2 emissions.

[13]Nikkei Business Daily, ed. Sony ha yomigaeruka (Will Sony Revive). 2009. 35.

televisions, and more importantly, how they may have affected the competitive environment.

2.1 The Top Runner Program

The Top Runner Program was implemented in 1998 to regulate the energy efficiency of television sets. In general, the regulation dictates that the energy efficiency of products sold by a television manufacturer during the *target year* must be as efficient as the most efficient product of the *base year* when the regulator is setting the standard.[14]

Under the regulation, each television belongs to a product group g that is defined by unique combinations of a vector of product characteristics. The vector is

$$x_j^g = \begin{cases} size_j \in \{(10,19),[19,32),[32,\infty)\} & \text{Screen size groups} \\ fps_j \in \{60,120,240\} & \text{Display speed: 60/120/240 fps} \\ FHD_j & \text{Full HD} \\ features_j = DT_j + DVD_j + HDD_j + BR_j & \text{Number of additional features} \end{cases} \tag{1}$$

where the variables DT_j, DVD_j, HDD_j and BR_j take a value of one when the product features double tuners, an internal DVD recorder, an internal HDD recorder, and an internal BlueRay recorder, respectively. For instance, televisions with screen size larger than or equal to 32 inches with a full-HD panel, display images at 120 fps and have two additional features belong in one product category (group DG2). With regards to features, only the number of features is used for grouping products.

In addition to the vector x^g, energy consumption level $energycon$ is the major observable characteristic of a television. Energy consumption $energycon$ is measured in $kWh/year$, and reflects the yearly energy consumption of a television under normal household usage conditions.

The regulation aims to limit $energycon$ by setting a target value for each product group. These values are adjusted for future potential demand and R&D, but generally reflect the most energy efficient product in each product group up to the time that the target values are set, T_{set}. Because screen size is a key determinant of energy consumption, within product groups, the target values are adjusted to be linear functions of screen size.

The achievement percentage is the ratio of the target value to the actual energy consumption level of a given television,

$$e_j = energytarget\left(g_j, size_j\right)/energycon_j$$

and can be interpreted as a normalized measure of energy efficiency. Firms abide by the standards by selling televisions that are more efficient than the target, i.e. have e_j greater than 100%, after they go into effect.

The regulation introduces three sets of time periods. In the initial time periods, leading up to T_{set}, firms realize that releasing an efficient product may change the future regulation level. In the latter time periods, the threshold goes into effect. There is a set of time periods in between, in which the threshold level has

[14] Formally, the firms meet the regulation by ensuring that the quantity-sold weighted average energy efficiency exceeds standards. Throughout this study, I assume that the regulation was a de facto minimum efficiency standard. A discussion on this point, and further details of the regulation, are in the appendix (Section 9.1.1).

been set, but has not gone into effect. These periods are intended to allow the firm to adjust to the new upcoming threshold.

I focus on the 2012 standards of the Japanese Top Runner Program for television sets. The standards were set around February 2009,[15] and enforced after April 2012. This was the third "cycle" in which the program was implemented in the television market. Importantly, it was widely acknowledged to be the last cycle. Therefore, I assume that firms were not concerned about the effect of its current behavior on other regulatory standards in the near future, such as potential future cycles of the Top Runner program.

Consumers can easily obtain information regarding energy efficiency. The government maintains an informational website and publishes a bi-annual catalog to facilitate consumers' purchase decisions. Additionally, retailers are required to accompany televisions with a standardized label that clearly displays estimated annual energy consumption and electricity costs, as well as the achievement percentage of the product. The label also shows the relative energy efficiency of a given TV on a five-star scale. The number of stars that a product is given is determined by whether the product's achievement percentage meets cut-off values. During the data period, there were three revisions of these cut-off values. For example, from April 2010 through March 2011, a product needed to have an achievement percentage greater than 100% to qualify for five stars; after April 2011, the cut-off increased to 155%.

2.2 Data

Televisions are an ideal product group to examine the changes in firm behavior under this regulation, as new products are regularly released at an average rate of 18 models per month. I use point-of-sales (POS) data from GfK for televisions sold in Japan. An observation is the product and quantity sold of a given television model in a given month-district. The data covers all five districts of Japan, ranging in size from 5.8 million to 20.5 million households in March 2012. In the main empirical exercise, I use a dataset with 854 unique television models, starting from April 2008 and ending in March 2012. There are 48,199 unique television model-month-district observations. Section 9.1.3 describes the procedure used for the construction of the dataset in detail.

A noteworthy feature of the data is the rapid decrease in the price of televisions, as shown in Figure 2. The quality adjusted price index, which controls for the improvement in televisions attributes over time, suggests that prices of televisions decreased by a factor of three and a half over the course of five years. Both rapid technological improvements and market expansion led to decreased costs and more competition, which decreased prices. Therefore, in my model, I flexibly allow for marginal and fixed costs to fluctuate over time.

I focus on six major domestic manufacturers that produced a large proportion of products. Table 1 shows that the six firms are responsible for about 97% of the units of televisions sold. Each of the six firms released at least one product that affected the threshold level in some product group. According to a consumer survey, the six companies generally coincide with the six most recognized television brands by consumers, as well

[15] Throughout this study, I assume that firms knew the regulation was set around February 2009. I document supporting evidence for this claim in the appendix (Section 9.2).

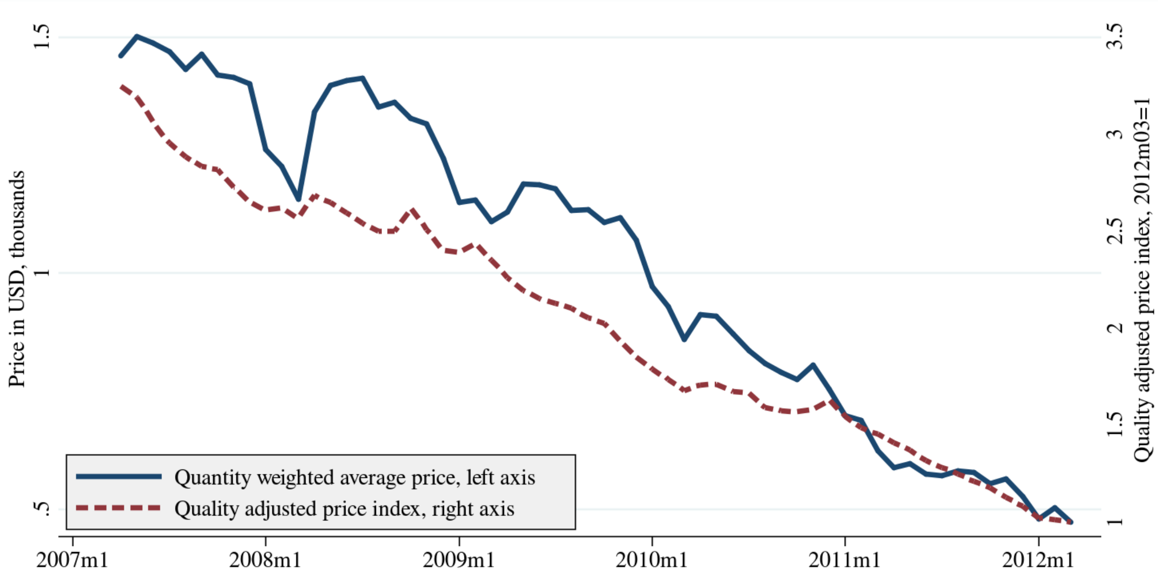


Figure 2: Trend of television prices. The solid line represents the sale-quantity weighted average price. The dashed line is a quality adjusted price index, where prices at the end of the data period are normalized to unity. The price index is a Fisher-style characteristic based hedonic price index, where a hedonic regression of prices on product characteristics $size$ and determinants of grp are used. Hedonic price indices attempt to control for improvements in product quality, which may be particularly relevant for markets in which technology is rapidly improving (see Triplett, 2004 for a discussion). The hedonic index suggests that prices decreased by a factor of three and a half.

as the six television brands that consumers have a favorable impression of.[16] The firms are characterized by their extensive product lines: each firm sold 34.0 unique model, including 2.1 new models, in the average month.

The rapid increase in the energy efficiency of televisions over time is suggestive of the extent to which technological change was taking place. In terms of actual energy savings, Table 2 shows that the average television introduced in 2011 used 52% less energy than that in 2008. This translates to an energy cost savings of roughly $300 over the life time of a television set, assuming ten years of usage. On average, the achievement percentage of new televisions improved by 21.8 percentage points every year.

The energy efficiency of products varied significantly within time periods as well. The standard deviation of achievement percentage, absorbing time-, region-, and product group-fixed effects, is 18.2 percentage points, corresponding to 45.3 kWh/yr or $136 in energy cost savings over 10 years. This suggests that relative to the mean price of televisions ($1339), the choice of television set can have non-trivial implications for energy cost savings. The variation of energy efficiency is still sizable within-firms: when firm-by-product group -fixed effects are added, the standard deviation of energy usage is 39.9 kWh/yr or $120 over 10 years.

The regulation allows me to observe multiple outcomes of the standard-setting process across product groups. For detailed analysis, I focus on five product groups in which the regulation played a meaningful role.[17] Table 3 shows that product groups vary significantly in the price and market shares, as well as the

[16]Based on a survey conducted by Nikkei Business Publications, and published in their 2010 edition of the annual publication "Digital consumer electronics (*dejitaru kaden shijyo souran*)."

[17]12 product groups saw more than one firm release products in the six months prior to T_{set}, and 11 product groups saw more

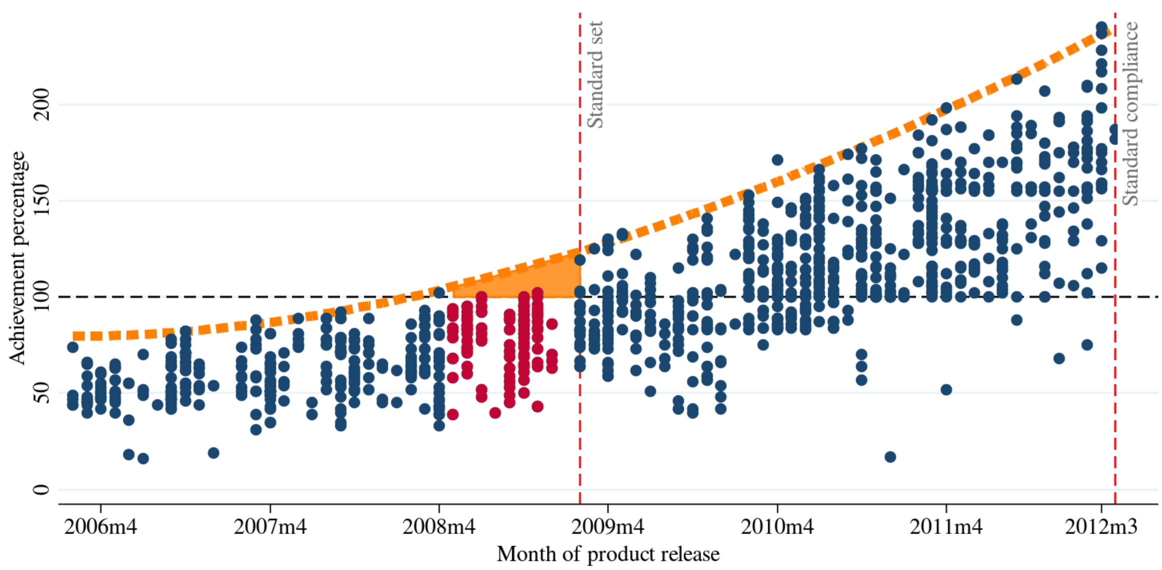


Figure 3: Energy efficiency of new models released over time. Each point represents the introduction of a unique television model. The y value of the point indicates the efficiency of the product (achievement percentage, described in Section 2). There is a jump in the trend of the most efficient goods around February 2009 (shaded triangular area). A test of structural change suggests that there was a statistically significant jump in the efficiency of the most efficient products sold. See Section 9.2 for details.

number of firms and number of products released by each firm. For example, there was an average of 11 active firms in group DK, a product group for budget televisions, while group DG1, a more premium product group, saw three. In the next subsection, I discuss how the outcomes under the regulatory regime differed across these product groups.

2.3 Understanding strategic behavior

A first glance at the data shows behavior consistent with firms waiting on releasing more efficient products until after the future threshold is set. Figure 3 shows the transition of a normalized measure of energy efficiency of all newly released televisions in this market over time. Around February 2009, when the regulator is setting the threshold (T_{set}), there is a noticeable jump in the energy efficiency of the most efficient products, consistent with ratcheting down behavior. Across regulatory sub-markets, however, I find that ratcheting down behavior is less pronounced in some product groups.

What explains the variation in ratcheting down across product groups? To answer this question, I first gain intuition using a simple model of endogenous standards. The empirical context of this paper is most closely related to the theoretical literature that examines minimum quality standards. Using a duopoly model

than on firm release products in the last six months of the data period, immediately before the regulation was to be enforced. Out of these groups, I focus on the five product groups that fall into both categories (one product group was excluded because only two products were released prior to T_{set}).

In other product groups, due to the limited number of product releases, the threshold levels that were implemented deviated from the basic standard-setting procedures (i.e. setting the threshold at the most efficient level). Instead, they were set by interpolation from other product groups' threshold levels.

of vertical product differentiation, Ronnen (1991) studies a base case in which the standard is exogenous. I extend this model to two time periods in order to allow the regulation to be endogenous, analogous to the Japanese regulation. To the best of my knowledge, no study has examined the case in which the regulator has committed to a schedule of standard-setting, and plays a passive role of merely enforcing the threshold,[18] when consumers are elastic.

The model extends a canonical model of duopolistic competition with vertical differentiation by introducing two time periods: one before, and one after, the regulation is enforced. When both firms are in the market across the two time periods, the higher quality firm necessarily has an incentive to decrease its product quality today, so as to loosen standards tomorrow. A key finding is that the cost advantage of the higher quality firm determines the extent to which it ratchets down quality. That is, the greater cost advantage it has, the less the firm ratchets down on quality. In Section 9.3 of the appendix, I describe the model in detail.

The model suggests that the cost differences across firms are an important determinant of market outcomes. There are various reasons for why firms' costs of producing more efficient products might vary. LCD modules display images by allowing light, emitted from a backlight unit, to travel through a LCD panel which controls the amount and color of light that passes through. Some margins for improving energy efficiency are relatively established, such as the use of optical films, and hence the costs are predictable and similar across firms. Other margins of improvements, however, particularly those that involve changes in the design of the LCD module, are closely tied to the manufacturing process and the R&D stock. Because manufacturers rely on their own proprietary technology to improve panel transmittance, they face different costs of enhancing energy efficiency. Strong demand for more energy efficient models has also altered how television manufacturers manage their supply chains. As a result, some manufacturers internalized the entire process of LCD module production, while others continued to rely on upstream manufacturers.

I find that energy efficiency trends are consistent with the logic developed in my theory model. As a case study, the top panel of Figure 4 illustrates variation in energy efficiency across the type of panel used. Full-HD panels refers to panels that have more than 1080 vertical pixels, and are generally assumed to be of higher quality because images can be shown in finer detail. Because full-HD panels are newer in technology, the number of suppliers able to manufacture these panels is limited.[19] Therefore, the cost of producing full-HD televisions are more homogeneous across firms because firms source their panels from a similar set of suppliers.

The top panel of Figure 4 shows the trend of efficiency by whether the television has a full-HD panel. By the end of the data period, firms must release products with an achievement percentage greater than 100% to meet the standards. The contrast of the two groups is vivid around February 2009, when regulators are setting future standards: televisions with a full-HD panel exhibit the jump in energy efficiency, while the

[18] It is worth noting that a regulatory regime with a predetermined schedule of renewals is not by any means unique to my empirical context. For example, in the United States, the DOE is required by law to renew efficiency standards every six years, for appliances ranging from air conditioning units to laundry machines.

[19] For example, in the first half of 2006, seven suppliers manufactured non-FHD 32 inch panels; while three manufactured full-HD 32 inch panels (Fuji Chimera Research Institute, 2006). The number of suppliers are limited because full-HD panels require more advanced production lines which cannot be easily diverted from traditional lines. Moreover, full-HD panels tend to be larger, and are costlier to manufacturer because such panels introduce unique challenges in the production and inspection procedures (Minami et al., 2007). I further discuss the source of cost differences across firms in the appendix (Section 9.1.2).

non-FHD televisions do not. The figures suggest that there is more ratcheting down in the Full-HD groups. These trends of ratcheting generally hold within each product group as well. Table 4 shows that full-HD product groups generally see a large increase in energy efficiency following the setting of the threshold, consistent with ratcheting down.

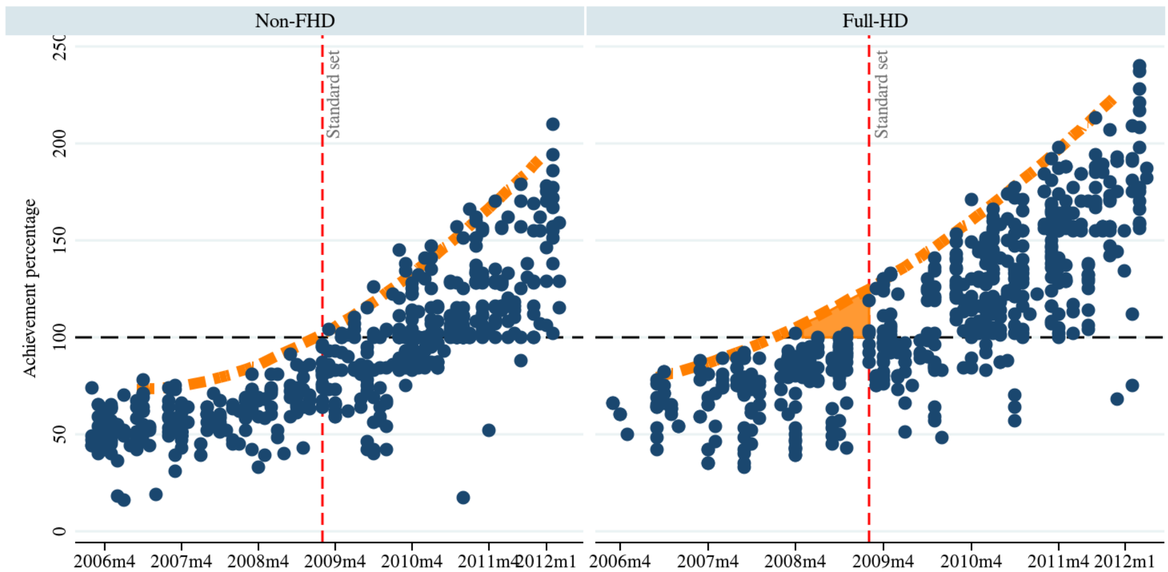
Table 4 also shows the share of sales, in terms of energy efficiency, that took place near the threshold level (100% achievement percentage). In the six month period prior to the *setting* of the threshold, there were fewer sales of televisions near the eventual regulation level within non-FHD product groups (column (A)). This suggests that, in non-FHD product groups, firms released highly efficient products that did not gain significant market shares. This is in line with ratcheting up: a firm may decide to release a highly efficient product in an attempt to ratchet up the threshold, even if the product is not profitable per se. On the other hand, in the six months prior to the *enforcement* of the regulation, the sales of non-FHD televisions were concentrated near the threshold level (column (B)). This is consistent with some firms' product offerings and consumer demand "binding" at the minimum efficiency threshold as a result of the threshold being ratcheted up. Opposite trends hold for the full-HD product groups.

The theory model implies that firms' abilities to manufacture full-HD televisions are more homogeneous, because we observe more ratcheting down in these product groups. This is compatible with anecdotal evidence of firms' cost structures: firms are more similar in the costs of making full-HD televisions due to the limited number of suppliers and kinds of panels. To support the claim that firms were more homogeneous in costs in the full-HD groups, I show how the firms' product offerings varied in terms of energy efficiency. The bottom panel of Figure 4 shows a kernel density plot of the quantity of televisions sold in the last six months of my dataset, immediately prior to the enforcement of the regulation. Each line corresponds to the density of televisions sold at a given level of efficiency for a particular firm.

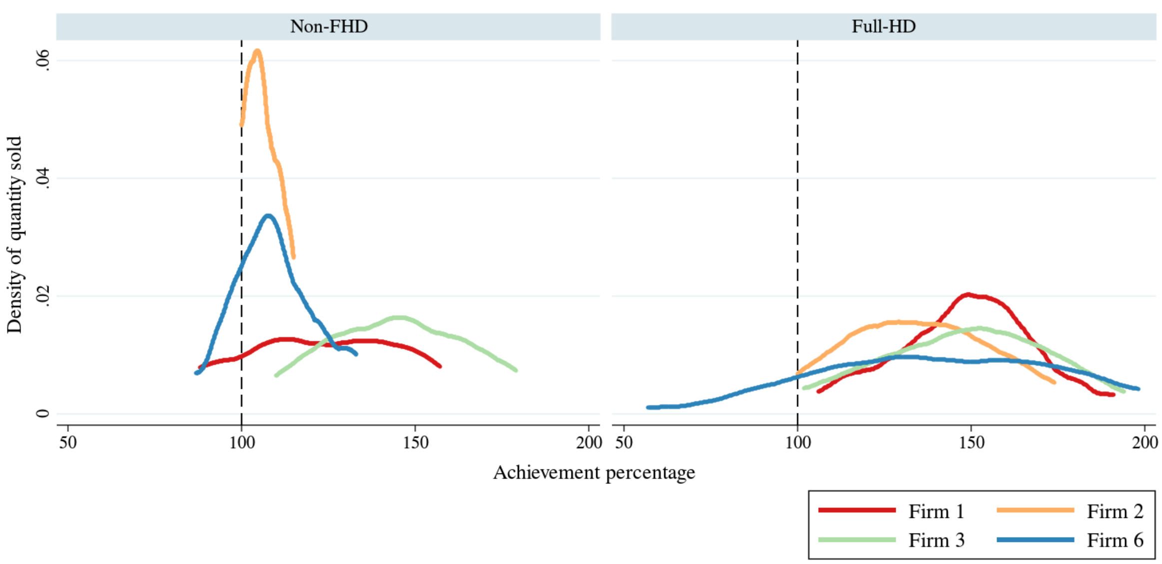
These density plots are helpful for two reasons. First, if firms are offering products within different ranges of efficiency levels, it suggests that they face different costs in provisioning efficiency. The range of products offered by each firm is represented by the length of the line. In the non-FHD product group, some firms release products that just meet the threshold level (firm 2), while others release products along a range of efficiency levels (firm 3). This observation is consistent with some firms having a cost advantage in manufacturing energy efficient televisions compared to others.

Second, the density of purchases is suggestive of how able a manufacturer is at producing televisions at a given level of efficiency. For instance, even if a firm is manufacturing highly efficient televisions, the mass of sales may be concentrated at less efficient models because it is costly for the firm to provision efficiency. For the full-HD televisions, we observe not only that all firms are selling televisions across the energy efficiency spectrum, but also that the purchases are generally distributed equally across this spectrum, as indicated by the flatter lines. This is consistent with firms having similar cost structures.

In summary, the data shows trends that are in line with the intuition of a simple model of competition: when firms face similar costs, they ratchet down more. However, the inferences that can be drawn from a comparison between full-HD and non-FHD televisions are limited. Product groups may vary in ways that are not cost based, such as heterogeneity in the kinds of consumers who prefer a given type of television, or the number of rival firms. Additionally, the theory model does not capture other margins in which firms



(a) Energy efficiency of new models released over time, by resolution of panel. The Full-HD televisions show a visible jump, while the non-FHD ones do not.



(b) Density of quantity of televisions sold in last six months of data, immediately prior to the enforcement of standards. Firms are more homogeneous in their product offerings for full-HD televisions.

Figure 4: Varying behavior across non-FHD and full-HD product groups.

can respond to the regulation, such as changing the non-regulated quality of the good, or the length of the product line. In the next section, I describe an empirical model that captures these other responses, and estimate it using data from the Japanese television market.

3 Empirical model of product line decisions

I construct an empirical model of product line decisions in which firms anticipate the regulatory constraint and, in response, can change product offerings. The crux of my model is in understanding how firms' product offerings are affected when they realize that current decisions can affect future profits by virtue of the regulation: in earlier time periods, firms realize that releasing a product more efficient than their competitors will increase future regulatory levels.

The aim of this model is to study firms' medium-run responses in which the level of technological change is foreseeable and accessible to all firms. This is consistent with a key feature of this industry: some of the key innovations that enable greater energy efficiency are encapsulated in the components that manufacturers purchase from suppliers. Thus, the pace of innovation is assumed to be exogenous, and I abstract away from firms' investments in R&D.[20]

The main drivers of improvement in energy efficiency are the gradual decreases in marginal and fixed costs of provisioning efficiency. The effect of these changes can be captured with a static model of product introduction. In other words, without the regulation, there are no obvious supply side incentives for firms to make forward-looking product introduction decisions. It is the regulation that introduces a clear motive for the firm to be forward looking in terms of how its behavior can affect future profits after the thresholds have been enforced. In this context, I abstract away from the dynamic product introduction decision other than by virtue of the regulation, by assuming that the additional costs that firms incur to introduce new models are not sunk. Fully accounting for the dynamics of product introduction through a sunk cost model is a challenging problem that would require the consideration of billions of states.[21]

In this section, I first describe the static base model in which firms' decisions do not interact across time periods (Subsection 3.1). Then, in Subsection 3.2, I discuss how the regulation is imposed on the base model. Additional implications of the simplifying assumptions are discussed in Subsection 3.3.

3.1 Static base model

The basic building blocks of the model are individual time periods, which proceed in two stages. Within each time period, first, firms decide on the set of goods J to offer in that time period, and incur a fixed cost

[20] I furture elaborate on this point at the end of this section in Subsection 3.3.

[21] There is an empirical literature that estimates the primitives of dynamic games following the insights of Hotz et al. (1994). Applications of these methods, such as the analysis of the cement industry by Ryan (2012), have been largely in markets with less differentiated goods (allowing for a smaller state space), and richer geographical variation in the firms' actions (providing more observations of firms' actions under various states in the state space). In contrast, in the Japanese TV market, six major firms release an average of 12 unique models per period. Geographical variation is also limited because firms introduce the similar products across markets. Finally, not only is a fully dynamic specification intractable, but it also arguably deviates from manufacturers' actual business practices. For example, firms may rely on heuristics such as hurdle rates (Wollman, 2014) to evaluate dynamic payoffs.

for the set of products. Then, firms make pricing decisions and consumers make purchases. The two stages interact because in the first stage firms use backwards induction to evaluate the profits that would be gained in the second stage from a given set of product offerings. The role of the second stage is to obtain a function $\pi_{ft}(\cdot)$ that can be used to inform first stage decisions.

I describe the base model by working backwards from the demand side of the second stage.

3.1.1 The second stage: Demand

Following Nevo (2001), demand is modeled by a logit specification with product dummies, and is assumed to be static. Consumers purchase at most one good in a given period. The utility from purchasing good j at time t in region r is

$$\begin{aligned} u_{ijrt} + \varepsilon_{ijrt} &= d_j + \tilde{\xi}_{jrt} + \beta_{ft} + \beta_r + \sum_{\check{t}=1}^{3} \sum_{k=2}^{5} \beta_{k,\check{t}}^{stars} \cdot \mathbb{1}\left(stars_{j\check{t}} = k\right) \\ &\quad - \exp\left(\beta_{p,i}\right) \cdot p_{jrt} + \beta_{0,i} + \varepsilon_{ijrt} \end{aligned} \tag{2}$$

The expression is split into two lines, so that the first and second lines correspond to components of utility common across individuals, and components that are different, respectively. In the first line: d_j is a product dummy unique to each product. Product dummies d capture the component of utility that is associated with the product, such that the mean product unobservable, $\bar{\xi}_j$, is absorbed by the product dummy. The remainder of the unobservable, $\tilde{\xi}_{jrt}$, is a demand shifter that is specific to each region and time period.

The β_{ft} and β_r terms are manufacturer-by-month and region fixed effects, respectively. A key source of demand shocks that are observed in this market are at the manufacturer-by-month level. For instance, firms commonly market and advertise their brands, and not particular products. A firm may be an sponsor of the International Olympic Committee, and benefit in demand during the Olympic Games. The β_{ft} fixed effects capture these shocks.

$\mathbb{1}\left(stars_{j\check{t}} = k\right)$ are dummies that take the value one when product j is labeled with k stars in labeling regime $\check{t}$. Because the cut-off values to qualify for a given number of stars were tightened over time, the same product can be sold with varying levels of stars over time. I therefore observe within product variation in $stars_{j\check{t}}$ over time. There are 5 star levels (k), and three different cut-off value regimes ($\check{t}$). $\beta_{k\check{t}}^{stars}$ are coefficients on these dummies.[22]

On the second line are household specific terms. In estimation, I couple the market share data with micro data obtained from the Japanese expenditure survey, which provides information on the quantity and prices of televisions purchased by household income brackets. Hence, I allow for discrete heterogeneity across six income brackets. Heterogeneity is allowed for coefficients on price (β_p), and the constant (β_0).

[22] I allow each labeling regime to have its own set of dummies, because the cut-off values for a given number of stars changed drastically across these regimes. For example, from April 2010 through March 2011, a product needed to have an achievement percentage greater than 100% to qualify for five stars; after April 2011, the cut-off increased to 155%. Empirically, I find that these dummies are estimated tightly, and that the estimates for the dummies on same number of stars can vary significantly across regimes.

Once the product dummies d are estimated, they are projected onto a set of product characteristics,

$$d_j = \beta_e \cdot e_j + \beta_{size} \cdot size_j + \beta_{size2} \cdot size_j^2 + \beta_g + x_j \beta + \overline{\xi}_j \tag{3}$$

where e_j is achievement percentage (energy efficiency), $size_j$ is screen size, β_g are product group fixed effects, and x_j is a vector of 28 product characteristics. $\overline{\xi}_j$ are mean product unobservables. The overall demand shock can be expressed as $\xi_{jrt} = \overline{\xi}_j + \tilde{\xi}_{jrt}$.

Combinations of product group and screen size determine the level of regulation that a product is subject to. Given that product groups were pre-determined jointly by the regulator and relevant stakeholders, they are arguably the key observable product characteristics that affect energy efficiency as well as consumer preferences. In addition, in Equation (3), I include a rich set of 28 covariates x_j, which captures other key attributes of televisions that are commonly listed in product catalogs. These are listed in Table 10.

Although televisions are categorized by a large variety of product attributes, the focus of my model are firms' choices of energy efficiency. Therefore, I collapse non-energy efficiency attributes from the decomposed product dummy (Equation 3) into a scalar, which I define as quality,

$$q_j = \beta_{size} \cdot size_j + \beta_{size2} \cdot size_j^2 + \beta_g + x_j \beta$$

This allows me to characterize the key attributes of a television by a given firm using the vector (g_j, q_j, e_j), which signifies the product group, quality, and energy efficiency of the television.

By assuming that ε_{ijrt} are i.i.d. Type-I extreme value shocks, and normalizing utility from the outside option to be $u_{i0rt} = 0$, the market share of a given good is

$$s_{jtr} = \sum_i w_{itr} \cdot \frac{\exp(u_{ijtr})}{1 + \sum_{m \in J_{tr}} \exp(u_{imtr})} \tag{4}$$

where w_{itr} is the weight of consumer type i, and J_{tr} is the set of televisions available at time t in region r.

3.1.2 The second stage: Pricing

On the supply side, the pricing decision is made conditional on predetermined product offering decisions from the first stage, and with full knowledge of the realization of demand shocks ξ and marginal cost shocks ω. I assume the existence of a unique Nash-Bertrand pricing equilibrium for any possible product assortment combination. For each region and month, the firms optimally choose prices by satisfying the first order condition

$$p - mc = [\Omega \odot \Delta(p)]^{-1} \cdot s(p) \tag{5}$$

where Ω is the ownership matrix, $\Delta(p)$ is the derivative of the market share of products with respect to prices, and $\odot$ is the Hadamard product.

Equation 5 allows me to estimate marginal costs from the observed prices and shares, and estimated price elasticities. The estimated marginal costs are projected on a set of covariates that flexibly capture heterogeneity across firms and product groups, as well as decreasing marginal costs through time dummies

$$mc_{jrt} = \gamma_0 + fhd_j \cdot (\gamma_{q,fhd} \cdot q_j + \gamma_{e,fhd} \cdot e_j) + (1 - fhd_j) \cdot (\gamma_{q,nfhd} \cdot q_j + \gamma_{e,nfhd} \cdot e_j) + \gamma_{fg} + \gamma_t + \omega_{jrt} \tag{6}$$

where ω is a marginal cost shock; γ_q and γ_e are coefficients on quality and energy efficiency respectively, which I allow to vary based on whether the television has a full-HD panel (fhd). γ_{fg} and γ_t are manufacturer-by-product group, and time fixed effects.

In summary, the second stage provides an expected variable profit function that firms use to evaluate profits from any product assortment choice J in the first stage. A product assortment choice J_{ft} comprises of any number of vectors (g_j, q_j, e_j) such that $g \in \mathbf{G}$, where $\mathbf{G}$ is the set of all Top Runner product groups, $q \in \mathbb{R}$, and $e \in \mathbb{N}$:

$$J_{ft} = \{(g_j, q_j, e_j)\}_{j=1}^{|J_{ft}|}$$

In the first stage, assuming that firms know the distribution of these shocks, but not the realized values, the firms' expected second stage variable profits are given by

$$\pi_{ft}(J_{ft}, J_{-ft}) = \sum_r M_{rt} \cdot \int_{\xi,\omega} \sum_{j \in J_{ftr}} s_{jtr}(J_{ftr}, J_{-ftr}) \left[p_{jtr}(J_{ftr}, J_{-ftr}) - mc_{jtr}\right] dF_{(\xi,\omega)}$$

where M is the market size, and the integral is taken over the demand and marginal cost shocks. The pricing equilibrium gives predicted market shares s from Equation (4), prices p from Equation (5), and marginal costs mc from Equation (6).

Changing any element of J_{ft} affects the firms' expected second stage profits. For instance, increasing the efficiency of a product to $e'_j = e_j + \Delta e$ changes the consumers' utility in Equation (2) (through a increase in d_j as well as by potentially affecting $stars$), the firm's marginal cost in Equation (6), and subsequently the equlibrium prices and market shares through Equations (4) and (5).

3.1.3 The first stage: Product introduction

In the first stage, using the expected profit function π_{ft}, firms simultaneously decide on a set of goods to release for the time period, J_{ft}.

Base model Firstly, I describe the model in the absence of regulation. At the beginning of the first stage, firms observe realizations of fixed costs shocks ν_{jt} associated with the release of all possible products. The firms then decide on a set of products to introduce in that time period, J_{ft} (the domain of J_{ft} is defined in the previous subsection).

Firms incur a fixed cost of $F_{ft} = \sum_{j \in J_{ft}} (F_{jt} + \nu_{jt})$, which is additive in the fixed costs associated with each product. A functional form for $F_{jt} = F(f, t, g_j, q_j, e_j)$, and restrictions on ν are discussed in the next section.

The function π_{ft}^{F} captures the total expected profits from the current period, net of fixed costs,

$$\pi_{ft}^{F}\left(J_{ft}, J_{-f,t}\right) = \underbrace{\pi_{ft}\left(J_{ft}, J_{-f,t}\right)}_{\text{second-stage expected profits}} - \underbrace{\sum_{j\in J_{ft}}\left(F_{jt}+\nu_{jt}\right)}_{\text{fixed costs}}$$

To clarify notation, for now I assume that firms have perfect information about rivals' contemporary cost shocks and strategies when making decisions about J_{ft}.[23] Based on the assumption of static demand and no sunk costs, in the absence of regulation, each period firms simultaneously set J_{ft} so as to maximize the current total expected profits in every period

$$\max_{J_{ft}} \pi_{ft}^{F}\left(J_{ft}, J_{-f,t}\right) \tag{7}$$

In summary, the firm's problem without the regulation is independent over time periods, and the firm chooses the number of televisions to release, as well as the product group, quality, and efficiency of each of the products.

3.2 The regulation

The regulation introduces a series of restrictions on the firm's action space. In this section, I drop the subscripts related to product groups (g), because the regulation plays out independently across groups.

From the firm's perspective, the regulation changes its incentives depending on the timing of the decisions. Before the setting of the standard, T_{pre}, firms realize that releasing an efficient product may change the future regulation level. Specifically, for each product group, firms believe that the most efficient product sets the minimum efficiency threshold after the regulation goes into effect T_{post}:

$$\overline{e}_{reg} \equiv \max_{j\in J_{T_{pre}}} e_j \leq \min_{j\in J_{T_{post}}} e_j \tag{8}$$

There is also an interim period $T_{interim}$ in which the future threshold level has been determined, but the regulation is not yet enforced. The threshold values are set following the last period of T_{pre}. I now describe how the regulation changes the firm's problem in each of these time periods.

3.2.1 The firm's problem in T_{post}

In $t \in T_{post}$, the constraints are exogenous because firms' actions cannot affect the standards. In these time periods, I modify the firm's problem, Equation (7), such that it solves

$$\max_{J_{ft}} \pi_{ft}^{F}\left(J_{ft}, J_{-f,t}\right) \quad \text{s.t.} \quad \min_{j\in J_{ft}} e_j \geq \overline{e}_{reg} \tag{9}$$

[23] In the estimation procedure, I employ moment inequalities to estimate the fixed costs parameters. These inequalities rely on the logic of revealed preferences, and allow me to be agnostic about the specific equilibrium selection mechanism that lead to the observed outcomes (see Section 4). These assumptions about the firms' information sets are not necessary, but are introduced here to simplify notation.

every period: firms must sell televisions that are more efficient than $\overline{e}_{reg}$.

To simplify subsequent notation, for a moment I assume the presence of a unique equilibrium to the firms' problem shown in Equation (9), and define

$$\Pi_{f,T_{post}}\left(\overline{e}_{reg}\right) \equiv \sum_{t \in T_{post}} \delta^{t-t_{post(1)}} \cdot \pi_{ft}^{F}\left(J_{ft}^{*}, J_{-f,t}^{*}\right) \tag{10}$$

where $\left(J_{ft}^{*}, J_{-f,t}^{*}\right)$ is the equilibrium product offerings that solves Equation (9) for all firms, and $t_{post(1)}$ refers to the first period in T_{post}. This expression highlights that the firm's profits in T_{post} are determined solely by the standard level $\overline{e}_{reg}$.

3.2.2 The firm's problem in $T_{interim}$

The regulation does not affect the firm's problem in $t \in T_{interim}$. The future regulatory level has already been set, and because by construction the base problem is static, the firm's actions in $T_{interim}$ do not influence market outcomes in T_{post}. Therefore, the firm's problem is not affected, and firms merely compete in a static equlibrium with payoffs determined by Equation (7) every period.

3.2.3 The firm's problem in T_{pre}

What remains to be specified is the firm's problem for $t \in T_{pre}$. The firm's problem in T_{pre} is a finite-horizon dynamic problem: the firm's action today affects the future stream of profits in T_{post} by changing the level of the standard that is implemented. Recall that in the absence of the regulation, each time period does not interact with each other. Therefore, to capture the regulated firms' forward-looking incentives, I need to specify (1) state variables that firms are endowed with, as well as (2) beliefs about future regulation levels and profits based on the state variables.

In practice, I model T_{pre} to be comprised of several time periods. Because the threshold values are set immediately after the last period of T_{pre}, denoted as t_{set}, this means that firms have several opportunities to tighten the future standard level in the months leading up to t_{set}. A state variable $\overline{e}_{t-1}$ is defined to represent the maximum efficiency of products released across firms up to the previous time period $t-1$,

$$\overline{e}_{t-1} = \max_{j} e_j, \quad j \in \{J_\tau | \, \tau \leq t-1\}$$

where J_τ is the set of all televisions released at time τ. The state variable is relevant because the most efficient product released up to the end of T_{pre} defines the future efficiency standard, $\overline{e}_{reg} = \overline{e}_{t_{set}}$, and influences profits in T_{post} by affecting $\Pi_{f,T_{post}}\left(\overline{e}_{reg}\right)$. The state variable is updated at the end of each period if the most efficient product released in the current period is more efficient than $\overline{e}_{t-1}$,

$$\overline{e}_t = \max\left(\overline{e}_{t-1}, \max_{j \in J_t} e_j\right)$$

Firms make product release decisions with knowledge of the realization of the state variable $\overline{e}_{t-1}$.

The firm's problem in the last month of T_{pre} illustrates the transition of the state variable. In this month, the firms maximize the sum of profits that can be earned in this month, and those that be made once the standard is enforced in T_{post},

$$\max_{J_{ft}} \underbrace{\pi^F_{ft}\left(J_{ft}, J_{-f,t}\right)}_{\text{today's profits}} + \underbrace{\delta^{t_{post(1)}-t} \cdot \Pi_{f,T_{post}}\left(\bar{e}_{reg}\right)}_{\text{expected total profits in } T_{post}} \quad \text{s.t. } \min_{j \in J_{ft}} e_j \geq \bar{e}_{t-1}$$

where $t_{post(1)}$ refers to the first period in T_{post}. $\bar{e}_{reg}$ is given by $\bar{e}_{reg} = \max\left(\bar{e}_{t-1}, \max_{j \in \left\{J_{ft}, J_{-f,t}\right\}} e_j\right)$: firms know that the future standard level is either the most efficienct product released up to $t-1$, or the most efficienct product released today. The procedure used to empirically estimate the function $\Pi_{T_{post}}$ are described in Section 4.

In the more general case, when there are trailing periods in T_{pre}, firms need to have expectations about future product offerings $J_{f\tau}$, standard levels $\bar{e}_{reg}$, and demand and cost shocks based on the current state variable $\bar{e}_{t-1}$ and actions J_t. To exhibit the most general form of the firm's problem, I explicitly write out the firm's problem as a finite sum of the future stream of profits, because the problem is finite-horizon:

$$\max_{J_{ft}} \underbrace{\pi^F_{ft}\left(J_{ft}, J_{-f,t}\right)}_{\text{today's profits}} + \underbrace{\sum_{\tau \in T_{pre}, \tau > t} \delta^{\tau - t} \cdot E\left[\pi^F_{f\tau}\left(J_{f\tau}, J_{-f,\tau}\right) \middle| \bar{e}_t\right]}_{\text{expected total profits in subsequent periods of } T_{pre}}$$

$$+ \underbrace{\delta^{t_{post(1)}-t} \cdot E\left[\Pi_{f,T_{post}}\left(\bar{e}\right) \middle| \bar{e}_t\right]}_{\text{expected total profits in } T_{post}} \quad \text{s.t. } \min_{j \in J_{f\tau}} e_j \geq \bar{e}_{\tau-1} \; \forall \tau \in T_{pre}, \tau \geq t \tag{11}$$

where $\bar{e}_t$ is endogenously determined as $\bar{e}_t = \max\left(\bar{e}_{t-1}, \max_{j \in \left\{J_{ft}, J_{-f,t}\right\}} e_j\right)$, δ is a monthly discount factor, and $t_{post(1)}$ refers to the first period in T_{post}.

In Equation (11), evaluating $\pi^F_{f\tau}\left(J_{f\tau}, J_{-f,\tau}\right)$ for each of the subsequent periods involves specifying beliefs about future product offerings $\left(J_{f\tau}, J_{-f,\tau}\right)$ as a function of $\bar{e}_t$, which can be costly to evaluate. In this study the general expression in Equation (11) is simplified to Equation (12) by making assumptions that keeps the model tractable:

$$\max_{J_{ft} | \bar{e}_{t-1}} \underbrace{\pi^F_{ft}\left(J_{ft}, J_{-f,t}\right)}_{\text{today's profits}} + \underbrace{\sum_{\tau \in T_{pre}, \tau > t} \delta^{\tau - t} \cdot \left[\pi_{f\tau}\left(J_{ft}, J_{-f,t}\right) - \sum_{j \in J_{ft}} F_{j\tau}\right]}_{\text{expected total profits in subsequent periods of } T_{pre}}$$

$$+ \underbrace{\delta^{t_{post(1)}-t} \cdot \Pi_{f,T_{post}}\left(\bar{e}_t\right)}_{\text{expected total profits in } T_{post}} \quad \text{s.t. } \min_{j \in J_{ft}} e_j \geq \bar{e}_{t-1} \tag{12}$$

where $\bar{e}_t = \max\left(\bar{e}_{t-1}, \max_{j \in \left\{J_{ft}, J_{-f,t}\right\}} e_j\right)$. The key assumptions are that, firms have perfect information about $\pi_{f\tau}$ for $\tau \in T_{pre}$, $\tau > t$; and firms proxy for future product offerings by substituting them with today's, $E\left[J_\tau\right] = J_t$ for $t, \tau \in T_{pre}$, $\tau > t$. I elaborate on the assumptions that lead to the expression in

Equation (12) in the remainder of this section, as well as the limitations of this approach.

Firms commonly use simplifying heuristics to solve difficult dynamic problems. The operations literature documents how firms often make future production plans — an infinite horizon problem — by solving a series of finite horizon problems to approximate the optimal solution. In particular, firms commonly use rolling horizon decision rules (Baker, 1977, Sethi and Sorger, 1991), in which every period, a finite horizon period is solved and only the first period decision is implemented. The following period's decisions are made by solving the finite horizon problem again, but with updated information from the previous period. These decision rules are practical for firms because extensive future forecasting is costly and the projections tend to be noisy.

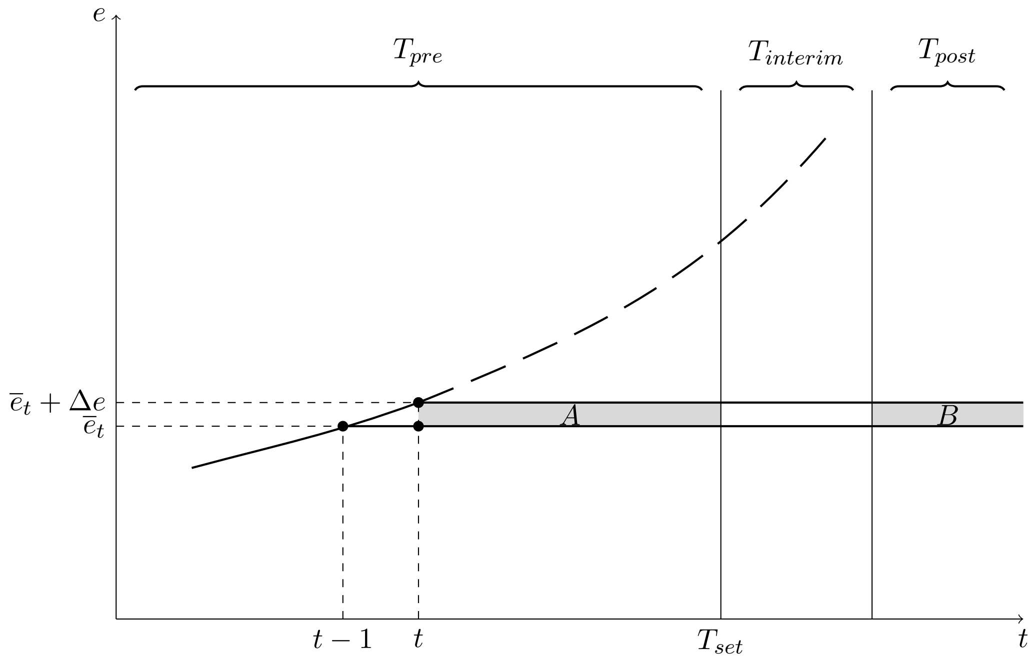
In the context of televisions, the projections may be noisy because popular trends in functionality and designs — the consumer reception of the non-energy efficiency component of televisions — fluctuate rapidly over time. For example, 3D televisions were intensively promoted at Japanese retailers around 2011, but quickly lost popularity after the 2012 London Olympics. It may have been difficult to predict the abrupt decline in popularity of 3D televisions after the Olympics. Because these projections can be noisy and costly for firms, I assume that a reasonable proxy that firms use for future product offerings, within the time frames of T_{pre}, is the current period's product offerings. This assumption would be less tenable if firms could accurately predict upcoming trends in TV design and functionality, or if the window of projection were longer. In my model, the time span of T_{pre} is at most 10 months (April 2008 through February 2009); i.e. firms need only make projections for up to 9 months into the future.

On the other hand, the assumption that firms know future π means that firms have foresight about how mean marginal costs and demand shocks will transition over the future time periods. In particular, firms know the future time-fixed effects for demand (β_{ft} in Equation (2)), marginal costs (γ_t in Equation (6)), as well as time-varying components of fixed costs. Technological change has been assumed to be exogenous, and many of the demand shocks in this market are seasonal or known well in advance, such as end-of-the-year sales or the termination of analog broadcasting (Figure 8 in the appendix illustrates demand shocks in this market). The rolling decisions in T_{pre} are thus assumed to be made conditional on knowledge of the time varying components of demand and costs, but with a simple heuristic for future product offerings within T_{pre}. The decisions are rolling in the sense that every period, the choices are made with updated information about the future minimum efficiency threshold, captured by $\overline{e}_{t-1}$.

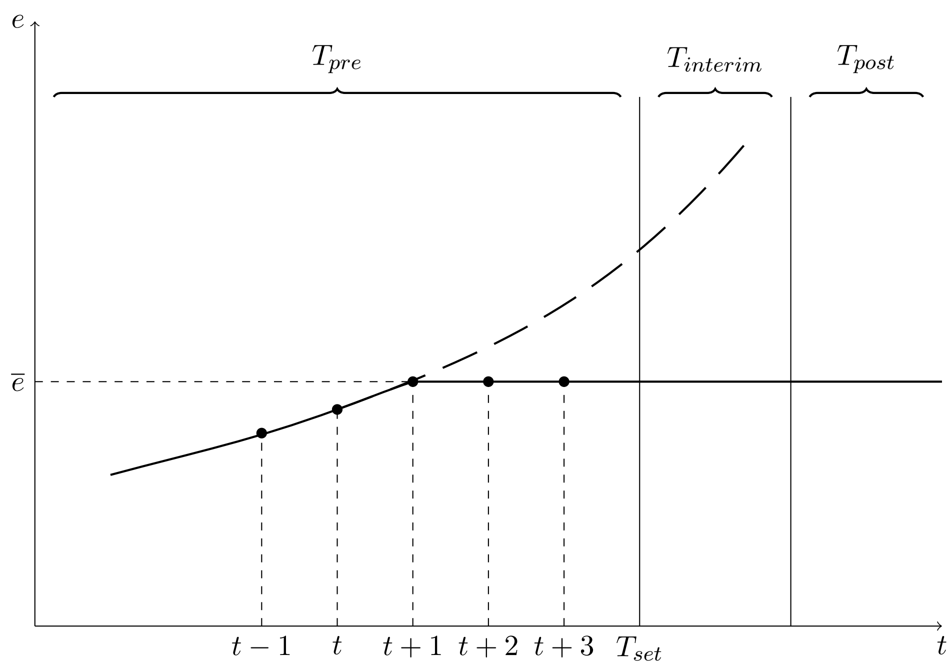
A key implication of the assumptions is that the firm believes that the future threshold level $\overline{e}_{reg}$ is $\overline{e}_t$:

$$E\left[\overline{e}_{reg}|\,\overline{e}_t\right] = \overline{e}_t$$

Figure 5a shows the trade off that a firm faces when it is deciding to release a new product. In period t, suppose that we observe a firm releasing a product with efficiency of $\overline{e}_{t-1} + \Delta e$. This is Δe more efficient than the most efficient product that has been released thus far. By releasing this product, the firm is now able to release products with efficiency of up to $\overline{e}_{t-1} + \Delta e$ without affecting the future standard in the subsequent periods of T_{pre} (shaded area (A) in Figure 5a). The trade off is that, because the firm has tightened the future threshold value by Δe, it can no longer sell products that are less efficient than $\overline{e}_{t-1} + \Delta e$ after the regulation is enforced (shaded area (B) in Figure 5a).



(a) The firm makes a trade off between the ability to sell more efficient products in T_{pre} (i.e. to sell products that lie in shaded area (A)), and the inability to sell products less efficient products in T_{post} (product that lie in shaded area (B)). The dotted line indicates the trend of the most efficient product that would have been sold if the regulation did not exist.



(b) The firm is willing to increase the maximum efficiency of its products up to period $t+1$. After $t+1$, it is no longer willing to do so.

Figure 5: Heuristic for firms' beliefs

In Figure 5a, the fact that the firm was willing to release the product at $\overline{e}_{t-1}+\Delta e$ means that the expected change in profits by making this trade off was positive. Equation (12) implies that the change in profits from being able to introduce products in the shaded area (A) in Figure 5a is given by

$$\underbrace{\sum_{\tau\in T_{pre},\tau\geq t}\left\{\delta^{\tau-t}\cdot\left[\pi_{f\tau}\left(J_{ft},J_{-f,t}\right)-\sum_{j\in J_{ft}}F_{j\tau}\right]\right\}}_{\text{Expected base profits in } T_{pre} \text{ from perspective of } t}-\underbrace{\sum_{\tau\in T_{pre},\tau\geq t}\left\{\delta^{\tau-t}\cdot\left[\pi_{f\tau}\left(J'_{ft},J_{-f,t}\right)-\sum_{j\in J'_{ft}}F_{j\tau}\right]\right\}}_{\text{Expected ctrfactual profits in } T_{pre} \text{ from perspective of } t} \tag{13}$$

where J_{ft} is the product assortment without the good j' that has efficiency $\overline{e}_{t-1}+\Delta e$, and J'_{ft} is the product assortment with j'. The change in profits due to the inability to sell products in the shaded area (B) in Figure 5a, i.e. the firms' expected change in profits in T_{post}, is given by

$$\Delta\Pi_{f,T_{post}}=\Pi_{f,T_{post}}\left(\overline{e}_{t-1}\right)-\Pi_{f,T_{post}}\left(\overline{e}_{t-1}+\Delta e\right) \tag{14}$$

What forces are this heuristic able to capture? Take for example a market in which the firm is willing to gradually increase the threshold in $t-1$ through $t+1$, as illustrated in Figure 5b. Under the heuristic assumed in Equation (12), at time $t-1$ firms believe that the eventual minimum threshold that is implemented is $\overline{e}$. In other words, firms have no beliefs about how the threshold level may continue to tighten in the following time periods. A pattern of a gradual increases in efficiency in data would be rationalized by the exogenous decreases in costs over time.

On the other hand, the heuristic does captures how the firm's trade off between profits in T_{pre} and T_{post} changes as the number of periods remaining in T_{pre} decrease. Intuitively, the firm should be more willing to increase efficiency in T_{pre}, even if it adversely affects profits in T_{post}, when there are many periods remaining until the threshold value is set. In the diagram, the efficiency of most efficient product settles at $\overline{e}$ at period $t+2$. The firm is no longer willing to increase the threshold, because the loss of profits in T_{post} becomes more significant relative to the gains in profits in T_{pre}.[24]

A key limitation is that the heuristic does not capture the change in product offerings in the remaining periods of T_{pre}. More specifically, the heuristic does not capture rivals' responses to changes in the threshold level. Imagine that at period t, a rival firm increases the future threshold level to $\overline{e}$. In response to this, other firms are likely to re-optimize their product offerings: it is now "free" for the other firms to increase the efficiency of its products up to $\overline{e}_t$, in the sense that the firms' actions do not affect the future threshold and profits. In turn, this force may decrease the benefits of raising the threshold level in the first place. This situation may be particularly problematic if there are many months left in the pre-regulatory regime (T_{pre}).[25]

[24]In the Appendix, I further elaborate whether the assumption $E\left[\overline{e}_{reg}|\,\overline{e}_t\right]=\overline{e}_t$ is reasonable by looking at firm behavior in T_{pre} (see Section 9.1.4).

[25]One solution is to prepare a function Π_{TPre}, which calculates the firms' expected profits in (A) in Figure 5a, as function of $\overline{e}_t$. That is, just as future profits in T_{pre} are proxied by the function Π_{TPost} (which only takes $\overline{e}_t$ as arguments), a similar function could be constructed for future expected profits within T_{pre}.

3.3 Discussion

In this section, I discuss the implications of assuming static demand and exogenous techological change.

Static demand In technology markets, dynamic demand typically allows firms to strategically price and design products for consumers whose composition is changing over time. For example, early products tend to have a higher markup and attract a group of consumers who are different from those who can wait until the market has matured and prices have stabilized. Such forces are particularly important for highly differentiated goods such as gaming software or books, where consumers clearly have an incentive to take advantage of firms' skimming strategies (Nair, 2007). They can also be important for products in which clear improvements in a product's key attribute induce consumers' forward-looking behavior, such as the clock speed of CPUs (Gordon, 2009).

Unlike these studies, I assume static demand. Because particular television models are less differentiated compared to software or books, consumers do not necessarily have to make intertemporal substitutions and can instead opt to purchase a similar product that is currently available. Consumers often make replacement decisions when their current television reaches its end of useful life or when consumers move to a new house.[26] This would suggest that intertemporal dynamics are less significant in this market. Conlon (2010) estimates a dynamic demand system in the U.S. television market, and finds that in response to an increase in the price of a Sony television today, roughly 70% of consumers who substitute to other models do so within the same time period.

Yet the rapid improvement in the functionalities of televisions, coupled with the decline in prices, suggests a clear opportunity for consumers to gain from being forward-looking. While a static model cannot fully account for such dynamics, I attempt to mitigate this limitation by estimating heterogeneity across consumers using a set of macro moments. These macro moments explicitly capture how the type of consumer (households by income brackets) purchasing televisions evolves over time. Part of the change in composition of consumers over time, driven by forward-looking behavior, will be captured by this heterogeneity.

Finally, the assumption of static demand assumes away any interaction of dynamic demand with the regulation. The provision of technology is fundamentally a dynamic question that interacts with forward-looking consumers, as firms need to decide when to eliminate older products in favor of newer ones. If a firm hopes to disregard certain technologies in the future to encourage consumers to purchase today, the regulation may help the firm commit to such a strategy. This is typically a challenge even for the durable good monopolist (Coase, 1972). In practice, however, consumers did not have an opportunity to learn about the firms' dynamic incentives because the Top Runner program was not described on standardized product labels. Firms also did not advertise the dynamic incentives that they faced under the regulation.

Technological change In the model I have assumed that technological change is exogenous. Anecdotally, it is unlikely that the regulations in the Japanese television market were drivers in determining these multi-

[26]While consumers are most likely to purchase televisions in December, my data suggests that March is also a month of high demand for televisions (see trend of purchases in Figure 8). Because the fiscal year starts in April, students and new workers typically move to new residences in March. Such purchases are likely to be made without intertemporal considerations.

national firms' investments in R&D. The Japanese television market is no more than a few percentage points of the world television market by share of quantity sold. Moreover, a main driver of reductions in costs in this industry is economies of scale achieved by investments in larger production lines by upstream panel manufacturers. Such roadmaps are laid out years in advance in response to the global outlook of demand, not only for televisions, but also for other applications of LCD panels such as computer monitors and mobile devices. Finally, some of the improvements in technology that enable greater efficiency, such as advances in LED technology, are arguably exogenous to the conditions in the television market. The assumption of exogenous technological change is consistent with a model of technological change in which, similar to Moore's law in the production of integrated circuits, the pace of technological improvement in the near future is foreseeable.[27]

This model also assumes that the costs associated with product introduction are not sunk. In practice, as discussed in Section 2, some of the investments necessary for improving efficient efficiency are sunk in nature. These include developing custom circuits to implement local dimming technologies, and researching better configurations of LED backlights and optical films to enhance energy efficiency. While these costs may be sunk, because the some components of thin-panel televisions are highly modular, and product designs are based on common architectures, the incremental costs that firms incur to localize models to meet the demands of the Japanese market are may be reasonably approximated by fixed costs.[28]

One aspect of technological change is that it can enable a more preferable trade-off between attributes in a product. Klier and Linn (2012), for instance, use a linear model to capture the trade-off of automobile characteristics, such as weight, horsepower, and miles per gallon. Unlike the characteristics in the automobile industry, however, energy efficiency and quality can be provisioned independently in television sets. For example, product design and advertising improve the perceived quality of the television, without affecting efficiency.

The firms' costs of improving quality, similar to costs of improving energy efficiency, are assumed to be exogenous. A determinant of the cost of increasing quality is the firm's past stock of consumer goodwill and reputation, which is independent of the technological change that is happening in this market. The Sony brand, for instance, is said to have gained global prominence after its successful CRT television sets, Trinitrion, sold almost three hundred million units worldwide.[29] This may make it easier for Sony to improve quality relative to efficiency in LCD televisions.

[27] Haitz's Law, the LED counterpart of Moore's Law, suggests that the cost per lumen from LEDs decreases over time by a constant factor. Nishimura's law predicts that the production technology used for flat panel displays advances by one generation every three years. The presence of such laws suggest some predictability and stability in the path of future innovation.

An alternative formulation is to explicitly model firms' competitive incentives to invest in innovation as Goettler and Gordon (2011) do in the duopolistic CPU market. In the time horizon considered in this study, competitive forces within the television industry are not the main drivers of improvements in energy efficiency and decreases in costs.

[28] Similar to how automobiles are designed around common vehicle frames (chassis), televisions are based on common architectures, from which features are manipulated to meet design specifications (Luh et al., 2006).

[29] Ohga, Norio. Doing It Our Way, A Sony Memoir. 2008. 32-37.

4 Estimation and identification

4.1 Second stage

The estimation procedure for the second stage model closely follows Nevo (2001), complemented with macro data for identifying heterogeneity, as in Petrin (2002). In this subsection I primarily discuss issues regarding sources of endogeneity and identification of heterogeneity.

In the consumer's utility function, Equation (2), there are two unobservables from the econometrician's perspective. ε is assumed i.i.d. and has the extreme value distribution, while $\tilde{\xi}$ is unobserved product quality, which is region and time period specific. We may be concerned that $\tilde{\xi}_{jrt}$ affects pricing decisions.

Many of the demand shocks for televisions are likely to occur at the same time across regions, because holidays are common across Japan, and major sport events are broadcasted nationally. A potential source of concern are demand shocks that are firm specific, and common across regions. For example, a firm may be an sponsor of the International Olympic Committee, and hence benefit in demand during the Olympic Games. These firm-time specific shocks are controlled by firm-by-period fixed effects. The remaining variation in $\tilde{\xi}_{jrt}$ is region and product specific deviations from the average firm-period demand shock. These may include shocks for specific kinds of television within firms (such as for full-HD Toshiba televisions). BLP instruments which help control for these shocks are discussed below.

Identification of heterogeneity is another challenge for estimation when using aggregate data. Heterogeneity in the relative trade off that consumers are willing to make between price and energy efficiency will affect how firms position goods along the energy efficiency spectrum. In my model I assume discrete heterogeneity, allowing for six household types that correspond to six income brackets. I estimate heterogeneity by supplementing macro moments which explicitly capture the change in composition of consumers over time. I use data from the Japanese household expenditure survey, which shows the average quantity and purchase price of televisions by groups of finely defined household income brackets. This strategy is similar to previous studies that couple aggregate market shares data with other data that summarizes consumer behavior across another margin (Petrin, 2002, Albuquerque and Bronnenberg, 2009). The moments that I match are the sales weighted purchase price, and share of consumers who purchase any television, for each income group:

$$\begin{cases} E\left[\sum_{j\in J_t} s_{ijt}\cdot p_{jt} \Big/ \sum_{j\in J_t} s_{ijt}\right] \\ E\left[\sum_{j\in J_t} s_{ijt}\right] \end{cases} \quad \text{for } i\in\{1,\ldots,6\} \tag{15}$$

For normalization, the moments are evaluated relative to that of the lowest income group, $i = 1$.

These moments are extremely helpful in identifying heterogeneity. Within time periods, the macro-data indicates that higher income households tend to purchase more televisions and that those televisions tend to be more expensive. On average across the four years, the highest income group (household income of over \$100,000) purchased televisions that were 1.27 times more expensive than those purchased by the lowest income group (less than \$20,000). Over time periods, the macro data shows how the market initially attracted more high income households. Only in the latter half of the data period did more low income households purchase more larger shares of televisions. In 2008, the highest income group purchased 27% of all televisions; in 2011 they purchased 21%. Recalling that prices decreased drastically over the data period, the macro data is able to attribute the early television purchases to those by generally more high income households.

The model incorporates heterogeneity for price sensitivity and the constant. While the macro-moments provide information on the quantity and price of televisions that were purchased by income groups, they do not directly inform the type of television that was purchased. To control for endogeneity in prices and to identify heterogeneity, a series of BLP instruments are used to form additional moments. BLP instruments reflect the number of unique models sold by own- and rival-firms: for all TVs; for TVs that have the same pixel density (FHD); and for TVs that are in the same TV size group, within a given period and region.

In the estimation procedure for the main second stage model, I estimate the demand equation first, then plug in the estimated price coefficients in the supply side equation. The demand model is estimated with GMM using the moment conditions $E\left[\tilde{\xi}_{jrt} z^d_{jrt}\right] = 0$, and macro-moments specified in Equation (15). z^d are demand instruments, namely the covariates in the indirect utility function (excluding price), and BLP instruments.[30] With the demand model estimates, supply side parameters γ can be backed out using OLS on Equation (6).

Decomposing the product dummy The timing assumption, that the demand shocks (ξ) and marginal cost shocks (ω) are revealed after product assortments are chosen, allows me to consistently estimate the equation

$$d_j = \beta_e \cdot e_j + \beta_{size} \cdot size_j + \beta_{size2} \cdot size_j^2 + \beta_g + x_j \beta + \overline{\xi}_j \tag{16}$$

using OLS.

Although the timing assumption is a commonly maintained assumption for estimating models with endogenous product characteristics (Sweeting, 2013), the extent to which this assumption is valid will affect the estimate of a key coefficient β_e. The more the covariates capture the systematic determinants of product quality, the less likely the coefficients will be biased. To this end, the vector x_j includes a extended set of covariates as shown in Table 10. These covariates include many quantifiable variables that are listed in manufacturers' product catalogs. For example, the contrast ratio of the screen (a indicator of the image quality of the screen), as well as speaker type and the kind of ports that the television has, are included.

The direction of the potential bias is difficult to sign. One variable that was found consistently in manufacturer catalogs, but missing from the detailed covariates is speaker wattage. A television with speakers of high wattage consumes more energy, and would have a large unobservable shock because it is considered a preferable attribute. This would bias the coefficient β_e downwards. On the other hand, manufacturers' catalog suggests that more premium models tend to be coupled with more superior energy efficiency levels. This is consistent with accounts of technical reports which suggest that firms are typically only willing to design custom drivers that improve energy efficiency for premium models (Park, 2011). In this case, the presence of any unobservable that is not captured, such as product design, is likely to introduce a upward bias for β_e.

[30] The GMM objective function is listed in the appendix (Section 9.1.5).

4.2 First stage

I recover the fixed cost parameters by relying on the logic of revealed preferences. A set of inequalities are constructed to back out parameters that best rationalize the behavior observed in the data, by calculating counterfactual profits that a firm would have made if another set of products were released. This paper follows the estimation procedure developed in Pakes et al. (2015).

Accounting for the regulation in T_{pre} helps rationalize the observed pattern of ratcheting, and better understand heterogeneity across firms in terms of their fixed costs. If firms are ratcheting down in T_{pre}, their product offerings will seem similar because their respective products are bunched around the standard level (100% achievement percentage). Hence, if the regulation is not accounted for, the fixed cost estimates across firms will tend to look similar. On the other hand, once the regulation is accounted for, firms' expected profits in T_{post} will inform how costly it was to hold back on releasing more efficient products. For instance, it may be that some firms are forgoing more profits than others by avoiding the introduction of more efficient products. Conversely, some firms may have offered a relatively similar set of products even if the regulation didn't exist. By specifying firms to have beliefs that are consistent with the regulation, I can control for ratcheting patterns in the data for estimation.

The underlying intuition of the inequalities are straightforward. Assume for a moment that we have the true function π, and a simple additive fixed cost shock ν. If the model was limited to a single time period, the profit that a firm makes from releasing the set of products that it did in the data J_f^{Data} must be at least as large as the profit from releasing J_f^{Data} and an additional product j:

$$\pi_f^F\left(J_f^{Data}, J_{-f}^{Data}\right) \geq \pi_f^F\left(J_f^{Data} \cup j, J_{-f}^{Data}\right) \tag{17}$$

or identically,

$$\pi_f\left(J_f^{Data}, J_{-f}^{Data}\right) - \sum_{k \in J_f^{Data}} (F_k + \nu_k) \geq \pi_f\left(J_f^{Data} \cup j, J_{-f}^{Data}\right) - \sum_{k \in J_f^{Data}} (F_k + \nu_k) - \underbrace{(F_j + \nu_j)}_{\text{additional fixed costs}}$$

which implies

$$F_j + \nu_j \geq \pi_f\left(J_f^{Data} \cup j, J_{-f}^{Data}\right) - \pi_f\left(J_f^{Data}, J_{-f}^{Data}\right) \tag{18}$$

In words, the fact that the firm released J_f^{Data} instead of $J_f^{Data} \cup j$ gives us an lower bound on the fixed cost of releasing product j: the firm was not willing to introduce an additional model and enjoy larger second stage profits. It suggests that the increase in fixed costs that would have been necessary to do so must have been larger than the additional second stage profits. Estimation amounts to making empirical analogues of the means of such inequalities, to average out the error terms without causing selection. By creating similar inequalities that consider other alternative product sets, we can create bounds on various fixed cost parameters.

A commonly noted benefit of this methodology is that an equilibrium selection mechanism need not be specified. Entry games are known to have multiple equilibria, and hence, different parameter values can lead to the same observed outcome (Berry and Reiss, 2007). One solution to this is to take a stance on how the entry game was played (such as assuming a sequential ordering of firms, so that one firm is allowed to play before another). In this study, I can avoid taking such a stance (in the static case) by relying on the necessary conditions implied from the logic of reveal preferences.

An additional benefit of this methodology is that I am able to construct inequalities that are intuitive and relevant for my particular empirical setting. For example, if firms in a particular product group are manufacturing televisions with similar efficiency levels, we might think that these firms have similar costs to provision energy efficiency. Using this intuition, I can make a series of inequalities in which I evaluate changes in a firm's profit from introducing a product similar to her competitors to better infer the how firms' costs are similar (or dissimilar) to each other.

In practice, I do not have the true π function, and do not know the true fixed cost shocks ν. Therefore, additional assumptions are necessary on the structure of the shocks. Firstly, I assume a functional form for fixed costs that allows for rich heterogeneity across firms. When a product is introduced, firms incur a one-time fixed cost to release the product, expressed as

$$F_{jt} + \nu_{jt} = \underbrace{F^0_{fg} + F^{0,t}_{fg} \cdot t + \nu^0_{1,jt} + \nu^0_{2,gt}}_{\text{constant}} + \underbrace{\left(F^e_{fg} + F^{e,t}_{fg} \cdot t + \nu^e_{1,jt}\right) \cdot e_j}_{\text{efficiency}} + \underbrace{\left(F^q_{fg} + F^{q,t}_{fg} \cdot t + \nu^q_{1,jt}\right) \cdot q_j}_{\text{quality}} \tag{19}$$

where F^0_{fg}, $F^{0,t}_{f}$, F^e_{fg}, $F^{e,t}_{fg}$, F^q_{fg} and $F^{q,t}_{fg}$ are parameters to estimate. The ν shocks are decomposed into two parts. ν_2 shocks are those that firms condition on when deciding on product releases. On the other hand, ν_1 shocks are random shocks that are unknown to the firm when it is deciding on J_{ft}. They generate ex-post regret that firms seem to experience from the perspective of the econometrician. Both ν_1 and ν_2 shocks are assumed have unconditional expectations of zero over t.

In this formulation, the only "structural" shock that firms condition on, the $\nu^0_{2,gt}$ term, is common across firms within a product group and time period, and do not interact with energy efficiency. All else equal, this formulation means that in the earlier time periods before the threshold is set, a firm may be reluctant to release a highly efficient product because they believe that the future profit losses due to a more stringent threshold is large, or because the realization of the unobservable fixed cost shock was large. Because the draw is common across firms, the assumption allows me to use information from other firms to infer the magnitude of the unobserved shock, and decompose the magnitude of these two forces. If these shocks were independent across firms ($\nu^0_{2,fgt}$), or if a shock pertinent to F^e existed (ν^e_2) the current set of inequalities would not be sufficient to estimate the parameters.

For the purpose of exposition, I define the functions r, Δr, and ΔF, which form the basis of the inequalities. r returns the expected profits that are relevant for the firm's current product assortment decisions; Δr is the change in expected profits from considering an alternative set of products; and ΔF is associated change in fixed costs.

The function r returns the expected profits from offering the set of goods J_{ft} given rivals' product offerings $J_{-f,t}$ and fixed cost parameters F. For $t \in T_{interim}$ and $t \in T_{post}$, the estimated expected profits are given by

$$r_{ft,1}\left(J_{ft} \middle| J_{-ft}\right) = \hat{\pi}_{ft}\left(J_{ft}, J_{-f,t}\right)$$

For $t \in T_{pre}$, the firm is evaluating the profits not only for this time period, but for the remaining periods in $t \in T_{pre}$, and well as for $t \in T_{post}$. Therefore, for $t \in T_{pre}$, the estimated expected profits that are relevant for choosing product offerings are given by

$$r_{ft,2}\left(J_{ft}\middle|\, J_{-f,t}, \overline{e}_{t-1}, F\right) = \sum_{\tau\in T_{pre},\tau\geq t}\left[\delta^{\tau-t}\cdot\hat{\pi}_{f\tau}\left(J_{ft}, J_{-f,t}\right)\right] + \delta^{t_{post(1)}-t}\cdot\hat{\Pi}_{f,T_{post}}\left(\overline{e}_t\middle|\, F\right)$$

where each element of $\overline{e}_t$ is endogenously determined such that $\overline{e}_{g,t} = \max\left\{\max_{j\in J_{g,t}}\left(e_j\right), \overline{e}_{g,t-1}\right\}$.

The function Δr represents the change in expected profits from releasing the counterfactual set of products J'_{ft} instead of the observed set of products J^{Data}_{ft},

$$\Delta r_{ft}\left(J'_{ft}\middle|\, J^{Data}_{ft}, J^{Data}_{-f,t}, \overline{e}^{Data}_{t-1}, F\right) = \begin{cases} r_{ft,2}\left(J^{Data}_{ft}\middle|\, J^{Data}_{-f,t}, \overline{e}^{Data}_{t-1}, F\right) - r_{ft,2}\left(J'_{ft}\middle|\, J^{Data}_{-f,t}, \overline{e}^{Data}_{t-1}, F\right) & \cdots \text{if } t\in T_{pre} \\ r_{ft,1}\left(J^{Data}_{ft}\middle|\, J^{Data}_{-f,t}\right) - r_{ft,1}\left(J'_{ft}\middle|\, J^{Data}_{-f,t}\right) & \cdots \text{if } t\notin T_{pre} \end{cases} \tag{20}$$

is $\left\{J^{Data}_{ft}, J^{Data}_{-f,t}\right\}$ the observed set of products in the data, and J'_{ft} is any modified product offering for firm f.

The function ΔF represents the change in fixed costs from releasing the counterfactual set of products J'_{ft} instead of the observed set of products J^{Data}_{ft},

$$\Delta F_{ft}\left(J'_{ft}\middle|\, J^{Data}_{ft}, F\right) = \begin{cases} \sum_{j\in J'_{ft}} F_{jt} - \sum_{j\in J^{Data}_{ft}} F_{jt} & \cdots \text{if } t\in T_{pre} \\ \sum_{\tau\in T_{pre},\tau\geq t}\left[\delta^{\tau-t}\cdot\left(\sum_{j\in J'_{ft}} F_{j\tau} - \sum_{j\in J^{Data}_{ft}} F_{j\tau}\right)\right] & \cdots \text{if } t\notin T_{pre} \end{cases}$$

The logic of revealed preferences implies that the expected total profits from offering any alternative product set J'_{ft} would be weakly smaller. Using the aforementioned notation this means that

$$\mathcal{E}\left[\Delta r_{ft}\left(J'_{ft}\middle|\, J^{Data}_{ft}, J^{Data}_{-f,t}, F\right) + \nu^{\Delta r}_{1,J'_{ft}}\middle|\, \mathcal{J}_{ft}\right] + \mathcal{E}\left[\Delta F_{ft}\left(J'_{ft}\middle|\, J^{Data}_{ft}, F\right) + \sum_{j\in J'_{ft}}\nu_{jt} - \sum_{j\in J^{Data}_{ft}}\nu_{jt}\middle|\, \mathcal{J}_{ft}\right] \geq 0 \tag{21}$$

where $\nu^{\Delta r}_{1,J'_{ft}}$ is a J'_{ft} specific shock that captures the random error in calculating expected profits using the estimated $\hat{\pi}$ and $\hat{\Pi}$ instead of the true ones. The estimation procedure amounts to constructing sample analogues of Equation (21) in which the ν shocks average out and enable me to infer bounds on F.[31]

I estimate fixed cost parameters for the six major firms, and for the five product groups in which the regulation played a meaningful role, as discussed in Section 2. Parameters for (f, g) combinations in which no product was observed in data are not estimated. In other words, the possibility of firms entering a new product group are not considered. Within the time frame considered in this model, firms respond to

[31] Compare Equation (21) to the expression from the simple example in Equation (18). Equation (18) can be rewritten as

$$\underbrace{\pi_f\left(J^{Data}_f, J^{Data}_{-f}\right) - \pi_f\left(J^{Data}_f \cup j, J^{Data}_{-f}\right)}_{\Delta r\left(J^{Data}_f\cup j\middle|\, J^{Data}_{ft}, J^{Data}_{-f,t}\right)} + \underbrace{\left(F_j\right)}_{\Delta F\left(J^{Data}_f\cup j\middle|\, J^{Data}_{ft}, F\right)} + \nu_j \geq 0$$

Taking the expectation over this expression roughly corresponds to the expression in Equation (21).

regulation by altering the number and attributes of their products, but not by entering new product groups, which would require additional R&D investments.

A key element of the estimation procedure is devising informative counterfactual product offerings. I consider a series of counterfactual product offerings that are informative of the restrictions imposed by the unique structure of the regulation. For instance, consider the example shown in Equation (17), intended to obtain lower bounds on the fixed costs of product introduction. Formally, these bounds are obtained by considering sample analogues of the mean of counterfactual changes in total profits from introducing an additional product

$$\mathcal{E}\left[\Delta r_{ft}\left(J_{ft}^{Data}\cup j'\middle|\, J_{ft}^{Data},J_{-f,t}^{Data},F\right)+\nu_{1,J_f'}^{\Delta r}\right]+\mathcal{E}\left[\Delta F_{ft}\left(J_{ft}^{Data}\cup j'\middle|\, J_{ft}^{Data},F\right)+\sum_{j\in J_{ft}^{Data}\cup j'}\nu_{jt}-\sum_{j\in J_{ft}^{Data}}\nu_{jt}\right]\geq 0$$

When constructing the empirical analogue of this expression, I consider two kinds of counterfactual profits. Firstly, I consider the introduction of an additional product j' that is characterized by quality and energy efficiency equal to the mean of other products in J_{fgt},

$$j'_{fgt,1}\text{ s.t. } q_{j'}=\frac{1}{|J_{fgt}|}\sum_{j\in J_{fgt}}q_j,\ e_{j'}=\frac{1}{|J_{fgt}|}\sum_{j\in J_{fgt}}e_j$$

Secondly, I consider a series of counterfactual profits in $t\in T_{pre}$ in which firms are forced to make products that affect $\bar{e}_t$, and therefore, the stream of future profits. This counterfactual is intended to capture how firms differ in their costs of increasing the future threshold level. For example, some firms may find it very costly to release a highly efficient product that changes the future threshold level. This is accomplished by considering

$$j'_{fgt,2}\text{ s.t. } q_{j'}=\frac{1}{|J_{fgt}|}\sum_{j\in J_{fgt}}q_j,\ e_{j'}=\max{}_{j\in J_{gt}}e_j+\Delta e$$

Let J'_{fgt} be the set of additional products that are considered for a given time period: $J'_{fgt}=\left\{j'_{fgt,1},j'_{fgt,2}\right\}$ if $t\in T_{pre}$, and $J'_{fgt}=\left\{j'_{fgt,1}\right\}$ if $t\notin T_{pre}$. Combining these counterfactual outcomes, the sample analogue is given by

$m_{fg}^{intro}\left(F,z^F\right)=\frac{1}{T}\sum_{t=1}^{T}g\left(z^F\right)\cdot\frac{1}{\left|J'_{fgt}\right|}\times$

$$\left\{\sum_{j'\in J'_{fgt}}\left[\Delta r_{ft}\left(J_{ft}^{Data}\cup j'\middle|\, J_{ft}^{Data},J_{-ft}^{Data},F\right)+\nu_{1,j't}^{\Delta r}+\Delta F_{ft}\left(J_{ft}^{Data}\cup j'\middle|\, J_{ft}^{Data},F\right)+\nu_{j't}\right]\right\}$$

where $\left|J'_{fgt}\right|$ is the size of the set of additional products that were considered for a given time period. Because each time period receives the same ν_2 draw (encapsulated in the $\nu_{j't}$ term), the $\frac{1}{|J_{fgt}|}$ term ensures that time periods are weighted equally. This expression is constructed for each (f,g) combination.

The non-negative function $g\left(z^F\right)$ allows me to interact the moments with any instrument within the firm's information set that is independent of the ν_2 shocks such that $E\left[\nu_2^t\middle|\, z_t^F\right]=0$. An instrument that places more weight on particular time periods, without selecting on ν_2 shocks, are necessary to identify the variation of fixed costs over time. Variables that capture demand shocks that are exogenous to the systematic shock in fixed costs ν_2 are a candidate.

In the Japanese television market, a economic stimulus program which encouraged the replacement of television sets significantly increased the demand for televisions during Q3 2010 through Q1 2011. The timing of the economic stimulus program, which was designed in response to the global economic crisis but implemented with significant delay, is unlikely to be correlated with unobserved cost shocks related to the release of televisions. A set of instruments Z_t^F[32] are chosen to select time periods in relation to this economic stimulus program:

$$z_t^F \in Z_t^F = \{1, \mathbb{1}\left(t \in T_{pre\_eco}\right), \mathbb{1}\left(t \in T_{during\_eco}\right), \mathbb{1}\left(t \in T_{post\_eco}\right)\}$$

where T_{pre_eco}, T_{during_eco} and T_{post_eco} are time periods before, during, and after the economic stimulus program was in place. $g(\cdot)$ is assumed to be the identify function, such that $g(z) = z$.

These instruments identify the parts of fixed costs that vary over time ($F^{0,t}$, $F^{e,t}$, and $F^{q,t}$). For example, the instruments $\mathbb{1}\left(t \in T_{pre\_eco}\right)$ and $\mathbb{1}\left(t \in T_{post\_eco}\right)$ allow me to construct inequalities $m_{fg}^{intro}\left(F, z^F\right)$ in which only the counterfactual profits in the earlier time periods ($t \in T_{pre\_eco}$) and latter time periods ($t \in T_{post\_eco}$), respectively, are considered. Intuitively, the difference in the average counterfactual profits between these two sets of time periods should be indicative of how fixed costs varied over time. Capturing the change in fixed costs over time is important in an market where technology was rapidly changing: the decline in fixed costs over time are likely to have contributed to the general expansion of product line length during the data period.

Similar sets of inequalities that shift the number of products, as well as energy efficiency and quality of particular products, identify the full set of fixed cost parameters. A listing of the moments and counterfactuals used is provided in the appendix in Section (9.1.6). One noteworthy set of inequalities are those obtained by retracting an existing model. These inequalities are informative of the upper bound of fixed costs

$$m_{fg}^{retrac}\left(F, z^F\right) \quad = \quad \left\{\text{sample analogue of (21) s.t. } J_f' = J_f^{Data} \backslash j\right\}$$

This particular set of inequalities is subject to the selection problem. If no products have been not released in a given (f, g, t) combination, I am not able to consider counterfactual profits from removing a product. Ignoring these time periods would result in selecting on periods in which the realization of ν_2 shocks are likely to be small.

In other words, draws of ν_2 from some time periods would be systematically weighted more than others. My solution is pragmatic, and relies on the fact that there is always at least one firm that releases a product within a (g, t) combination: I assume that structural shocks are common across firms within (g, t). When an observation is missing in a (f, g, t) combination, I reweight other Δr and ΔF terms in the same (g, t) combination, so that ν_2 shocks of all periods are equally weighted.

The fixed costs parameters are estimated by minimizing the objective function, the sum of the squared

[32] The notation z^F is used to distinguish these variables from second stage demand instruments (z^d).

violation of the moments

$$\hat{F} = \arg\min_{F} \sum_{f} \sum_{g} \sum_{k \in \{\text{set of moments}\}} \sum_{z^F \in Z^F} \left[\min \left(m_{fg}^{k} \left(F, z^F \right), 0 \right) \right]^2$$

Calculating the function Π In the remainder of this section, I describe how I estimate $\Pi_{T_{post}}$. What is necessary is a procedure that returns the expected equilibrium profits in T_{post} (from solving Equation (9)) under any given estimates of the fixed cost parameters F and counterfactual values of $\overline{e}_{reg}$. The challenge is that, in response to a change in the value of $\overline{e}_{reg}$, we would expect firms to reoptimize their product offerings, and hence, I need to simulate these counterfactual product offerings.

The function $\Pi_{T_{post}}$ is defined for each firm f, product group g, and threshold value $\overline{e}_{reg,g}$. The function returns the expected profits in T_{post} for firm f when the standard level in group g is $\overline{e}_{reg,g}$. I approximate for Equation (9) empirically based on similar assumptions as the heuristics used to proxy for future profits in T_{pre} (as discussed in Section 3). Namely, firms proxy for profits in T_{post} by solving for future equilibrium outcomes assuming that $J_{f,\tau} = J_{f,\tau'}$ for $\tau, \tau' \in T_{post}$. This means that firms decide on one counterfactual product offering throughout T_{post}. This significantly decreases the number of counterfactual product offerings that need to be simulated. I also assume firms have knowledge of future mean time-fixed effects and mean costs through $\pi_{f\tau}$.

Based on these heuristics, $\hat{\Pi}_{fg,T_{post}}$ is defined as

$$\hat{\Pi}_{fg,T_{post}} \left(\overline{e}_g \middle| F \right) = \psi \times \sum_{\tau \in [\text{Oct 2011}, \cdots, \text{Mar 2012}]} \left\{ \delta^{\tau - t_{post(1)}} \cdot \left[\pi_{f\tau} \left(J_{fg}^{*} \cup J_{f,-g}^{Data}, J_{-f,g}^{*} \cup J_{-f,-g}^{Data} \right) - \sum_{j \in J_{fg}^{*}} F_{j\tau} \right] \right\} \tag{22}$$

where ψ is a scaling factor, and $\left(J_{f=1,g}^{*}, \cdots, J_{f=F,g}^{*} \right)$ is the equilibrium product offering that satisfies

$$J_{fg}^{*} = \arg\max_{J_{fg}} \sum_{\tau \in [\text{Oct 2011}, \cdots, \text{Mar 2012}]} \left\{ \delta^{\tau - t_{post(1)}} \cdot \left[\pi_{f\tau} \left(J_{fg} \cup J_{f,-g}^{Data}, J_{-f,g}^{*} \cup J_{-f,-g}^{Data} \right) - \sum_{j \in J_{fg}} F_{j\tau} \right] \right\} \quad \forall f$$

I obtain this counterfactual product offerings by using a iterative best response logic. For every counterfactual standard level $\overline{e}$, and from an initial set of product offerings, firms sequentially take "turns" changing its product offerings. To be able to estimate my model in a reasonable amount of time, in each turn firms are allowed to make one of the following changes to its product offerings: (1) introduce or retract one good; (2) change the efficiency of one good; or (3) do none of the above. On its turn, a firm takes one of these actions so as to maximize its expected profits in T_{post}, taking as given rivals' product offerings from the previous turns. The next firm is then allowed to take its turn, and this procedure is repeated across firms until no firm has any more profitable deviations. The resulting product offering is assumed to be the counterfactual equilibrium outcome.

This procedure is embedded in the estimation routine. To limit the state space, when evaluating changes to $\overline{e}_g$ for group g, I keep the product offerings of all other groups fixed.[33] The product offerings in the last six months of my data set are used to define product assortments in other product groups $(-g)$ and initial conditions. In the main results, firms take turns in the order of the total profits that they make in the second stage, so that larger firms get to take turns earlier on. Finally, in the current draft, the number of goods that can be introduced, as well as the value of energy efficiency and quality that a good can take are restricted.[34]

The issue of multiple equilibria is well known in entry games. One solution to the issue of multiple equilibria is to explicitly consider all possible points in the state space, and rule out states that would not be an equilibrium, as considered in Eizenberg (2014) or Lee and Pakes (2009). Given the large number of firms and kinds of products that can be released, this approach would be extremely time consuming. I instead rely on best response dynamics.[35] I attempt to maintain the consistency of counterfactual outcomes across conditions by starting from the same initial condition. As a robustness test, the equilibrium outcome under an alternative ordering of firms can be considered.

5 Results

I first discuss the estimates for the coefficients that constitute the second stage, namely β and γ. Then, I discuss the estimates for the fixed cost coefficient, F, from the first stage.

5.1 Second stage

Simple logit models are helpful in understanding the full demand system. Table 5 shows the results from linear regressions, as in Berry (1994). Column (1) and (2) estimate the demand specification without any instruments or product dummies. Column (1) only uses a set of limited covariates: achievement percentage, product group dummies, manufacturer dummies, and screen size. These are the covariates that describe the relevant product characteristics with respect to the regulation. On the other hand, column (2) uses all covariates, including both the limited covariates and those listed in Table 10. The increase in magnitude of the price coefficient and the decrease of the coefficient on energy efficiency suggest that the extended covariates capture product quality that is positively correlated with prices and energy efficiency. This result is intuitive: the extended covariates include variables that are closely linked to the quality of the television (such as the screen's contrast ratio). Columns (3) and (4) exhibit the role of the product dummies and BLP-style instruments. The addition of product dummies increases the magnitude of the price coefficient.

[33] In constructing the moment inequalities, I only consider unilateral deviations in which the future threshold level of (at most) one group changes. In other words, even though $\Pi_{T_{post}}$ is a function of the vector $\overline{e}$, I only consider values of $\overline{e}$ such that $\overline{e}_g \neq 100\%$ for one g, and $\overline{e}_{g'} = 100\%$ for all other groups $g' \neq g$.

[34] Firms are allow to release up to two more, or two fewer goods than the number of goods that they do in data. In the current draft, I assume that the quality of goods are fixed within a given (f, g, t) combination, and is equal to $q = \frac{1}{|J_{fgt}|} \sum_{j \in J_{fgt}} q_j^{Data}$. Because quality is fixed, in each turn, firms choose the number of products, and the efficiency of each product. Efficiency is chosen from the grid $[50, 55, 60, \cdots, 200]$ subject to the constraint that the chosen efficiency is greater than $\overline{e}_g$.

[35] As Equation (14) exhibits, in estimation, only relative changes in $\Pi_{T_{post}}$ $(\Delta\Pi_{f,T_{post}})$ need be evaluated to construct the inequalities (i.e. the absolute level of $\Pi_{f,T_{post}}(\overline{e}_{reg})$ does not affect the estimated parameters). To the extent that local changes in $\overline{e}_{reg}$ are likely to result in product offerings that do not drastically deviate from the observed product offerings in data, it may be reasonable to use best response dynamic (which are likely to find an equilibrium that is "similar" to the one observed in data) to find counterfactuals.

While the BLP instruments are intended to help identify heterogeneity, they also contribute to a larger price coefficient and suggest that the instruments also help to control for unobservables. Finally, columns (5) and (6) illustrate the decomposition of the product dummies. Like columns (1) and (2), the inclusion of the full set of covariates in column (6) leads to smaller estimates for the coefficient on energy efficiency.

Table 5 also shows the estimated coefficients on the dummies for the number of stars on product labels, for the labeling regime during fical 2010. The coefficients on the number of stars are evaluated relative to the excluded category (products with one or two stars).[36] I allow each cut-off value regime to have its own set of dummies, because the cut-off values for a given number of stars changed drastically across these regimes. For example, from April 2010 through March 2011, a product needed to have an achievement percentage greater than 100% to qualify for five stars; after April 2011, the cut-off increased to 155%. Empirically, I find that these dummies are estimated tightly, and that the estimates for the dummies on same number of stars can vary significantly across regimes. For example, five-star labels between April 2010 and March 2011 had a coefficient of 2.161 ($s.e. = 0.092$), while five-star labels after April 2011 had 3.986 ($s.e. = 0.109$). Across all three cut-off value regimes, labels with more stars are always valued more.

Results from the full model are shown in Table 6. Panel (1) of the table presents the coefficients obtained from the main GMM routine, including parameters that are allowed to vary by household. I allow for six discrete household types, corresponding to six incomes brackets ("annual income less than \$20,000," "between \$20,000-40,000," "between \$40,000-60,000," "between \$60,000-\$80,000," "between \$80,000-100,000," and "greater than \$100,000"). The household constants are evaluated relative to those of the lowest income household's (the lowest income household's constant is absorbed by the product dummies).[37] Higher income households have a larger constant, and are generally less price sensitive. The estimates suggest that the least price-sensitive consumers are lower income households. The product dummies have a large standard deviation, in part reflecting the vast differences in market shares across television models.

Panel (2) reports the results of decomposing the product dummies. The relative magnitudes of the coefficients on energy efficiency and screen size are generally comparable to those in column (6) of Table 5.

To help interpret these results, panel (3) shows the implied willingness to pay for upgrades in television characteristics. This is obtained for each household by dividing the changes in utils by the respective price coefficients. The estimates suggest that households are willing to pay between \$37 to \$51 for a 10 percentage-point increase in the achievement percentage of a television, keeping constant other covariates, including the number of stars on the product label. A 10 percentage-point increase in achievement percentage corresponds on average to a 25 kWh/yr decrease in energy consumption, or a \$74 savings in electricity bills, assuming 30 cents per kWh and a usage of 10 years with no discounting.[38]

When the increase in energy efficiency is accompanied by an increase in the number of stars on the product labels, there is a significant over-evaluation of energy efficiency. For televisions sold during fiscal 2010,

[36] One and two stars are grouped together because the number of products that have such labels are limited.

[37] Without any restrictions, the coefficients are allowed the vary flexibly across the six households. Due to limited data, particularly on heterogeneity on the kind of television purchased by household, the household constants ($\beta_{0,i}$) are assumed to be the same within households 3 and 4, as well as within 5 and 6.

[38] Absorbing month-, region-, and product group-fixed effects, a standard deviation of achievement percentage and energy costs are 18.2pp. and \$135.60, respectively. Therefore, I approximate one achievement percentage to be roughly equivalent to \$7.40 in energy costs.

the average five-star television was 34 percentage points more efficient than the average four-star television. Consumers are willing to pay more than \$500 for this increase, while the implied savings in electricity bills is on average \$250, and up to \$807 (the most efficient five-star television saved \$807 of electricity bills compared to the least efficient four-star television). While previous literature has found evidence of consumers over-evaluating energy savings when energy savings are labeled or subject to certification, my findings are on the higher end. Houde (2014) finds that American consumers value energy star labels on refrigerators as much as \$152, while the label implies an average energy bill savings of \$83.[39]

Anecdotal evidence and product line choices suggest that consumers do react to information on energy efficiency. An interview suggested that manufacturers were extremely sensitive to the number of stars that their products were labeled with because they significantly affected consumer demand. According to some observers, a major reason why PDP (plasma) televisions sets, despite being initially more superior in image quality, were not able to gain market shares was because the labels made it salient that PDP televisions consume more energy. Manufacturers also made televisions with efficiency levels that just met cutoff values to receive an additional star, suggesting that consumers place a high value on the number of stars on a label, and that firms reacted to such behavior (Houde, 2013).

The large point estimates may also reflect the pervasiveness of energy efficiency information that is provided to consumers. In general, stars on product labels, a notched labeling scheme, may have been implemented by a regulator concerned that consumers are not fully incorporating the energy savings brought about by purchasing a more efficient television (Sallee, 2013). In Japan, a labeling scheme similar to what was introduced in the TV market was implemented for many categories of durable goods. It may be that consumers were particularly responsive to these labels because of their high visibility across a variety of product categories. These include larger durable goods such as automobiles and air conditioning units, in which energy efficiency improvements imply more substantial energy bill savings.

The final row of Table 6 shows the change in the total inside market share from a 1% increase in the price of all televisions. The median elasticity across all time periods is -3.5, and ranges from -1.1 to -5.9. The median elasticity is comparable to the elasticity of home personal computers (-3.6) reported in Eizenberg (2014).

The estimates from the marginal cost equation are presented in Table 7. Due to the month fixed effects, the marginal costs are decreasing over time, which partly explains the decrease in prices over time. Ceteris paribus, the marginal cost decreased \$64 per month. Consistent with intuition, markup and prices and positively correlated.

5.2 First stage

Table 8 presents the estimated fixed cost parameters.

The fixed costs parameters, albeit being estimated using inequalities, are point estimates. There are two reasons for this. Firstly, the functional form used for estimating fixed costs are generally not be flexible

[39] Part of the over-evaluation of energy efficiency is likely to be a story of heterogeneity. The model can be extended to incorporate heterogeneity in how consumers react to stars. For example, following Houde (2014), it may be reasonable to assume that a share of consumers are irresponsive to the number of stars.

enough to accommodate all of the inequalities. This is particularly true when product attributes can take a wide range of values. For instance, a firm may simultaneously sell two products with a low and a high level of efficiency respectively. The current functional form assumes that the change in fixed costs from forcing the firm to increase the energy efficiency of either good by Δe are the same. However, the law of diminishing marginal returns would suggest that it would be costlier to improve the efficiency of an already highly efficient product. Using a more flexible specification of fixed costs would improve fit, but require the use of additional inequalities to identify all parameters.

Secondly, the fixed costs may be point identified because a multitude of inequalities are used. Inequalities are random variables, and hence, the likelihood of finding a range of parameters in which all inequalities are satisfied decreases as the number of inequalities increase (Ishii, 2005).

The results presented here are preliminary. A key component driving the fixed cost estimates is the function $\Pi_{T_{post}}$, which determines the firms' beliefs about profits in T_{post}. The parameter estimates may be sensitive to the scaling of this function (the ψ coefficient in Equation (22)). In this draft, I scale the function so that $\Pi_{T_{post}}$ is equivalent to four years' worth of future profits.

Panel (1) of Table 8 presents the fixed cost parameters F^e, F^q and F^0, for a representative full-HD (group DG) and non-FHD (group DK) product group. To interpret the magnitude of these estimates, Table 9 decomposes the revenues from a television model into markup, fixed costs, and marginal costs. The table shows the decomposition of these economic costs for the average television sold in group DG for firm 1. These numbers suggest that fixed costs are a moderate fraction, 22%, of the total revenue.

For comparison, a decomposition of accounting costs is shown in the lower half of Table 9. While it is difficult to compare the two set figures, my estimates suggest a smaller profit ratio for firms ($1663/(1067 + 428) - 1 = 11.2\%$), compared to the accounting estimates (94.5%). One cause is that the accounting estimates merely add on retailer margins to the cost price of the television set so that the retailer's margins constitute 35% of the total price. Therefore, the accounting estimates do not account for any costs incurred by retailers — if the retailer made no profits, the profit ratio would be a comparable 15.7%.

Table 9 shows that, of the \$1,663 average retail price of full-HD (group DG) televisions sold by firm 1, the firm incurred \$217 per unit on (average) fixed costs associated with energy efficiency. To compare the magnitude of the fixed costs across product groups and firms, I present "normalized" fixed costs parameters in panel (2) of Table 8. These reflect the per unit fixed costs associated with introducing a television of the average efficiency level in the respective product group (for example, firm 1 incurs energy efficiency related fixed costs of \$203 per unit to sell a full-HD (group DG) television of the average efficiency level. This is roughly comparable to the \$217 in Table 9). These figures suggest that the costs associated with energy efficiency are more heterogeneous across firms in the non-FHD product group (group DK). For instance, in the non-FHD product group, the most expensive firm incurs 12.7 times more costs than the cheapest firm to produce the same amount of efficiency. In the full-HD group, the most expensive firm incurs costs that are 5.4 times greater than the cheapest firm.

Table 8 also shows a decomposition of revenues and costs for the average firm. The estimates suggests that fixed costs are 43% of the total costs that firms incur, and 35% of total revenues.

6 Counterfactuals

The regulatory constraint that is imposed on firms in the model is

$$\max_{j \in J_{g,T_{pre}}} e_j \leq \min_{j \in J_{g,T_{post}}} e_j \quad \forall g \tag{23}$$

The role of counterfactual simulations is to decompose the forces that contributed to the varying outcomes that were observed across product groups. To this end, I consider three counterfactual regulatory regimes to separate within- and cross-firm incentives. The outcomes under each regime can then be compared to the baseline scenario, in which product offerings are simulated under no regulatory constraints.

In the classic ratchet effect (Freixas et al., 1985, Weitzman, 1980), a single agent ratchets down its quality today because its actions only affect its own future constraints, not any other agents'. In a similar spirit, *firm-by-firm constraints* can simulate the magnitude of this effect in the market for television sets, by subjecting firms to a regulation that only affects each firm independently:

$$\max_{j \in J_{fg,T_{pre}}} e_j \leq \min_{j \in J_{fg,T_{post}}} e_j \quad \forall f, g$$

Under this regime, each firm's future threshold level is set by the most efficient product released by that firm. There are no interactions between firms by virtue of the regulation. Therefore, under this regime, firms can no longer affect the constraints that its rivals will be subject to. The outcome under this regime are suggestive of the magnitude of within-firm incentives.

On the other hand, I can consider regulatory constraints that are designed to only impose an externality (*leave-own-out constraints*)

$$\max_{j \in J_{(f),g,T_{pre}}} e_j \leq \min_{j \in J_{-(f),g,T_{post}}} e_j \quad \forall g$$

where (f) is the firm that released the most efficient product in that product group, and $-(f)$ refers to all other firms. Under this regime, all firms but (f) are subject to the standards set by the leading firm (f). The leading firm is not subject to the constraints, and therefore, has no direct incentive to ratchet down quality.[40] The outcome of this regime is indicative of the magnitude of cross-firm incentives.

These counterfactuals are obtained by calculating alternative versions of the Π function corresponding to each of the regulatory regimes.

7 Conclusion

In many markets, the diffusion of innovation is heavily influenced by the presence of policy intervention. In these markets, firms have incentives to alter their product offerings because they realize their actions can influence future policy. If firms significantly hold back on quality, they and their rivals are able to continue

[40]This design introduces a strong incentive to be the leading firm in T_{pre}, because the leading firm is uniquely free from any constraints in T_{post}. As an alternative design, the leading firm could be subject to a constraint less stringent than other firms: $\max_{j \in J_{(f),g,t}} e_j - \tilde{e} \leq \min_{j \in J_{(f),g,T_{post}}} e_j$ for some fixed $\tilde{e}$.

selling less efficient products for the foreseeable future. Therefore, the firms' ratcheting incentives can have significant influence on the pace at which technological change diffuses.

Using data from the Japanese television market, which is subject to a unique regulatory regime, I show that the incentive to ratchet down energy efficiency was significant in some regulatory submarkets. My empirical analysis implies that such ratcheting down is more likely to happen when firms are similar in their cost structures. This suggests that the firms' ratcheting incentives can affect the distribution of market shares and profits across competitive firms: for example, a firm that has an advantage in making energy efficient television sets may further benefit by being able to induce tighter regulatory standards.

The model makes several simplifications for the purpose of maintaining tractability. Some of the limitations brought about by these simplifications can be addressed by modifying the current model, at the cost of requiring more computational resources. For example, if there are many months left in the pre-regulatory regime (T_{pre}), firms are most likely to reoptimize their product offerings in response to the increase of the threshold level induced by a rival firm in a previous time period. This in turn would decrease the benefits of raising the threshold in the first place. This force is not captured in the current model, but future extensions could address this issue (see discussion at the end of Section 3.1.3)

A potential avenue for future research is considering firm behavior under alternative policy designs that are less likely to encourage ratcheting down. Gersbach and Glazer (1999) theoretically show that tradable permits, combined with minimum quality standards, can mitigate firms' incentives to ratchet down. The effectiveness of such schemes in practice is open to further empirical investigation, and can be evaluated within the framework of this model.

Finally, the standards considered in this study speak to the "diffusion" stage of new technology in Schumpeter's trilogy of technological change. Minimum quality standards contribute to the diffusion of newer technology by preventing lower quality goods from being produced, and thereby encouraging the purchase of newer technology. Standards are commonly introduced hand-in-hand with financial incentives and informational campaigns with the intent that such policies ultimately affect the pace at which R&D in a particular direction is conducted (Geller and Nadel 1994). While the drivers of innovation are outside the scope of this paper, theories of innovation suggest that standards would be more likely to stimulate innovation if standards encourage the diffusion of more efficient products (Newell et al., 1999).[41] The extent to which standards, which affect the "costs" of provisioning certain product attributes, play in influencing the upstream innovation process is an open question.

[41] For example, Hick's induced innovation hypothesis suggests that innovation occurs in response to changes in the relative prices of input, so that more costly inputs are economized. Standards change the shadow price of energy (in)efficiency. Manufacturers respond by investing in R&D to improve energy efficiency, because energy inefficiency is now more costly. While the magnitude of these effects remain "uncertain" (Jaffe et al., 2003), there is some anecdotal evidence for this force. For instance, some manufacturers have stated that appliance standards have encouraged them to "develop leading edge technology for efficiency" (McInerney and Anderson, 1997).

8 Tables

Table 1: Inside shares by firm and television type

	All	Non-HD		Full HD	
		<32	≥32	<32	≥32
Firm 1 (Sharp)	39.5%	12.3%	14.1%	1.2%	12%
Firm 2 (Sony)	13%	3.6%	3.8%	-	5.7%
Firm 3 (Panasonic)	18.1%	4.8%	6.5%	0.3%	6.5%
Firm 4 (Mitsubishi)	2.7%	0.7%	1.4%	-	0.6%
Firm 5 (Hitachi)	4.4%	0.4%	2.6%	-	1.4%
Firm 6 (Toshiba)	19.8%	6.1%	7.4%	0%	6.3%
Other	2.4%	1.9%	0.4%	0.1%	0.1%

Table 2: Summary statistics by product

	Overall ($n = 854$)		2008 ($n = 145$)		2011 ($n = 184$)	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Average price	$1339	1083	$1837	1156	$964	847
Achievement percentage	102.5	34.5	74.5	16.2	140.2	26.5
Energy consumption (kWh/yr)	138.5	91.4	192.3	103	92.1	47.9
Has plasma screen	12.3%		15.2%		9.8%	
Has full-HD screen	55.2%		63.4%		56.5%	
Screen size (inches)	35.8	11.4	37.9	10.5	35	11.9
Less than 32 inches	12.3%		15.2%		9.8%	
Greater than 42 inches	55.2%		63.4%		56.5%	
Variation in achievement percentage across months and regions explained by...						
... month, and region fixed effects	0.545					
... month, region, and product group	0.690					
... month, region, and manu-by-product group	0.822					
Variation in price across months and regions explained by...						
... month, and region fixed effects	0.102					
... month, region, and product group	0.583					
... month, region, and manu-by-product group	0.729					

Notes: An observation is a product. Second and third set of columns correspond to products introduced in 2008 and 2011, respectively. Average price is the average selling price over all months and regions that the product was sold.

Notes on decomposition of variation: Each figure corresponds to the R^2 of a regression of the variable on the listed set of fixed effects, using the full dataset of product-region-month observations ($n = 46951$). The standard deviation of achievement percentage, absorbing month, region, and product-group fixed effects is 18.2.

Table 3: Summary statistics by product groups

Product group	Resolution	Size	Display speed	Features	Inside share	Price	Firms	Products per firm
DG	Full-HD	Over 32	120fps	0	14.8%	$1473	5.7	5.8
DG1	Full-HD	Over 32	120fps	1	7.1%	$2136	3.3	8.6
DG2	Full-HD	Over 32	120fps	2	2.3%	$2097	3.4	4.7
DK	Non-HD	19 to 32	60fps	0	24.1%	$460	11.1	3.7
DN	Non-HD	Over 32	60fps	0	26.4%	$704	7.4	2.7
Average					3.3%	$1398	2.6	2.5
Average active product groups				22				

Notes: An observation is a product group. For each product group, the data was averaged across time periods, ignoring periods in which no product was released. In the average time period there were 22 active product groups. See footnote 17 for an explanation of how these five product groups were chosen.

Table 4: Varying outcomes across product groups

Product group		Cum. max efficiency Jan 09 (T_{set})	Jul 09	Diff.	Share of sales **(A)**	**(B)**
DG	Full-HD	102	132	30	77%	10%
DG1	Full-HD	100	103	3*	93%	6%
DG2	Full-HD	102	133	31	96%	0%
DK	Non-FHD	104	107	3	0%	48%
DN	Non-FHD	96	96	0	2%	27%

(A) Share of sales that are more efficient than 80% in six months prior to standard setting (T_{set}).

(B) Share of sales that are less efficient than 120% in six months prior to standard enforcement.

Notes: For each product group, the first set of columns indicate the cumulative maximum energy efficiency of televisions sold. There is generally a larger jump in efficiency after the threshold is set for full-HD product groups.

The second set of columns indicate the share of sales that were concentrated near the threshold. In the six month period prior to the *setting* of the threshold, there were fewer sales of televisions near the eventual regulation level within non-FHD product groups (see column (A)). This suggests that, in non-FHD product groups, firms released highly efficient products that did not gain significant market shares. This is in line with ratcheting up: a firm may decide to release a highly efficient product in an attempt to ratchet up the threshold, even if the product is not profitable per se. Opposite trends hold for full-HD product groups.

*In group **DG1**, a product with efficiency of 141% was released in September 09. The cumulative maximum efficiency of products in other products did not change from July 09 through September 09.

Table 5: Estimates of second stage parameters using a simple logit model

	(1) $\log(s_{jrt})$ $-\log(s_{0rt})$	(2) $\log(s_{jrt})$ $-\log(s_{0rt})$	(3) $\log(s_{jrt})$ $-\log(s_{0rt})$	(4) $\log(s_{jrt})$ $-\log(s_{0rt})$	(5) Prod. dummy from (3)	(6) Prod. dummy from (3)
p	-0.152***	-0.235***	-0.961***	-1.453***		
	(0.0161)	(0.0193)	(0.0251)	(0.150)		
ap	0.00544***	0.00449***			0.0319***	0.0103***
	(0.000568)	(0.000632)			(0.00244)	(0.00287)
$star3$	0.126	0.343***	0.631***	0.473***		
	(0.105)	(0.103)	(0.102)	(0.107)		
$star4$	1.412***	1.440***	1.414***	1.210***		
	(0.0848)	(0.0819)	(0.0854)	(0.0961)		
$star5$	2.007***	1.929***	2.289***	2.161***		
	(0.0882)	(0.0856)	(0.0881)	(0.0922)		
$tgDG$	0.555***	0.620***			1.264*	0.343
	(0.0660)	(0.127)			(0.642)	(1.088)
$tgDK$	1.513***	1.304***			2.604***	0.942
	(0.0617)	(0.126)			(0.587)	(1.070)
$size$	0.00705	-0.0380***			-0.199**	-0.166**
	(0.00735)	(0.00764)			(0.0738)	(0.0555)
$size^2$	-0.000840***	-0.000326***			0.00287***	0.00222***
	(0.0000882)	(0.0000916)			(0.000824)	(0.000611)
Covariates	Limited	Full	—	—	Limited	Full
Product dummies	No	No	Yes	Yes	—	—
IV	No	No	No	BLP	—	—
N	46951	46951	46951	46951	843	843
R^2	0.390	0.466	0.982		0.458	0.778

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors in parentheses. Standard errors in (3) and (4) not adjusted for estimation error of the product dummies. $stars$ are dummies for star labeling corresponding to the cut-off levels implemented in fiscal 2010. Coefficients for other product group and star labeling dummies are not shown. Limited covariates refer to a quadratic trend in screen size, product group fixed effects, and manufacturer fixed effects. Full covariates refer to limited covariates and variables listed in Table 10.

Table 6: Second stage demand side estimates from full model.

(1) Coefficients obtained from GMM routine						
	HH1	HH2	HH3	HH4	HH5	HH6
$p^{\dagger}$	-3.178***	-2.679***	-2.293***	-2.341***	-2.518***	-2.298***
	(0.382)	(0.366)	(0.364)	(0.418)	(0.314)	(0.23)
Constant	—	—	0.21***		0.835***	
			(0.025)		(0.075)	
$stars3$			0.902*** (0.125)			
$stars4$			1.313*** (0.135)			
$stars5$			2.696*** (0.149)			
Product dummies						
Mean			-3.858			
Stdev			3.281			

(2) Projection of product dummies on characteristics		
	OLS, limited covariates	OLS, all covariates
ap	0.038*** (0.002)	0.012*** (0.003)
$tgDG$	1.242 (0.623)	0.816 (0.499)
$tgDK$	2.563*** (0.57)	0.053 (1.191)
$size$	-0.174 (0.072)	-0.185 (0.057)
$size^2$	0.002** (0.001)	0.002 (0.001)

(3) Willingness to pay						
From screen size 32 to 46, caeteris paribus						
	\$26	\$30	\$36	\$35	\$32	\$35
From an average non-FHD TV to an average full-HD TV						
	\$323	\$383	\$447	\$438	\$407	\$446
A 10 percentage point increase in AP (no change in stars)						
	\$37	\$43	\$51	\$50	\$46	\$50
A increase from four to five stars						
	\$534	\$633	\$740	\$725	\$674	\$738
Elasticity			-3.4522			

Standard errors in parentheses. Standard errors not adjusted for estimation error.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: HH1 through HH6 refer to household types, corresponding to incomes brackets ("annual income less than 20k," "between 20k-40k," "between 40k-60k," "between 60k-80k," "between 80k-100k," and "greater than 100k"). The household specific constants are relative to that of the lowest household type. Note that the lowest household type's constant are absorbed by the product dummies. The household constants are assumed to be the same within households 3 and 4, as well as within 5 and 6. $stars$ are dummies for star labeling corresponding to the cut-off levels implemented during fiscal 2010. Coefficients for other product group and star labeling dummies are not shown. Limited covariates refer to a quadratic trend in screen size, product group fixed effects, and manufacturer fixed effects. Full covariates refer to limited covariates and variables listed in Table 10.

Notes for **Willingness to pay**: Willingness to pay of non-FHD to FHD is the increase in willingness to pay from a television in Group DK (non-FHD) to DG (FHD), accounting for the accompanying increase in the average screen size. Elasticity represents change in total inside share from a 1% increase in all television prices, averaged across all time periods.

Table 7: Estimates of marginal cost equation.

	(1)
	mc
$q \times \mathbb{1}\,(fhd = 0)$	0.061***
	(0.004678)
$q \times \mathbb{1}\,(fhd = 1)$	0.414***
	(0.003360)
$e \times \mathbb{1}\,(fhd = 0)$	0.000743***
	(0.000263)
$e \times \mathbb{1}\,(fhd = 1)$	0.0147***
	(0.000171)
N	48199
adj. R^2	0.813
Controls	Month, Firm×grp F.E.s
Median markup	\$442
Median $(p - mc)/p$	0.437
Corr. of p, $mkup$	0.108

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Fixed cost parameters.

(1) Fixed cost parameter estimates (unit: \$1000)						
	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6
F^e						
$grpDG$	816	608	224	96	—	416
$grpDK$	7200	13728	256	1360	3280	896
F^q						
$grpDG$	79	66	59	10	—	303
$grpDK$	29310	9335	8848	1911	1557	12783
F^0						
$grpDG$	-2963	-1936	992	-437	—	1644
$grpDK$	-19770	-6266	6864	5139	12563	14126
(2) Normalized fixed cost parameters (see footnote)						
F^e						
$grpDG$	\$203	\$206	\$59	\$320	—	\$54
$grpDK$	\$261	\$653	\$142	\$440	\$1808	\$135
(3) Median fixed costs of products released in data (unit: \$1000)						
$grpDG$	1697	1813	3279	50	—	4622
$grpDK$	8579	6209	3091	604	330	3303

(4) Revenues and costs of average firm (unit: million USD per year)	
Revenue	506 (100%)
Total marginal cost	235 (46%)
Total fixed cost	175 (35%)
Profits	96 (19%)

Notes for **Fixed cost parameters**: Every month, fixed costs are incurred for each unique model that is released. They are a function of the firm, product group, energy efficiency, quality, and time period of release of the television (see Equation 19). In this table, fixed costs parameters are evaluated at the level of February 2009. Coefficients F^e and F^q have been scaled so that it reflects a one standard deviation increase in e and q. The standard deviation of e and q demeaning period, region, and firm-by-product group fixed effects is 16.0 and 1.3, respectively.

Notes for **Normalized fixed costs**: These figures represent the per-unit average fixed costs associated with energy efficiency that a firm would incur, to produce a TV with the mean efficiency level within the corresponding product group. For example, firm 1 would incur \$203 of average fixed costs per unit to make a television that is of average energy efficiency in product group DG.

The fixed costs parameters are "normalized" by first dividing the raw parameters F^e_{fg} by the average number of units sold per model-month for televisions sold by firm f in group g. This is then multiplied by the average efficiency level of televisions in group g, following the procedure used to calculate fixed costs due to energy efficiency used in Table 9.

Notes for **Revenues and costs**: The total revenues and costs for each of the six major firms were calculated. The average across six firms is presented.

Table 9: Decomposition of fixed costs

Decomposition of economic costs (Firm 1, group DG television)	Per model ($1000 USD)	Per unit (USD)	Share
Revenue (price)	9076	1663	100%
Ave. quantity sold	5459		
Marginal cost	5824	1067	64%
... of which due to efficiency	5135	941	57%
Fixed cost	2337	428	26%
... of which due to efficiency	1187	217	13%
Profit	915	168	10%

Cf. Decomposition of accounting costs (46 inch, full-HD television)		
Retail price	1357	100%
of which retail margin	475	35%
Television set	311.3	23%
... of which TV set components	126.3	9%
... of which TV manu. Labor, SGA	43	3%
... of which TV manu. Margin	142	10%
Panel and module	570	42%
... of which panel components	191.3	14%
... of which module components	258.5	19%
... of which panel/module labor SGA, depreciation	78	6%
... of which panel/module margin	42.2	3%

Notes for **Decomposition of Economic Costs**: The average revenues, marginal costs, and fixed cost for televisions sold by Firm 1 in group DG is shown.

The marginal and fixed costs due to energy efficiency are calculated relative to the least efficient product within each period: if product j is $\tilde{e}_{jt}$ more efficient than the least efficient product sold (across firms) in period t, the firm incurs $F^e \cdot \tilde{e}_{jt}$ of fixed costs due to energy efficiency.

Notes for **Decomposition of Accounting Costs**: Replicated from Fuji Chimera Research Institute (2009*b*). The cost breakdown for a 46-inch full-HD television in the second quarter of 2010 is shown. Panel components include the color filter, prism sheets, and liquid crystal. Module components include the driver IC, and the backlight unit. Television set components include the tuner, graphics and sound engines, and power supply. The cost of components is adjusted for yield rates. SGA refers to selling, general and administrative expenses.

Table 10: Additional covariates used in product dummy decomposition.

	Description	Continuous	Ratio of yes	Discrete values and notes
1	Whether TV has an internal DVD recorder.		2.7%	
2	Whether TV has an internal BD recorder.		6.3%	
3	Whether TV has an internal HDD player, and amount of storage.		18%	None, 250 to 3000GB
4	Whether TV has double digital tuners.		18.3%	
5	Whether TV has a plasma display.		12.3%	
6	Whether TV has BS/CS receivers.		92.5%	
7	Whether TV supports split screen viewing.		26.2%	
8	Whether TV can connect to the internet.		62.8%	
9	Presence and class of D-terminal for video input/output.		96.7%	None, D4, D5
10	Presence and type of memory card supported.		36.7%	None, SD, SDHC, SDXC
11	Presence of IEEE1394 terminal.		14.8%	
12	Types of input terminals for PC signals.		68%	None, D-Sub, DVI-I, DVI-D
13	Contrast ratio of screen.			150:1 to 500000:1. 369 observations missing.
14	Presence of ethernet terminal.		91.9%	
15	Presence and type of electronic program guide.		98.8%	None, G-GUIDE, Other technology
16	Vertical resolution.	Yes		720 to 1080
17	Horizontal resolution.	Yes		1024 to 1920
18	Support for 1seg (mobile) broadcast.		0.2%	
19	Support for video recorder scheduling code.		1.5%	
20	Position of speaker, relative to screen.			Sides, or under screen. 5 observations missing.
21	Whether the speakers are detachable.		1.5%	11 observations missing.
22	Support for the DLNA standard for media sharing.		43.5%	
23	Support for the AKUBIRA standard for on-demand video streaming.			Not supported, basic, video, video-full, video-download
24	Support and standard of 3D video playback.		10.9%	Yes, no, 3-D ready
25	Support for BD-R 3.0 specification.		2.1%	
26	Number of 3D glasses in package.		4.7%	0 to 3
27	Support for Youtube playback.		14.1%	
28	Whether the TV supports downloading of apps.		1.7%	

Unit of observation is a television model. $N = 843$.

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9 Appendix

9.1 Additional details of the regulation, industry, data, and estimation

9.1.1 The Top Runner Program in the market for television sets

In this section, I provide a more detailed explanation of the regulation. For completeness, parts of the main text are reproduced.

In response to the enactment of the Kyoto Protocol, the Top Runner Program has regulated the energy efficiency of 23 kinds of appliances, including television sets, since 1998. Under the regulation, each television belongs to a product group g that is defined by unique combinations of a vector of product characteristics. The vector is

$$x_j^g = \begin{cases} size_j \in \{(10,19), [19,32), [32,\infty)\} & \text{Screen size groups} \\ fps_j \in \{60, 120, 240\} & \text{Display speed: 60/120/240 fps} \\ FHD_j & \text{Full HD} \\ features_j = DT_j + DVD_j + HDD_j + BR_j & \text{Number of additional features} \end{cases} \tag{24}$$

where the variables DT_j, DVD_j, HDD_j and BR_j take a value of one when the product features double tuners, an internal DVD recorder, an internal HDD recorder, and an internal BlueRay recorder, respectively. For instance, televisions with screen size larger than or equal to 32 inches with a full-HD panel, display images at 120 fps and have two additional features belong in one product category (group DG2). With regards to features, only the number of features is used for grouping products.

In addition to the vector x^g, energy consumption level $energycon$ is the major observable characteristic of a television. Energy consumption $energycon$ is measured in $kWh/year$, and reflects the yearly energy consumption of a television under normal household usage conditions (4.5 hours of daily viewing).

The regulation aims to limit $energycon$ by setting a target value for each product group. These values are adjusted for future potential demand and R&D, but generally reflect the most energy efficient product in each product group up to the time that the target values are set, T_{set}. The scheme is intended to establish a regulatory standard level, in the presence of asymmetric information between regulatory and firms.[42] Information asymmetry arises because manufacturers have better information about the pace at which technology will improve in the future, the feasibility of new product designs at high volume production, and consumer responses to new technology (McInerney and Anderson, 1997).

Because screen size is a key determinant of energy consumption, within product groups, the target values are adjusted to be linear functions of screen size. In practice, the target values are a kinked function of s. For example, televisions that are Full-HD, displays at 60 fps, and have no additional features are subject to standards given by the function

$$tr_g(s) \quad = \quad 74 + \mathbb{1}[s \in [19,32)] \times (2.0 \times s - 38) + \mathbb{1}[s \in [32,\infty)] \times (6.6 \times s - 185)$$

[42]The presence of information asymmetry is the basic premise underlying the well-established findings in the economics of regulation, such as ratcheting and regulatory capture. It creates rents that firms can attempt to obtain (Laffont and Tirole, 1991).

The 2012 standards roughly trace out the envelope of the most efficient products released around February 2009, as illustrated in the left panel of Figure 6.[43] Across product groups, the target values are vertical shifts of the standards illustrated in Figure 6.

The achievement percentage is the ratio of the target value to the actual energy consumption level of a given television,

$$e_j = energytarget\left(g_j, size_j\right)/energycon_j$$

and can be interpreted as a normalized measure of energy efficiency. Given the achievement percentage e, firms meet the regulation by ensuring that the quantity-sold weighted average achievement percentage exceeds 100% for all product groups,

$$E_{fg} = \frac{\sum_{j\in J_{fg}} e_j \cdot q_j}{\sum_{j\in J_{fg}} q_j} \geq 100\% \;\; \forall g$$

where J_{fg} is the set of products that a manufacturer sells in product group g, and q_j is the number of model j televisions sold during the target year.

In the data, there is a marked lack of products that achieve less than 100% as the target year approaches. For tractability in my empirical model, I assume throughout this study that the Top Runner standard acts as a lower bound on the energy efficiency that firms can achieve. In theory, under the factual Top Runner standard, firms could sell less efficient goods and still meet the standards by strategically price goods so as to affect the relative quantity of efficient televisions sold. Such "mix-shifting" has been a margin of response in the automobile industry under corporate average fuel economy (CAFE) standards. Jacobsen (2013) finds that relatively fuel efficient vehicles are priced more cheaply when manufacturers are subject to more stringent constraints, so that fleet averages can meet the CAFE standards. In the television market, the lack of products that achieve less than 100% suggests that firms did not intend to engage in such behavior. Firms may be sufficiently risk-averse in that they want to avoid any possibility of violating the regulation, or lack the ability to flexibly affect the downstream retailer's pricing.

Violators of the standard can be subject to "name and shame," in which the name of the violator is released to the public. Nordqvist (2006) suggests that such instruments are a sufficient penalty to induce local firms to abide by the standards.

The regulation introduces three sets of time periods. In the initial time periods (T_{pre}), leading up to T_{set}, firms realize that releasing an efficient product may change the future regulation level. In the latter time periods (T_{post}), the threshold goes into effect. There is a set of time periods in between, in which the threshold level has been set, but has not gone into effect ($T_{interim}$). These periods are intended to allow the firm to adjust to the new upcoming threshold.

I focus on the 2012 standards of the Japanese Top Runner Program for television sets. The standards were set around February 2009,[44] and enforced after April 2012. This was the third "cycle" in which the

[43] Although the standards were only officially announced in February 2010, firms generally knew when the standards were internally set. For example, the dataset that the government used to set the standards were provided by an industry group. In section 9.2 of the appendix, I provide further discussion on this point.

[44] Throughout this study, I assume that firms knew the regulation was set around February 2009. I document supporting evidence for this claim in the appendix (Section 9.2).

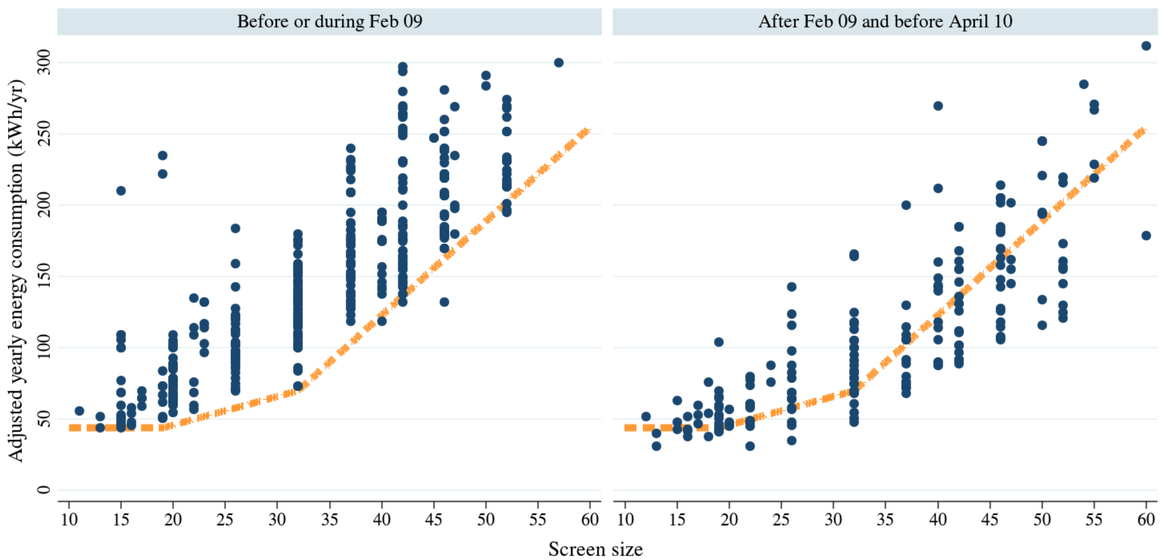


Figure 6: A plot of the energy consumption of products released between January 2006 and January 2009 (left panel), and between February 2009 and January 2010 (right panel). The threshold announced in April 2010 (dotted line), traces out the lower-bound of the energy consumption of products available prior to February 2009 (left panel), and firms released products that exceeded the threshold even before its official announcement (right panel).
The energy consumption levels (y axis) shown here are "adjusted" for the fact that, across product groups, target values are vertical shifts of the dotted line. For example, the target level for product group DG is 15 kWh/yr larger than those plotted here. Therefore, the energy consumption of televisions in product group DG are plotted by subtracting 15 from their actual values. This adjustment allows all televisions to be plotted in the same graph, while maintaining the relative distance of each television to its respective target value.

program was implemented in the television market.

9.1.2 Sources of cost differences across firms

I expand on the discussion in the main text to describe the sources of cost differences across firms. LCD modules display images by allowing light, emitted from a backlight unit, to travel through a LCD panel which controls the amount and color of light that passes through. About 4 to 6% of the luminance from the backlight is transmitted through the panel. Opportunities to improve efficiency include (1) increasing the efficiency of the backlight (by using a more efficient light source, or a better optical film), (2) improving the transmittance of the LCD panel (by improving the design of the LCD cells), and (3) improving power management (through the use of local dimming methods which can reduce brightness in darker parts of a picture).[45]

Some margins for improving energy efficiency are fairly established, such as the use of optical films and dimming technology, and hence the costs for improving energy efficiency are predictable.[46] Other margins of improvements, however, particularly those that involve changes in the design of the LCD module, are closely tied to the manufacturing process and the R&D stock. Because panel manufacturers rely on their own proprietary technology to improve panel transmittance, they vary in the cost of enhancing energy efficiency.

Strong demand for more energy efficient models has even altered how television manufacturers manage their supply chains. For example, firms conventionally relied on upstream panel manufacturers to choose and source backlighting for LCD modules. However, during the data period, television manufacturers increasingly sought to source their own backlight so as to have better control over the energy efficiency characteristics of their televisions. As a result, some manufacturers internalized the entire process of the LCD module production, while others continued to rely on upstream manufacturers.[47]

Finally, firms also differ in their abilities to improve energy efficiency relative to that of improving non-energy efficiency aspects of the television. This would make it preferable for some firms, at the margin, to improve non-energy efficiency attributes. The Sony brand, for instance, is said to have gained global prominence after its successful CRT television sets, Trinitrion, sold almost three hundred million units worldwide. This may make it easier for Sony to improve quality relative to efficiency in LCD televisions because of it past stock of reputation.[48]

9.1.3 Details of data construction

I obtained point-of-sales (POS) data from GfK for televisions sold in Japan, enabling me to observe the average price and quantity of television sets sold in retailers. The data covers on average 75% of the televisions shipped, inclusive of non-residential outlets (Figure 7). An observation is the price and quantity sold

[45] Park (2011) and Fuji Chimera Research Institute (2009*b*) provide a technical discussion of potential sources for improvements in energy efficiency of television sets.

[46] This does not necessarily mean that they are costless to implement: for example, while incorporating local dimming technologies can decrease power consumption by as much as 40%, the implementation requires custom designed integrated circuits, and are employed primarily in higher range products.

[47] Developments in backlight technology around 2009 are discussed extensively in Fuji Chimera Research Institute (2009*a*).

[48] Ohga, Norio. Doing It Our Way, A Sony Memoir. 2008. 32-37.

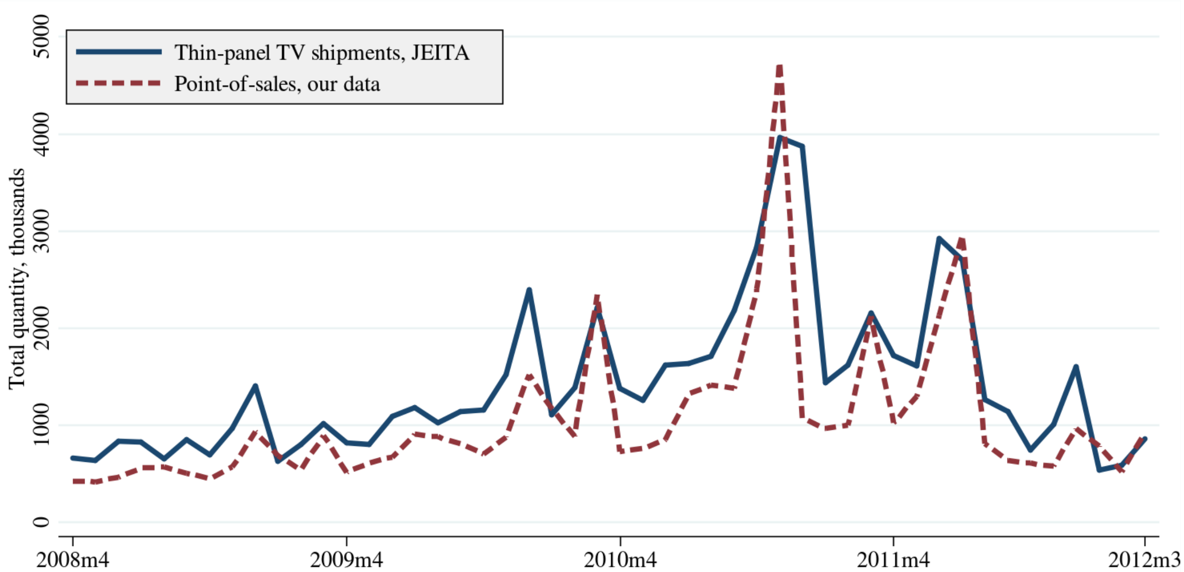


Figure 7: Data coverage. The plot shows the quantity of thin-panel televisions shipped according to a industry group, and the quantity of thin-panel televisions sold to households according to our point-of-sales data. On average the POS data covers 75% of quantity shipped.

of a given television model in a given month-district. There are five districts in our data which covers all of Japan, ranging in size from 5.8 million to 20.5 million households in March 2012. Throughout the period, I assume an exchange rate of ¥100 (JPY) =$1.00 (USD) to be able to present my findings in terms of USDs.

I focus on the 2012 Top Runner cycle, which was announced in February 2010 and enforced beginning in fiscal 2012 (April 2012 through March 2013). To be consistent with the televisions that were subject to the regulation, I use observations of televisions that were larger than 15 inches in size, designed for household viewing, and includes a digital tuner. Televisions models that sold less than 10 models in a given region month were excluded from the dataset.

Televisions with no publicly available measure of energy efficiency, or sufficient information about its functionalities to categorize how the product was subject to the regulation were dropped. Such televisions are primarily television either released by fringe firms with no remaining record of their products, or products released well in advance of the 2012 Top Runner cycle. To minimize missing data, I collect product attribute and energy efficiency data from a variety of sources. These include, in addition to the point-of-sales data: the regulator's website and bi-annual product catalog; price aggregator websites; individual manufacturers' website; and owner's manuals of televisions sets. Additionally, although I observed some televisions with necessary information from early 2006, I drop the first several months of data because many televisions in this period are missing information. As the focus of this study is on firm's strategic behavior leading up to the 2012 Top Runner cycle, the removal of data well in advance of this regulation is unlikely to change the qualitative results. Finally, because of my estimation strategy of using product fixed effects, I drop products which were not observed in the data for less than four months. This leaves 854 unique television models, starting from April 2008 and ending in March 2012.

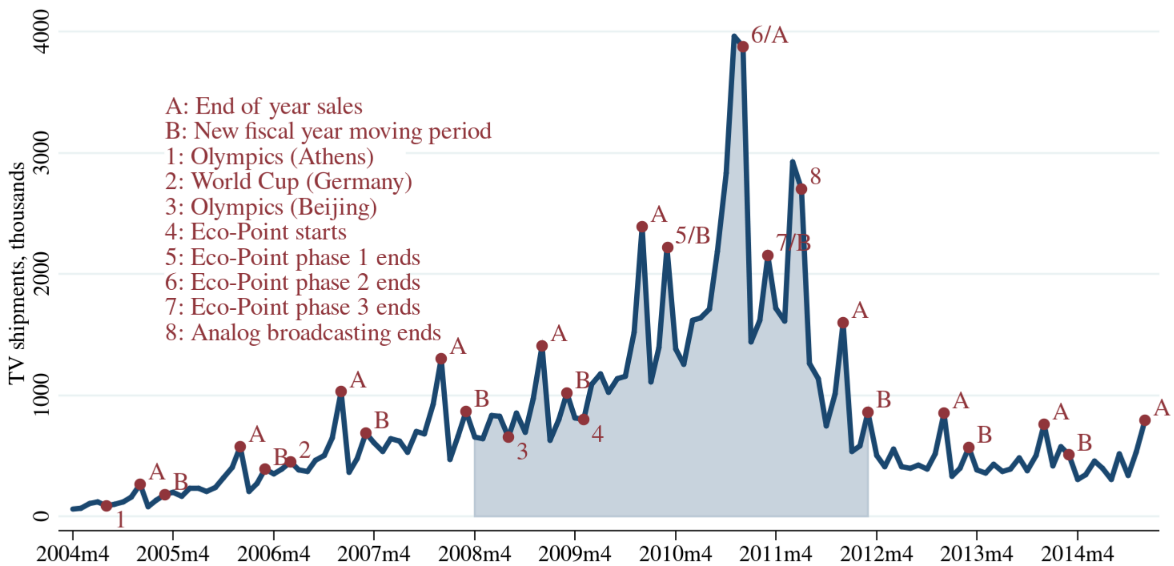


Figure 8: Shipment of thin-panel televisions by month, in thousands of units. The data period (shaded region) coincides with a phase in which demand was following an upwards trend. December coincides with the holiday selling season, during which retailers discount televisions models so as to decrease inventory and prepare for the new round of products which are introduced early in the subsequent year. As the fiscal year begins in April, March coincides with a moving period in which students and workers relocate, thereby increasing demand for durable goods such as televisions. During the data period, there were a host of major sporting events, such as the Olympics and World Cup, as well as an economic stimulus program, and the termination of analog broadcasting (source: JEITA).

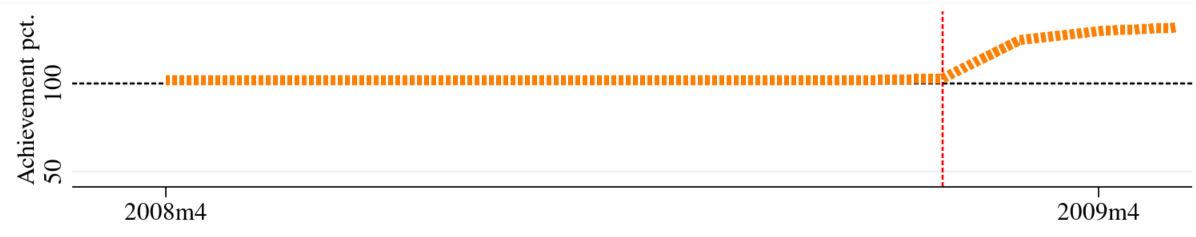
9.1.4 Firm behavior in T_{pre}

In this section, I further elaborate whether the assumption $E\left[\bar{e}_{reg}|\,\bar{e}_t\right] = \bar{e}_t$ is reasonable, by looking at firm behavior in T_{pre}. This section builds on the discussion in Section 3.2.3.

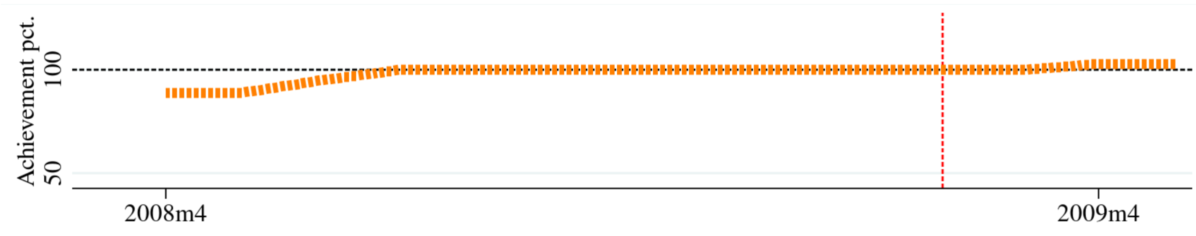
In estimation, I use sales data that starts in April 2008, ten months prior to the setting of the standard in Feberuary 2009 (in other words, T_{pre} is the period from April 2008 through February 2009). Figure 9 shows the trend of the most efficient product released across the five major product groups during this period (in orange).

In the full-HD product groups, in which we generally observe a pattern of holding back, a product with an efficiency level close to 100% (the eventual standard level) is already released at least eight months prior to February 2009 (i.e. the line of the most efficient product is generally flat from April 2008 through February 2009). This suggests that, throughout T_{pre}, firms did believe that $E\left[\bar{e}|\,\bar{e}_t\right] = \bar{e}_t$, and that the introduction of a more efficient product would have indeed tightened the future standard level.

On the other hand, in both of the non-FHD product groups, I observe that a product that was significantly more efficient than previous products was introduced immediately prior to the setting of the standard in February 2009. Ignoring this "last minute" jump of efficiency in February 2009, the trend of the most efficient products is also generally flat throughout T_{pre}. To the extent that it would have been difficult for firms to predict the jump in efficiency immediately before t_{set}, most firms in this market also plausibly believed that $E\left[\bar{e}_{reg}|\,\bar{e}_t\right] = \bar{e}_t$ throughout most of T_{pre}.

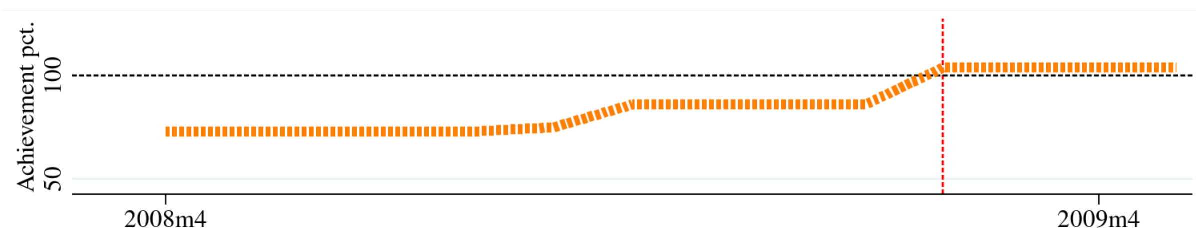


(a) Group DG (Full-HD)

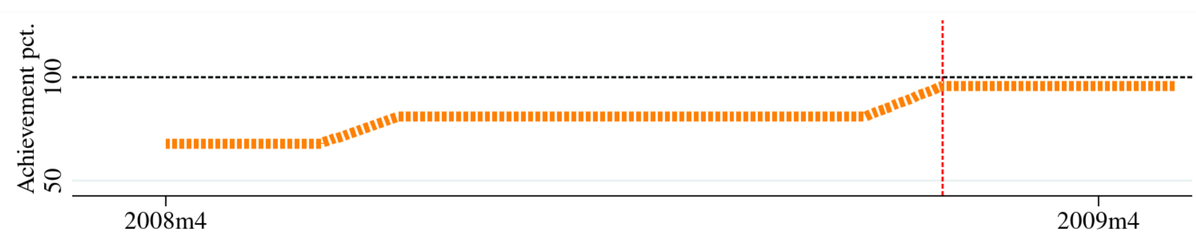


(b) Group DG1 (Full-HD)

(c) Group DG2 (Full-HD)



(d) Group DK (Non-FHD)



(e) Group DN (Non-FHD)

Figure 9: Trend of most efficient product released over time, by product group. The thick (orange) dotted line traces out the most efficient product released up to that month ($\overline{e}_t$).

9.1.5 Estimation of demand model

The GMM objective function is

$$Q_{demand}(\beta,d)=\left[\sum_{j,r,t} z'^{d}_{jrt}\tilde{\xi}_{jrt}(\beta,d)\right]' W_1 \left[\sum_{j,r,t} z'^{d}_{jrt}\tilde{\xi}_{jrt}(\beta,d)\right]+G(\beta,d)' W_2 G(\beta,d)$$

where $W_1=(Z'Z)^{-1}$, z^d_{jrt} is a row vector of demand instruments, and $G(\beta,d)$ are moments associated with the Japanese expenditure survey data, namely the difference between the terms listed in Equation 15 and the model predicted values. The identity matrix is used for W_2. The model is formulated as a MPEC problem. Consistent with the experience of Skrainka and Judd (2011), I find the optimizer CONOPT was ablest to solve my particular model.

9.1.6 Estimation of first stage model

The inequalities that are used to estimate the fixed cost parameters are shown below. Violations of these inequalities enter the objective function, shown in Equation 19. A proof that identification of the first stage model is accomplished using the set of inequalities is forthcoming.

A set of inequalities that shift energy efficiency provides bounds on F^e, by shifting the efficiency of individual goods.

$$\begin{aligned} m^{decr\_e}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } J_f=J^{Data}_{fg}\backslash j\cup j' \text{ where } e_{j'}=e_j-\Delta e\right\} \\ m^{incr\_e}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } J_f=J^{Data}_{fg}\backslash j\cup j' \text{ where } e_{j'}=e_j+\Delta e\right\} \end{aligned}$$

Another set of inequalities provide additional bounds on F^e, by shifting the energy efficiency of all goods produced in a given period.

$$\begin{aligned} m^{decr\_e2}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } e_{j'}=e_j-\Delta e \quad \forall j\in J^{Data}_{fgt}\right\} \\ m^{incr\_e2}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } e_{j'}=e_j+\Delta e \quad \forall j\in J^{Data}_{fgt}\right\} \end{aligned}$$

Another two sets of inequalities obtained provides bounds on F^q, by shifting the quality of individual goods.

$$\begin{aligned} m^{incr\_q}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } J_{fg}=J^{Data}_{fg}\backslash j\cup j' \text{ where } q_{j'}=q_j+\Delta q\right\} \\ m^{decr\_q}_{fg}(F) &= \left\{\text{sample analogue of (21) s.t. } J_{fg}=J^{Data}_{fg}\backslash j\cup j' \text{ where } q_{j'}=q_j-\Delta q\right\} \end{aligned}$$

Two sets of inequalities provides bounds on the constants F^0, by introducing or retracing goods. These two sets of inequalities are described in the main text.

Finally, two additional inequalities help identify heterogeneity in F^e and F^q. In the first set of inequalities, for each product released by firm f, the efficiency of the product is changed to the average efficiency of products released by a rival firm f' within the same product group and time period. This counterfactual is considered separately for each rival firm $f' \neq f$.

In the second set of inequalities, both the efficiency and quality of products are changed to the average of a rival firms' product offerings.

$$m_{fg}^{switch\_e}(F) = \left\{ \text{s.a. of (21) s.t. } J_f = J_f^{Data} \backslash j \cup j' \text{ where } e_{j'} = \frac{1}{|J_{f'gt}|} \sum_{j \in J_{f'gt}} e_j \; \forall f' \neq f \right\}$$

$$m_{fg}^{switch\_eq}(F) = \left\{ \text{s.a. of (21) s.t. } J_f = J_f^{Data} \backslash j \cup j' \text{ where } q_{j'} = \frac{1}{|J_{f'gt}|} \sum_{j \in J_{f'gt}} q_j,\; e_{j'} = \frac{1}{|J_{f'gt}|} \sum_{j \in J_{f'gt}} ap_j \; \forall f' \neq f \right\}$$

9.2 Evidence of structural change over time

A glance at the data suggests that some structural change took place around February 2009 (Figure 3 shows the energy efficiency of new models released over time). However, this may have been caused by a technological shock, rather than by the regulation. While no test can conclude the lack of a technological shock, I document evidence suggesting that the jump in energy efficiency around February 2009 was induced by the regulation.

Timing of regulation The jump in energy efficiency due to the regulation would only happen if firms knew the timing at which future regulation levels were set. While firms knew of the existence of the regulation, that a target level would be announced in February 2010, and that firms would need to abide to the said regulation by fiscal year 2012, there was no public announcement of when the regulator would set the regulation level.

Nevertheless, there is anecdotal evidence suggesting that firms may have been able to infer when the standards were set by the government. Firstly, industry groups played an important role in facilitating the government's administration of the regulation. For example, the data regarding the most efficient products in the market, which were used as a benchmark for setting the new target values, were compiled by an industry group. Secondly, two previous rounds of similar forms of regulation had been implemented prior to the current standards. Firms could have learned from previous rounds the timing at which the government set the new standards.

February 2009 seems to be the general timing at which the regulator set the regulation level. The left panel of Figure 6 shows the energy efficiency level all LCD televisions that were released between January 2006 and January 2009. The horizontal dotted line depicts the 2012 target values that was formally announced to the public in February 2010. The line seems to traces out the upper-bound of the energy efficiency of products available prior to February 2009. On the other hand, several products significantly exceeded the target levels prior to February 2010, when the standards were officially announced, as exhibited on the right panel of Figure 6.

Statistical significant of jump In conjunction with visual inspection, to establish the uniqueness of a jump, I implement a test of structural change of the distribution of the energy efficiency of televisions being sold. In particular, I implement a test that detects structural change with unknown timing in regression quantiles, developed by Qu (2008) and Oka and Qu (2011). The test suggests that the jump observed February 2009 is unique, in that the jump is the only statistically significant jump that the test can detect. This is consistent with the argument that the jump is different from other potential jumps in the data, which are likely to be driven by technological shocks.

I model the trend of energy efficiency, e, of televisions available on the market over time using a quadratic regression,

$$e_{jt} = \beta_0 + \beta_1 \cdot t + \beta_2 \cdot t^2 = x'_{jt}\beta$$

where t is a time index for the month of product sale. Based on this model, the conditional quantile function $Q_e(\tau|t)$ is defined as

$$Q_e(\tau|t) = \beta_0(\tau) + \beta_1(\tau) \cdot t + \beta_2(\tau) \cdot t^2 = x'_{jt}\beta(\tau)$$

that minimizes the standard quantile regression objective function

$$\begin{aligned} V(\tau) &= \sum_{e_{jt} < Q_e(\tau)} \{(1-\tau) \cdot |e_{jt} - Q_{e_t}(\tau|t)|\} + \sum_{e_{jt} > Q_e(\tau)} \{\tau \cdot |e_{jt} - Q_{e_t}(\tau|t)|\} \\ &= \left[1\left(e_{jt} - x'_{jt}\beta < 0\right) - \tau\right] \cdot \left(e_{jt} - x'_{jt}\beta\right) \end{aligned} \tag{25}$$

for a given quantile τ. I focus on the 90th and 95th percentiles to understand how the upper tail of the distribution of energy efficiency has changed over time.

The SQ-test (Qu, 2008 and Oka and Qu, 2011) examines the structural stability of a given quantile. It tests whether the null hypothesis

$$H_0: \ \beta = \beta^0 \text{ for all } t \text{ and for a given } \tau = \tilde{\tau}$$

can be rejected in favor of the alternative

$$H_1: \ \beta = \begin{cases} \beta^1 & \text{for } t = 1, \cdots, T_1 \\ \beta^2 & \text{for } t = T_1 + 1, \cdots, T_2 \\ & \vdots \end{cases} \text{ for a given } \tau = \tilde{\tau}$$

for a vector of break dates, $T^m = \{T_1, T_2, \cdots, T_m\}$ of unknown length, where β is a vector of the parameters in the quantile regression function.

The test is a sub-gradient based test. Using a fraction λ of the sample of size n, the sub-gradient of the objective function is

$$S(\lambda, \tau, b) = \frac{1}{n} \sum_{i=1}^{\lambda n} x_i \left[1(ap_i - x'_i b < 0) - \tau\right]$$

where b is the estimate of β using the entire sample. If structural change is present, using a sub-sample of the data will result in the sub-gradient taking on values that differ significantly from zero. Therefore, the statistic, which is the weighted sum of the sub-gradients,

$$H_{\lambda,n}(b) = \left(X'X\right)^{-1} \sum_{i=1}^{\lambda n} x_i \left[1(ap_i - x_i' b < 0) - \tau\right]$$

converges to a non-degenerate distribution under the null hypothesis, while it diverges for some λ in the presence of structural change. The SQ-test is based on a small-sample refinement of this statistic (Equation (5) of Qu, 2008).

Empirically, conditional on the number of break dates m, Oka and Qu (2011) discusses the recovery of the unknown break dates and structural parameters. It is based on minimizing a modified check function over all possible combination of break dates,

$$\left(\hat{\beta}, \hat{T}\right) = \arg\min \sum_{k=0}^{m} \sum_{i=1}^{\lambda n} \left[1(ap_i - x_i' \hat{\beta}^k < 0) - \tau\right] \cdot \left(ap_i - x_i' \hat{\beta}^k\right)$$

An additional test, $SQ_\tau\,(l+1|l)$-test, determines the number of structural changes, m.

To conduct this test, I construct a balanced panel of television model-price -month observations. During the period January 2006 through March 2014, there were a minimum of 443 model-price-region observations. Therefore, I randomly sample 443 data points from the full data set for each month during the period January 2006 through March 2012, using the seed 2014, to construct a balanced panel. The panel is reflective of the television models that were purchased by consumers in every month. They do not reflect the quantity of purchases of televisions, however, because the intent of this exercise is to see how the distribution of energy efficiency, across models, changed over time. The sub-sample is illustrated in Figure 10. I run the SQ-test using the `R` code provided by Oka and Qu (2011), allowing for a maximum of three structural breaks.

Table 11 presents the results of the SQ-test. One structural break is detected for both the 90th and 95th quantile, and is significant at the 5% significance level. The structural break of the 95th percentile is around April 2009, while that of the 90th percentile is November 2009.[49] Figure 10 illustrates the estimated quantile regression functions, where the solid lines denote the functions after the structural change. They suggest an upward jump in energy efficiency around the time of structural change, roughly around February 2009.

The findings of the test suggest that the jump around February 2009 is unique, in that it is distinct from other potential jumps that are observed in the data. This is consistent with the view that the jump in February 2009 was induced by regulation.

Comparison with American televisions Many manufacturers of televisions in Japan compete in foreign markets as well. The presence of more efficient televisions sold in other markets would be consistent with the assumption that the technology to make more efficient products did exist, but the firms decided not to provision the technology due to regulatory constraints. Therefore, this would also support the claim that the jump around February 2009 is not due to technological change.

[49] The ratcheting incentives suggest that the regulation affects the most efficient products that are introduced. Therefore, the efficiency of products at the 95th or 90th percentile are likely to experience a jump with a delay.

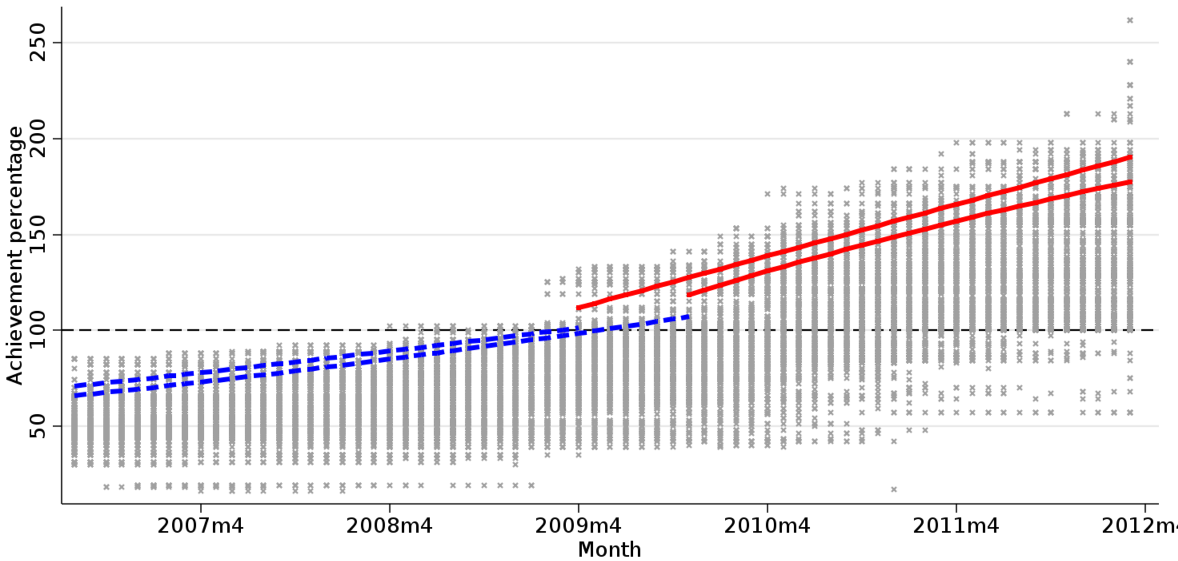


Figure 10: Oka-Qu test for estimating structural changes occurring at unknown dates in conditional quantile functions. A quadratic time trend was used to model the transition of the energy efficiency of televisions available over time. A SQ-test suggests the presence of a structural change in the time trend in both the 90th and 95th percentile. The estimated time trend under the two regimes are plotted for both the 90th and 95th percentile. The dotted lines illustrate the model under the first regime, prior to the structural change. The solid lines illustrate the model under the second regime.

Table 11: Oka-Qu test for estimating structural changes occurring at unknown dates in conditional quantile functions. A quadratic time trend was used to model the transition of the energy efficiency of televisions available over time. The hypothesis test examines the number of structural tests that can be detected. One significant structural change was detected for both the 90th and 95th percentile.

	0.9	0.95
Test (H_0 vs H_1)		
0 vs 1	4.61^{**}	5.41^{**}
1 vs 2	1.62	1.60
Number of breaks	1	1
First break date	2009m11	2009m4
95% C.I.	[2009m10, 2009m12]	[2009m3, 2009m5]
Regime 1		
β_0	1303.25	465.33
β_1	-5.27^{**}	-2.27
β_2	0.005^{**}	0.002
Regime 2		
β_0	-6427.51^{**}	-0.001
β_1	19.4^{**}	2.82
β_2	-0.01^{**}	0.002

I attempt to trace out the upper envelope of the most efficient products that were released in the U.S, by compiling data files on televisions that were qualified for the U.S. Energy Star program. The Energy Star program certifies products that exceed efficiency requirements, and hence, televisions that qualified for the program are likely to represent the most efficient products available in the U.S. The data files provide the date on which the televisions were qualified for the program, as well as manufacturers' self-report of when the television was released. Unfortunately, the data is not comprehensive, particularly for the self-reported product release date (see next section for details on data construction).

Figure 11 shows the energy efficiency of Energy Star television over time. I observe televisions exceeding 100% being released in the U.S. before February 2009. This is consistent with the argument that the technology to make efficient televisions did exist, but that Japanese manufacturers decided not to released them prior to February 2009.

In conclusion, the observed jump in energy efficiency is statistically significant and unique, and anecdotal evidence suggests that firms knew of when the regulator was to set the future regulation. Finally, these were more efficient televisions sold in other markets, prior to the jump. Hence, I conclude that the jump in energy efficiency around February 2009 was induced by the regulation.

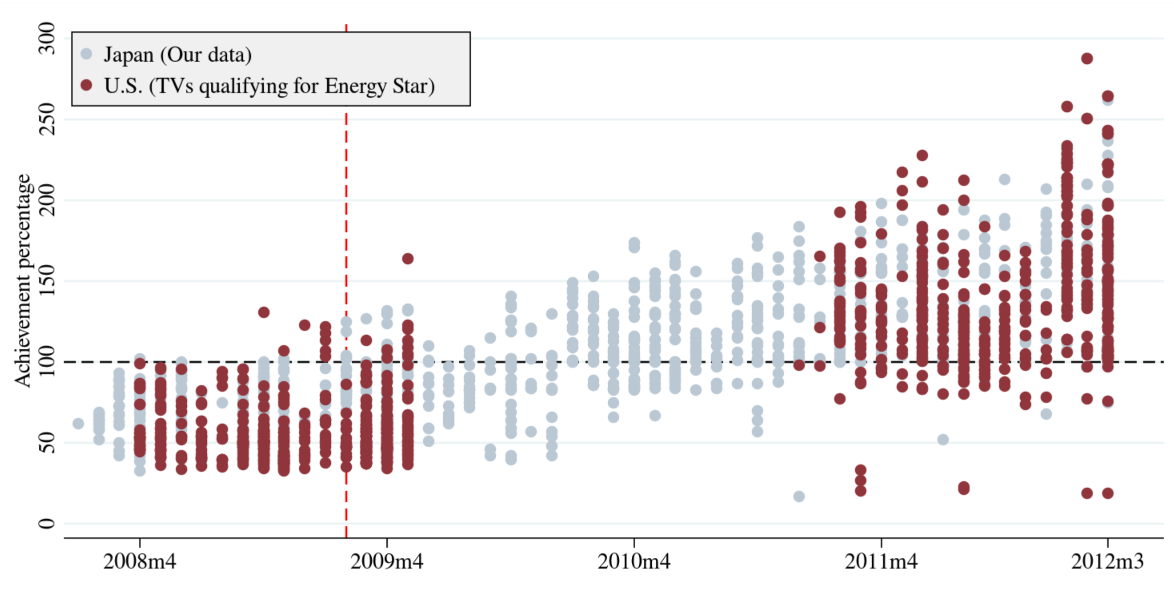
Data of Energy Star televisions The data on Energy Star televisions were obtained from various data files on the U.S. Environmental Protection Agency's Energy Star website (www.energystar.gov). The Energy Star requirements for televisions have been frequently updated. The final dataset includes televisions that qualified for version 3.0 of the Energy Star requirements from its inception in November 2008 through April 2009; version 4.0 from May 2010 through September 2011; and version 5.0 from September 2011 through May 2013. The dataset for version 3.0 televisions from May 2009 through April 2010 did not have information on neither product release dates nor qualification dates, and could not be used for the current analysis.

To make the data comparable to the Japanese data, I calculated pseudo-achievement percentages by categorizing U.S. televisions into product groups. To maintain consistency with the Japanese dataset, televisions with screen sizes smaller than 16 inches are dropped. The general trend and level of achievement percentages are comparable between the two datasets (Figure 11).

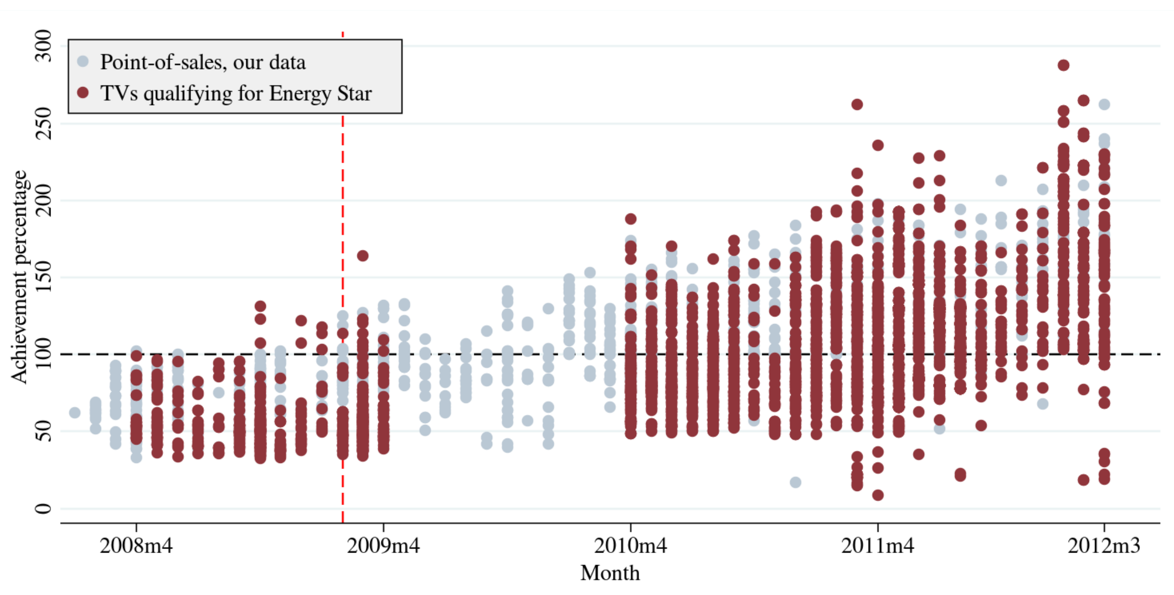
9.3 A simple model of firms under endogenous regulation

In order to gain insight into the forces at play under the regulation, I extend a model of duopolistic competition to allow for an endogenous environmental regulation. In the basic model, two potentially heterogeneous firms are competing in a market with vertically differentiated products.[50] The modifications that I propose to this model are twofold. Firstly, I introduce a simple form of dynamics, by allowing the same firm to compete over two time periods. This also enables exogenous technological change to take place. Secondly, I study firm behavior when a dynamic minimum quality regulation, akin to the Japanese regulation, is introduced in this market. The model suggests that firms' quality choices and resulting level of regulation can be used to

[50] Analogous models, without the regulation, have been studied in detail by Choi and Shin (1992), Wauthy (1996), and others.



(a) By date television was available on market



(b) By date television was qualified for Energy Star

Figure 11: Energy efficiency of televisions certified by the U.S. Energy Star program.

understand the underlying competitive environment that firms are placed in.[51]

In each of the two time periods, the two firms simultaneously first decide whether to enter, and if so, choose the quality of the product, s_{jt}. Second, conditional on product quality, the firms simultaneously decide on prices, p_{jt}. The firm's profit is given by

$$\pi_j = \sum_{t \in \{0,1\}} \beta^t \cdot (R_{jt} - C_{jt})$$

where β is the discount factor, $R_{jt} = p_{jt} \cdot q_{jt}$ is revenue, and C_{jt} is fixed cost. In the one period case, the firm's fixed cost is given by $C_j = \alpha_j \cdot s_j^{\gamma_j}$ where α_j and γ_j are firm specific parameters that alter the relative cost advantage between the two firms. The parameters α and γ enable firms to be heterogeneous. Following convention, I abstract away from marginal costs.

Consumers demand at most one quantity of the product in each time period. They differ in their appreciation for quality, a proxy for energy efficiency in my empirical application. Consumers are heterogeneous in their demand for quality, where a consumer of type θ_i derives utility of

$$u_i = \theta_i \cdot s_{jt} - p_{jt}$$

from purchasing good j at time t. θ_i is distributed uniformly on the interval $\left[\underline{\theta}, \overline{\theta}\right]$, such that the mass of consumers in any interval $[\theta_L, \theta_U]$ is $\frac{\theta_U - \theta_L}{\overline{\theta} - \underline{\theta}}$, where $\underline{\theta} \leq \theta_L < \theta_U \leq \overline{\theta}$.

Consumers have a zero-utility outside option if they choose not to purchase any good. When examining minimum quality standards for non-essential goods, such as televisions, firms' decisions under the standard are likely to be affected by the presence of an outside good because the regulation is likely inhibit firms' ability to sell goods to some consumers in the second period. This force would not be captured if consumers were inelastic.[52]

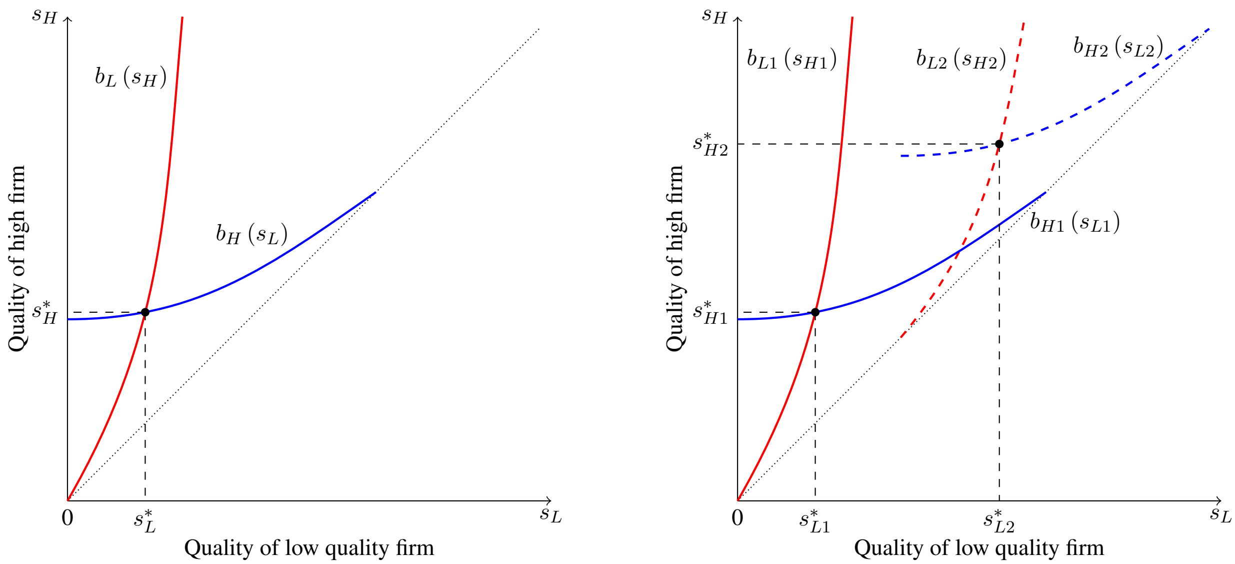
I study the case in which, in the absence of any constraints, $\overline{\theta} - \underline{\theta}$ is sufficiently large enough that both firms enter the market, and a mass of consumers purchase the outside good. When the two firms both decide to enter, they never choose the same level of quality because it induces perfect competition. I label the firm that chooses the higher quality H, and the lower quality L. Their quality choices are denoted s_H and s_L, such that $s_H > s_L$.

Conditional on the quality chosen by both firms, the firms' optimal prices are expressed in closed form as $p_L = \frac{\overline{\theta} s_L (s_H - s_L)}{4 s_H - s_L}$ and $p = \frac{2\overline{\theta} s_H (s_H - s_L)}{4 s_H - s_L}$. The revenues are $R_L = \frac{\overline{\theta}^2 s_L s_H (s_H - s_L)}{(4 s_H - s_L)^2}$ and $R_H = \frac{4\overline{\theta}^2 s_H^2 (s_H - s_L)}{(4 s_H - s_L)^2}$.

[51] A stream of theory literature has studied the effects of regulation using a similar model. Ronnen (1991) shows that an exogenous minimum quality standard can be welfare improving; increases quality for both firms; decreases profits for the high firm; and can increase profits for the low firm. On the other hand, if the high firm can commit to a quality level before the welfare maximizing regulator introduces a quality standard, Lutz et al. (2000) shows that a weaker regulation is introduced; both firms produce lower quality goods; the high firm's profits increase, but social welfare suffers.

My model is a middle ground of these regulatory schemes. The passive regulator merely sets the regulation level as the most efficient product in the previous period. The high firm is faced with dynamic incentives to alter the level of quality chosen today so as to induce a favorable level of regulation tomorrow.

[52] An analysis of dynamic regulation under the inelastic case is shown in Michaelis et al. (2015).



(a) One period case

(b) Two period case

Figure 12: Best response curves. $b_L(s_H)$ indicates the best response curve for the low firm. It describes what the best response of the low firm is as a function of the quality of the high firm. $b_H(s_L)$ indicates the best response curve for the high firm.

The best response condition for firm L, b_L, is implicitly defined by

$$\frac{\partial R_L}{\partial s_L} = \frac{\partial C_L}{\partial s_L} \iff \frac{\overline{\theta}^2 s_L^2 (4s_H - 7s_L)}{(4s_H - s_L)^3} = \alpha_L \gamma_L s_L^{(\gamma_L - 1)}$$

and is defined for any value of $s_L \in [0, s_H]$. Similarly, for the high firm, the best response condition

$$\frac{\partial R_L}{\partial s_L} = \frac{\partial C_L}{\partial s_L} \iff \frac{4\overline{\theta}^2 s_H \left(2s_L^2 - 3s_L s_H + 4s_H^2\right)}{(4s_H - s_L)^3} = \alpha_H \gamma_H s_H^{(\gamma_H - 1)} \tag{26}$$

is well defined in the interval $s_H \in [s_L, \infty]$.

An example of the best response curves and the equilibrium outcome is depicted in Figure 12. The slopes of both curves are strictly positive, making quality choices strategic complements. The intersection of the two best response curves may be an equilibrium, so long as both firms make positive profits, and some consumers decide not to purchase. I denote the equilibrium quality choices of the low and high quality firms in this unconstrained market as s_L^* and s_H^*, respectively.

One period case with exogenous constraints (Ronnen, 1991) When a minimum quality constraint s_{MQ} is introduced, three outcomes can prevail. When the constraint is smaller than s_L^*, the constraint does not change the firms' problems. On the other hand, if s_{MQ} is larger than some value s_O, the two firm can no longer both make positive profits, and one exits the market.

When s_{MQ} is larger than s_L^*, but smaller than some value s_O, such that both firms can still make positive profits, the low firm chooses $s_L = s_{MQ}$. The high firm chooses some quality level greater than its unconstrained level, $s_H > s_H^*$, because the best response of H is increasing in s_L. Ronnen (1991) shows the existence of such an equilibrium. Compared to the unconstrained equilibrium, the high firm's profits decreases and the low firm's increases. The high firm suffers because its profits are decreasing in the quality of the low firm, $\frac{\partial \pi_H}{\partial s_L} < 0$. For the low firm, the constraint s_{MQ} acts as a commitment device, enabling the low firm to effectively be the first mover. The two firms make products that are of similar quality, and thus, the firms engage in more intensive price competition.

Extension to two period case with endogenous minimum quality constraints The crux of my analysis is in extending the basic model to the two-period case. There are two additional assumptions I impose. Firstly, I assume an exogenous shift in the technology such that quality is cheaper to provision in the second period.

$$C_{jt} = \alpha_j \cdot (s_{jt} - (t-1)\tilde{s})^{\gamma_j}\ , \ \ \forall j \in \{1, 2\}\ , \ \ \forall t \in \{0, 1\}$$

where $\tilde{s}$ represents exogenous technical advances that uniformly enhances both firms' ability to produce the same quality of good at a lower cost over time. In the model $\tilde{s}$ allows for cases in which the regulation does not change market outcomes. $\tilde{s}$ also reflects the transition of technology that is pervasive in the markets that are commonly subject to these constraints.

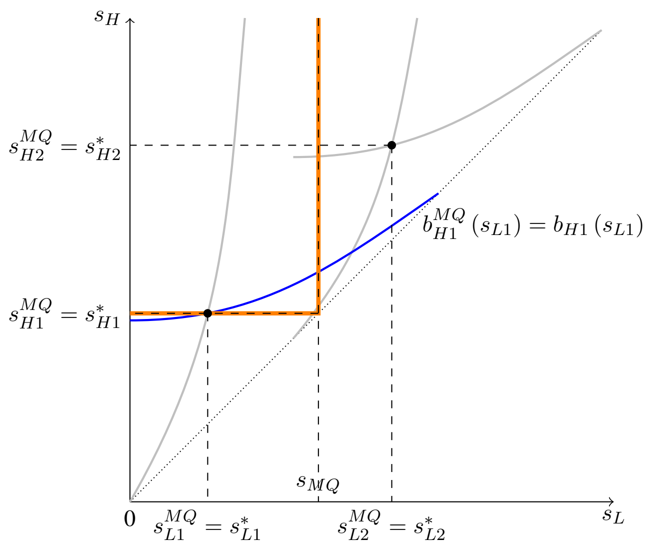
Secondly, I assume that the firm that chooses the higher quality in the first period also chooses the higher quality in the second period, and that the firm with the lower marginal costs chooses higher quality in equilibrium. In the unconstrained equilibrium the high firm always makes larger profits (Lehmann-Grube, 1997). The assumption implies that the high firm advantage perpetuates over time. A justification of these two assumptions is that the model is intended to capture medium-term behavior in which firms can change product attributes, but the level of technological advances and firms' relative positions in the market are stable. Multinational firms make research and development decisions based on long term evaluations of the global benefits from innovation, whereas quality constraints are typically implemented at more levels.

Without the minimum quality constraints, the decisions that firms make are independent over time. The best response curves shift northeast by $\tilde{s}$ in the second period, reflecting the technical advance that takes place each period. The optimal unconstrained market outcomes shift by $\tilde{s}$ as well. Let s_{jt}^* denote the unconstrained quality choice of firm j in period t, so that $s_{j2}^* = s_{j1}^* + \tilde{s}$.

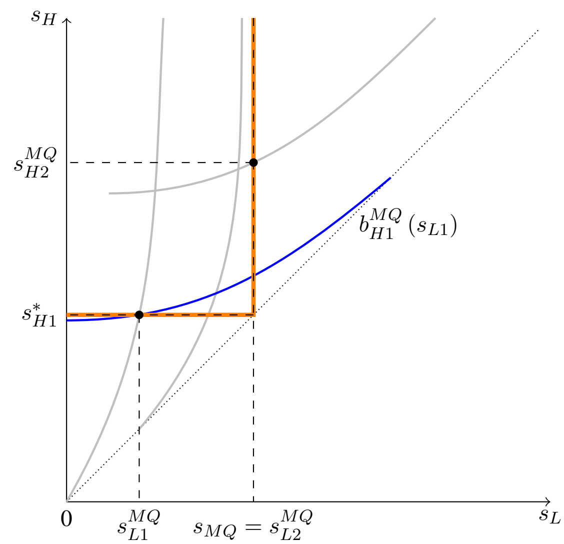
The main constraint I study is a dynamic minimum quality constraint. The minimum quality constraint of the second period is now defined endogenously to be the quality of the high firm in the first period

$$s_{MQ} = s_{H1}$$

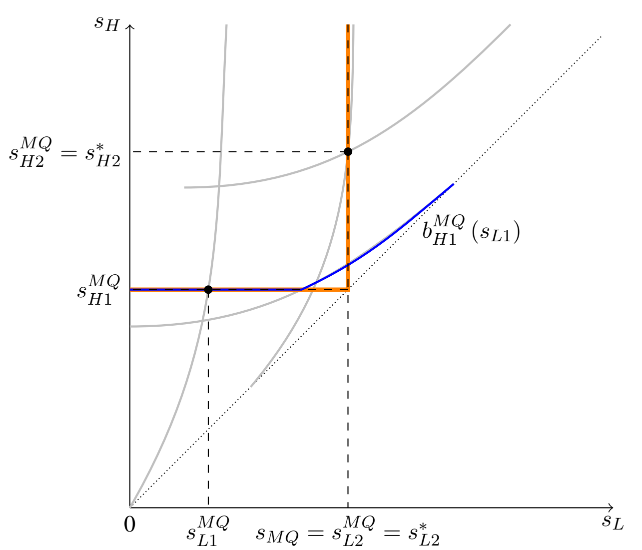
There are no minimum quality constraints in the first period. Under this new constraint, there are four classes of outcomes. When $\tilde{s}$ is large such that $s_{H1}^* \leq s_{L2}^* = s_{L1}^* + \tilde{s}$ the regulation does not change the outcomes of the game (**case 1**). This case is illustrated in Figure 13a. While it is clear that this outcome is more likely to happen when technological progress is large, but I later show this is also more likely to happen when the high firm has a small cost advantage.



(a) Case 1, $s_{H1}^* < s_{L2}^*$



(b) Case 2, $s_{L2}^{MQ} = s_{MQ} > s_{L2}^*$



(c) Case 3, $s_{L2}^{MQ} = s_{L2}^* > s_{MQ}$

Figure 13: Best response curves under regulation. The bold-solid (blue) line is the high firm's modified best response curve, anticipating the effect of its action on second period regulation. The shaded-dotted (orange) line represents the regulation: it projects the high firm's first period quality choice (y value) onto the 45-degree line and the x-axis. The low firm must choose a quality higher to the right of the vertical portion of the shaded-dotted (orange) line.

I now consider the outcomes that can happen when $s_{H1}^* \geq s_{L2}^*$, i.e. when the constraint is binding. If both firms are in production across both time periods, and when the second period constraint is binding for the low firm such that it chooses $s_{L2} = s_{MQ} > s_{L2}^*$, the high firm's best response condition in the first time period is modified to internalize this effect on second period revenues

$$b_{H1}^{MQ}(s_{L1}) = \left\{ b_{H1} | \frac{\partial R_{H1}}{\partial s_{H1}} + \beta \frac{\partial R_{H2}}{\partial s_{MQ}} \frac{\partial s_{MQ}}{\partial s_{H1}} = \frac{\partial C_{H1}}{\partial s_{H1}} \right\} \tag{27}$$

A negative wedge $\frac{\partial R_{H2}}{\partial s_{MQ}} \frac{\partial s_{MQ}}{\partial s_{H1}} = \frac{\partial R_{H2}}{\partial s_{H1}}$ is introduced in the condition (**case 2**). Compared to the unconstrained value of $s_{H1} = s_H^*$, the optimal first period quality s_{H1}^{MQ} is lower because the marginal revenue is decreasing in quality, and marginal cost is increasing in quality. Figure 13b illustrates the modified best response curves and optimal outcomes in this case. Because the constraint is binding in the second period, both firms choose higher levels of quality in the second period.

There is a corner case in which the optimal response is exactly $s_{H1}^{MQ} = s_{L2}^*$ (**case 3**). The condition 27 may not be necessary for equilibrium if it forces a quality choice below s_{L2}^*. The high firm does not need to reduce quality more than s_{L2}^*, because its first period choice no longer affects the constraint. Therefore, there can be a equilibrium in which $s_{H1}^{MQ} \neq b_{H1}^{MQ}(s_{L1})$, namely if $b_{H1}^{MQ}(s_{L1}) < s_{L2}^*$. In this case, the optimal choice of quality is exactly $s_{H1}^{MQ} = s_{L2}^*$ because revenues are increasing in s_{H1}. In this case, the quality of the low firm is unaltered in the second period, compared to a unconstrained market. Figure 13c shows how the high firm now chooses $s_{H1} = s_{L2}^*$ in the first period, and the accompanying outcomes.

Therefore, the quality choices defined by intersection of $\hat{b}_{H1}^{MQ}(s_{L1}) = \max\left\{ b_{H1}^{MQ}(s_{L1}), s_{L2}^* \right\}$ and $b_{L1}(s_{H1})$ are necessary conditions for an equilibrium when two firms enter the market for both periods, and the regulation is binding such that $s_{H1}^* > s_{L2}^*$.

Theorem 1. *There exists a unique point $\left(s_{H1}^{MQ}, s_{L1}^{MQ}\right)$ that satisfies the necessary conditions under the dynamic constraint.*

Proof 1. *The goal of the proof is to show that the root to the function $B(s) = \hat{b}_{H1}^{MQ}[b_{L1}(s)] - s$ exists. The technique used in this proof is similar to Ronnen (1991)*

The function b_{H1}^{MQ} is defined on $[0, \bar{s}]$ where $\bar{s}$ is the solution to $b_{H1}^{MQ}(\bar{s}) = \bar{s}$. Firstly I prove the case when $b_{H1}^{MQ}(s) > s_{L2}^*$ for all values of s in its domain, so $\hat{b}_{H1}^{MQ} = b_{H1}^{MQ}$. Fully differentiating 27 with respect to q_{L1} gives

$$\frac{\partial MR_{H1}}{\partial s_{H1}} \cdot \frac{\partial s_{H1}}{\partial s_{L1}} + \frac{\partial MR_{H1}}{\partial s_{L1}} + \frac{\partial R_{H2}}{\partial s_{L2}} \cdot \frac{\partial s_{H2}}{\partial s_{H1}} \cdot \frac{\partial s_{H1}}{\partial s_{L1}} + \frac{\partial R_{H2}}{\partial s_{L2}} \cdot \frac{\partial s_{H1}}{\partial s_{L1}} = \frac{\partial MC_{H1}}{\partial s_{H1}} \cdot \frac{\partial s_{H1}}{\partial s_{L1}}$$

Solving the expression for $\frac{\partial s_{H1}}{\partial s_{L1}} = \frac{\partial b_{H1}^{MQ}(s_{L1})}{\partial s_{L1}}$,

$$\frac{s_{H1}}{s_{L1}} > \frac{\partial b_{H1}^{MQ}(s_{L1})}{\partial s_{L1}} = \frac{\partial MR_{H1}}{\partial s_{L1}} \Big/ \left(\frac{\partial MC_{H1}}{\partial s_{H1}} - \frac{\partial s_{H1}}{\partial s_{L1}} - \frac{\partial R_{H2}}{\partial s_{L2}} \cdot \frac{\partial s_{H2}}{\partial s_{H1}} - \frac{\partial R_{H2}}{\partial s_{L2}} \right) > 0$$

where the first inequality follows from Euler's theorem: $s_{H1} \cdot \frac{\partial MR_{H1}}{\partial s_{H1}} + s_{L1} \cdot \frac{\partial MR_{H1}}{\partial s_{L1}} = 0$, and the second by signing each of the terms. A similar procedure bounds $\frac{s_{L1}}{s_{H1}} > \frac{\partial b_{L1}(s_{H1})}{\partial s_{H1}} > 0$, and hence $\frac{\partial B}{\partial s} = \frac{\partial b_{H1}^{MQ}}{\partial s} \cdot$

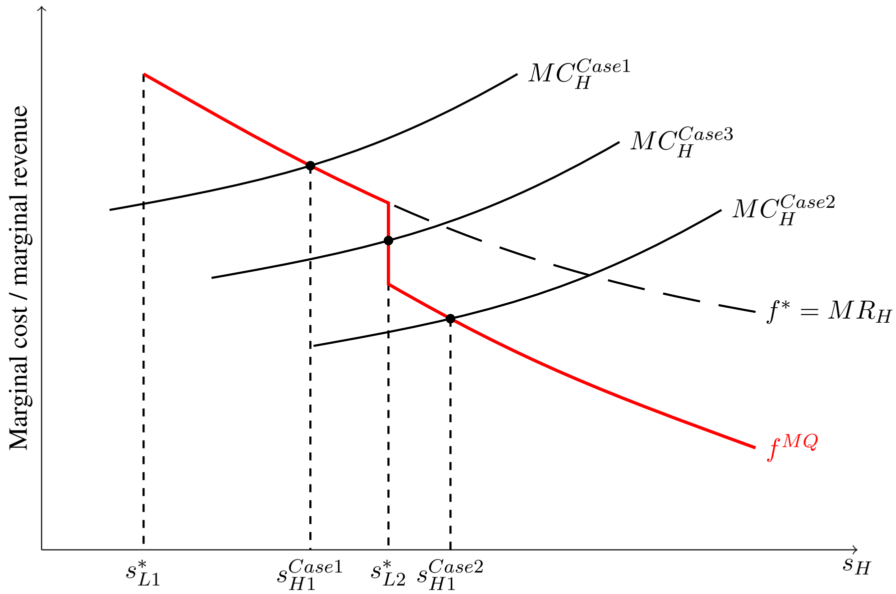


Figure 14: Necessary conditions for equilibrium of high firm in first period.

$\frac{\partial b_{L1}}{\partial s} - 1 < 0$. Because $b_{L1}(s)$ is always positive and smaller than $b_{H1}^{MQ}(s)$, $B(0) > 0$ and $B(\overline{s}) < 0$. Hence, a unique root to $B(s) = 0$ exists in the range of $s \in [0, \overline{s}]$.

When $b_{H1}^{MQ}(s) \leq s_{L2}^*$ for some $s > 0$, the function b_{H1}^{MQ} does not prescribe the firm's optimal response, because $\frac{\partial s_{MQ}}{\partial s_{H1}} = 0$ when $s_{H1} \leq s_{L2}^*$. Let $\hat{s}$ be the root of $b_{H1}^{MQ}(\hat{s}) = s_{L2}^*$. $\frac{\partial \hat{b}_{H1}}{\partial s_{H1}} = 0$ if $s < \hat{s}$, and $\frac{\partial \hat{b}_{H1}}{\partial s_{H1}} = \frac{\partial b_{H1}(s_{L1})}{\partial s_{L1}} > 0$ from the first part of the proof. Hence we have $\frac{\partial B}{\partial s} \leq 0$, $B(0) > 0$ and $B(\overline{s}) < 0$. Hence, a unique root exists.

As long as s_{L2}^* is sufficiently small that the constraint affects firms' behavior ($s_{H1}^* \geq s_{L2}^*$), I find that the high firm necessarily decreases its quality.

Theorem 2. *(Ratcheting down) When both firms enter the market for both periods, and the regulation is binding such that $s_{H1}^* > s_{L2}^*$, the high firm always decreases its first period quality relative to the unconstrained case $s_{H1}^{MQ} < s_{H1}^*$.*

Proof 2. *The marginal cost curve $MC_{H1}(\cdot)$ is strictly increasing in s_{H1}. On the other hand, for any given value of $\overline{s}_{L1}$ and $\overline{s}_{H2}$, the functions $f^*(s_{H1}) = MR_{H1}(s_{H1}, \overline{s}_{L1})$ and $f^{MQ}(s_{H1}) = MR_{H1}(s_{H1}, \overline{s}_{L1}) + \beta \tilde{f}(s_{H1}, \overline{s}_{H2})$, where $\tilde{f}(s_{H1}, s_{H2}) = \frac{\partial R_{H2}}{\partial s_{MQ}} \frac{\partial s_{MQ}}{\partial s_{H1}}$, are strictly decreasing in s_{H1}; and $f^*(s_{H1}) > f^{MQ}(s_{H1})$. If the intersection of $MC_{H1}(\cdot)$ and $f^{MQ}(\cdot)$ is greater than s_{L2}^*, the value of s_{H1} that satisfies the unconstrained best response condition 26 is strictly larger than the value of s_{H1} that satisfies the constrained best response condition 27, as shown in Figure 14. When $MC_{H1}(\cdot)$ does not intersect with $f^{MQ}(\cdot)$ in the range $[s_{L2}^*, \infty)$, this is the corner case described above. Then $s_{H1}^{MQ} = s_{L2}^*$, and trivially $s_{H1}^{MQ} < s_{H1}^*$.*

While ratcheting down necessarily occurs under the aforementioned conditions, the extent to which it occurs is driven by costs parameters α and γ. Any change in parameters that either increases the marginal costs of the low firms, or that decrease the marginal costs of the high firm results in the distance between the equilibrium outcomes $s_H^{MQ} - s_L^{MQ}$ to increase. This mitigates the effect of holding back.

Proposition 1. *(Effect of cost differences, 1) When both firms enter the market for both periods, as the high firms' marginal costs decreases, the equilibrium outcome transitions from **Case 1** to **Case 3**, then from **Case 3** to **Case 2**.*

For a given set of parameters, the necessary conditions for equilibrium are defined by the intersection of the marginal cost curve, and the thick (red) line in Figure 14. **Case 1** corresponds to the case when the marginal cost curve intersects with the thick curve along f^*; **Case 2** when it intersects along f^{MQ}; and **Case 3** when it intersects at s^*_{L2}. Decreasing the marginal cost curve therefore allows the equilibrium case to switch between these three. When **Case 2** plays out, the regulation forces the low firm to choose a higher quality such that $s^{MQ}_{L2} > s^*_{L2}$.

Proposition 2. *(Effect of cost differences, 2) When both firms enter the market for both periods, as the low firms' marginal costs increases, the equilibrium quality choice of the high firm in the first period weakly increases.*

This follows from the fact that f^{MQ} for $s_H > s^*_{L2}$ shifts up as the marginal cost of the low firm increases.

For completeness, I highlight the existence of a fourth outcome. Under some parameter values, the high firm would like to induce a monopoly outcome in the second period by deterring entry (**case 4**). There can exist an equilibrium in which the high firm chooses s_{H1} high enough so as to put the low firm out of business in the second period.

Limitations of theory model This simple model does not capture critical elements that characterize the action space of televisions manufacturers. These include decisions on the number of the television models to introduce. For example, in one product group, the most efficient firm floods the market by releasing multiple products. This may be another strategic behavior that firms can engage in to prevent entry.

Additionally, in practice, products may be characterized by multiple vertical or horizontal attributes. Anderson et al. (1992) summarizes that when products have two attributes, "minimum differentiation is possible in one dimension only if differentiation is sufficiently large in the other" (p. 317). When regulation forces products to be more homogeneous in one dimension, firms may compensate by differentiating on the other attributes.