Welfare Gains from Product and Process Innovations: The Case of LCD Panels, 2001–2011*

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Abstract

We study competition and innovation in the liquid crystal display (LCD) industry. New products and productivity growth account for 71% and 39% of total welfare, respectively. Social returns on technological investments were high, but most firms' private returns were low because of large sunk costs. We then investigate the effects of market structure on innovation by simulating all possible mergers among seven major firms. Some mergers could increase firms' incentive to innovate, but their effects become mostly negative when five or fewer firms exist. Our extensive sensitivity analysis shows mergers could be pro-innovation only under very low price-sensitivity of demand.

1 Introduction

Innovation and productivity growth play a central role in improving social welfare. Recent studies in industrial organization (IO) on the long-term evolution of market power rediscover the big benefits to consumers of technological progress, which tend to dwarf the impact of increasing market power (if any) in the wholesale (Ganapati 2021), automobile (Grieco, Murry, and Yurukoglu 2023), and cement (Miller, Osborne, Sheu, and Sileo 2023) industries. The renewed antitrust-policy interest in innovation is apparent in the most recent US

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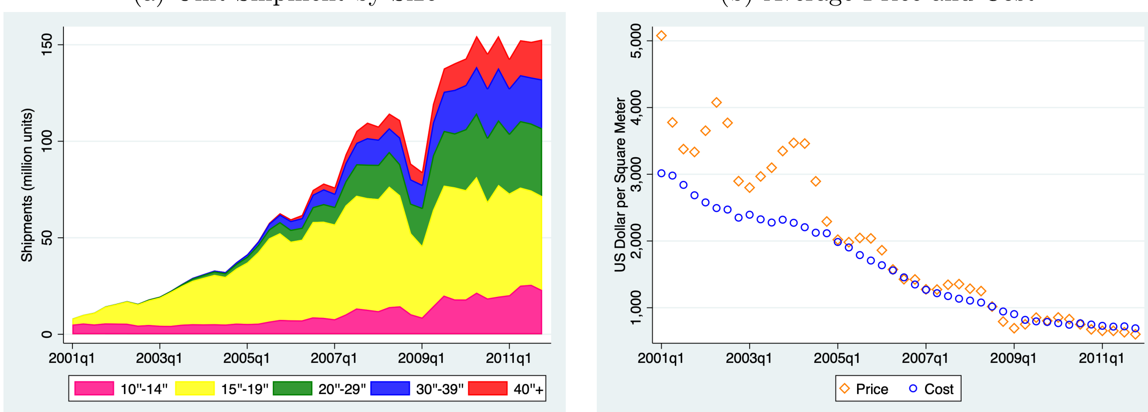
Merger Guidelines as well.[1] The economic literature has identified many types of innovation and determinants of productivity at the level of firms and industries. Product innovation is one of them. Process innovation—cost-reducing technical change— is another. The effects of firms' external environments, such as competition, improved inputs from suppliers ("upstream innovation"), and government policy, have been studied as well. Given that a multitude of factors can drive innovation and productivity growth, a natural question is: Which of them matters most? However, an influential survey by Syverson (2011) concludes that "the relative quantitative importance of each... is still unclear" (p. 358), limiting our ability to understand and explain the long-run welfare performance of innovative industries.

Figure 1: Product and Process Innovations in the LCD Industry

(a) Unit Shipment by Size

(b) Average Price and Cost



Note: Global, industry-wide aggregate in terms of (a) units of LCD panels and (b) square meters, respectively.

This paper presents concrete empirical evidence based on a decade-long study of the global market for liquid crystal display (LCD) panels. Most computers and electronic products rely on LCD panels as a key device, making them one of the most widely used new products in recent history. The industry experienced rapid technological progress during our sample period (2001–2011)—the use of larger new products became increasingly common while the average manufacturing cost per square meter (m^2) decreased by 77% from \$3,015 to \$692 (Figure 1). Unusually detailed data are available, including not only prices, sales volumes, and product characteristics but also the entire record of investments in fabrication plants ("fabs") at all major firms, as well as their technological specifications and fab-product-level manufacturing costs. The availability of cost data (in addition to the more conventional sales data) means that we can not only estimate a demand model to evaluate

[1] The 2023 Merger Guidelines, released by the Department of Justice and the Federal Trade Commission, is available at https://www.justice.gov/d9/2023-12/2023%20Merger%20Guidelines.pdf. This 50-page document mentions "innovation" and related concepts on almost every page.

the welfare gains from new products but also quantify the benefits of cost-reducing investments. Furthermore, the industry-wide record of fab investments allows us to conduct a comprehensive benefit-cost analysis to measure the return on technological investments. In short, the LCD industry presents a rare opportunity to measure the benefits and costs of various types of innovation in a highly relevant empirical context.

The richness of data allows us to conduct a systematic welfare analysis of innovation in five steps. First, we use the sales data to estimate a demand model for differentiated products—a prerequisite to quantifying the value of new products as in Trajtenberg (1989) and Petrin (2002). Second, we use the cost data to estimate the relationship between manufacturing cost and its determinants, including investments in new-generation fabs ("vintage capital") and the accumulation of know-how through experience ("learning by doing"). Third, these demand and cost estimates allow us to calculate equilibrium outcomes under various counterfactual scenarios. We compare welfare outcomes with and without each factor to quantify its benefits to consumers and producers. Fourth, we compare these benefits with the costs of fab investments—the main driver of both process and product innovations in this industry—to quantify their social and private returns. Fifth, we calculate and compare the return on investment (ROI) under all conceivable market structures to measure the effect of competition on innovation. Taken together, these analyses provide one of the most detailed and comprehensive assessments of technical change in the literature.

We find massive impacts of both types of innovation. Without product innovation, the global welfare in 2001–2011 would have been 70.6% lower; without process innovation, it would have been 38.9% lower.[2] Substantial heterogeneity exists underneath these overall effects. Process innovation played a relatively more important role in the notebook and monitor segments than in the TV segment, in which the impact of product innovation—especially the introduction of larger products—was disproportionately larger than any other factors.[3] Our benefit-cost analysis suggests social returns were large, with ROI of 68.9% even at a relatively high annual discount rate of 10%. However, the industry as a whole earned only modest profits relative to the sunk cost of fab investments. The industry-wide internal rate of return (IRR, a break-even discount rate at which the discounted present value of benefits exactly offsets that of costs) was only 4.05%. This level of IRR is unattractive for risky investments, such as those in a fast-changing global markets for high-tech products.

[2]Perceptive readers might wonder why the 77% decrease in manufacturing cost (in Figure 1) resulted in only a 39.4% welfare increase. The reason is that only about a half of the 77% cost reduction can be attributed to LCD-panel manufacturers' process innovation. The rest is due to reductions in input costs, the impact of which is separately measured in Appendix A.5.2.2.

[3]Tablet computers are not included in our dataset because they emerged as a major category after our sample period. Smaller LCD panels below 10 inches are not included either, because they tend to be manufactured by fringe firms with smaller, older fabs, and for miscellaneous niche applications.

Unsurprisingly, some firms' individual private returns were small or negative, but competitive pressure forced them to invest in new-generation fabs.

We further investigate the role of competition in shaping firms' incentive to innovate by simulating all possible mergers among seven major firms. Results suggest positive incentive effects of some mergers, but the outcomes become increasingly more heterogeneous and negative with the progress of industry consolidation. Once the number of main players reaches five or below, the majority of mergers hinders innovation. Our sensitivity analysis shows that these findings are robust to most changes—small and large—in parameter values; the overall patterns could qualitatively change only under extremely low price-sensitivity of demand.

We have organized the rest of the paper as follows. The remainder of this section reviews the related literature. Section 2 explains the institutional/technological context. Section 3 describes our data on sales, costs, and investments. Section 4 reports demand estimates. Section 5 quantifies the welfare impact of LCD innovations. Section 6 calculates the social and private returns on technological investments. Sections 7 and 8 present merger simulations and their sensitivity analysis, respectively. Section 9 concludes.

Related Literature and Contributions. This paper contributes to several strands of the empirical literature in IO and the economics of innovation. First, the estimation of the value of new products has a long tradition in economics since Griliches (1957) and is one of the most popular applications of modern demand analysis, as exemplified by Trajtenberg (1989), Hausman (1996), Greenstein (1996), and Petrin (2002). More recent contributions include Eizenberg (2014); Ciliberto, Moschini, and Perry (2019); and Grieco, Murry, and Yurukoglu (2023). Whereas most of these studies rely on sales data alone, our plant-level data on costs and investments allow us to directly measure costs—without additional assumptions on firms' competitive conduct—and to study the effects of both product and process innovations.

Second, process innovation has been studied within a large literature on productivity. Syverson's (2011) survey lists more than ten determinants of firm-level productivity, two of which are closely related to process innovation: vintage capital and learning by doing. Thompson's (2010, 2012) reviews of the learning-by-doing literature point out that vintage capital and other determinants of production costs are typically unobserved and create an omitted variable problem. Benkard (2000); Levitt, List, and Syverson (2013); and Sinclair, Klepper, and Cohen (2000) address this problem by focusing on a single product, plant, and firm, respectively, for which detailed data are available. We take a similar, data-driven approach but cover the global markets for LCD panels including all major firms and their fabs. With such data, we can not only measure each factor's contribution to physical productivity but also conduct an industry-wide welfare analysis, evaluate social and private returns on investments, and assess the impact of competition on innovation.[4]

Third, the relationship between competition and innovation is one of the most studied topics in economics.[5] Its popularity reflects both the importance of the research question and the difficulty in convincingly answering it. One challenge is modeling, as it requires a delicate balance between realism and tractability. Nevertheless, recent papers have made progress in clarifying and narrowing the range of plausible results,[6] and a growing number of empirical IO papers study information technology (IT) and other innovative industries.[7] Another challenge is measurement. Innovation can take many different forms, each of which requires good data and careful econometrics (see above); measuring competition is nontrivial as well.[8] We address these problems with a combination of rich data and a simple, static model of demand and supply, thereby complementing these dynamic-structural works with concrete evidence from a more data-driven approach.[9]

2 Innovations in the LCD Industry

This section provides the institutional context: industry background (section 2.1), production technology (section 2.2), and the definition of various types of innovation (section 2.3).

[4]With our eventual analysis of benefits and costs of innovation, this research also joins the long list of papers that estimate returns to investments in research and development (R&D) and other innovation assets, a comprehensive survey of which is offered by Hall, Mairesse, and Mohnen (2010).

[5]See reviews by Cohen (2010); Shapiro (2012); Gilbert (2020); Federico, Scott Morton, and Shapiro (2020); Bryan and Williams (2021); Griffith and Van Reenen (2023); and Lefouili and Madio (2024).

[6]Marshall and Parra's (2019) computational theory work offers a catalogue of possible results under different assumptions and parameter values. Igami and Uetake's (2020) structural econometric work proposes a tractable model of a dynamic oligopoly game and shows empirical patterns that resemble one of the numerical examples in Marshall and Parra (2019).

[7]See, for example, Goettler and Gordon (2011), Conlon (2012), Igami (2017, 2018), Björkegren (2019), Yang (2020), Mohapatra and Zhang (2023), Khmelnitskaya (2023), and Qiu (2023).

[8]Many of the commonly used statistics are either problematic or insufficient for antitrust purposes. See Miller et al. (2022) for the endogeneity problem with the Herfindahl-Hirschman Index (HHI). Markups are equally endogenous, and they can be influenced by price-fixing collusion as well. The number of firms is not a sufficient statistic in most of the realistic models of oligopoly. Structural parameters of demand that determine the degree of horizontal product differentiation, such as the variance of idiosyncratic preference shocks, is not policy-relevant because it cannot be controlled by the regulators.

[9]Finally, this paper joins recent papers in empirical IO that investigate long-run industry trends. Examples include Collard-Wexler and de Loecker's (2015) study of the steel industry; Asker, Collard-Wexler, and de Loecker's (2019) welfare analysis of the crude-oil cartel; Backus, Conlon, and Sinkinson's (2021) study of common ownership in the cereal industry; Grieco, Murry, and Yurukoglu's (2023) study of market power and welfare in the automobile industry; and Miller, Osborne, Sheu, and Sileo's (2023) study of technology adoption and market power in the cement industry. Whereas most papers examine mature industries, we study innovation in a new industry with rapid technological changes.

2.1 Industry Background

Japanese electronics makers (e.g., Sharp, Panasonic, Sony, Hitachi, and Toshiba) pioneered the development and commercialization of the LCD technology until the early 1990s, but two Korean manufacturers, Samsung and LG, rapidly caught up and expanded market shares in the late 1990s. In response to these low-cost rivals, Japanese firms recruited Taiwanese firms as contract manufacturers because manufacturing costs are even lower in Taiwan. However, they eventually became independent competitors and almost drove Japanese firms out of the global markets for IT applications (notebook PCs and desktop monitors) by 2001.

The dot-com bust in 2001 dampened the demand for many IT products including LCD panels. The resulting price decreases motivated AU Optronics (AUO), the largest Taiwanese producer at the time, to organize a price-fixing scheme with three other Taiwanese firms (CMO, CPT, and HS) as well as Samsung and LG. This collusive arrangement—called the "crystal cartel"—started its monthly price-targeting meetings in October 2001 and lasted until February 2006, when Samsung and LG applied for the corporate leniency programs at the US Department of Justice and the European Commission.[10]

LCD-TVs became mainstream household products in Japan and other East Asian economies since around 2004 and then in North America since around 2007. Macroeconomic downturns hit the industry in the Great Recession (2008:Q4–2009:Q2), temporarily suppressing the demand for all applications. Samsung and LG expanded market shares during and after this crisis, whereas some of the weaker Taiwanese firms reduced their presence in the global market around this period.

Most of the once-dominant Japanese firms exited the "large-area display" markets (as these IT/TV segments with 10-inch panels or larger are collectively known) by the end of the decade. The only exception was Sharp, which kept investing in new-generation fabs. Meanwhile, mainland Chinese firms started entering low-end product categories, sometimes by purchasing the used equipment from Japan, but their market shares were negligible throughout the 2000s. Thus, the six crystal-cartel firms (and Sharp) are the only players of strategic importance in our main sample period (2001:Q1–2011:Q4).

2.2 Production Technology

The production process for LCD panels is capital-intensive. Firms have to invest billions of dollars in fabs and manufacturing equipment. The technology is knowledge-intensive as well, because these physical assets are commercially useless unless production engineers

[10] We take these developments as given and leave the task of endogenizing collusion and innovation (within a dynamic-game framework) to Igami, Qiu, and Sugaya (2023).

tune their parameters to improve yield (the rate of defect-less products in total output). Nevertheless, once these physical requirements are satisfied, the costs of more basic inputs such as labor and electricity play a critical role in competition and survival, as the exit of relatively high-cost Japanese firms illustrates.

LCD panels contain many different components and materials, including sheet glass, color filters, polarizers, backlights, and liquid crystal. Their suppliers are mostly located in Japan for historical/technological reasons (i.e., engineering, fine chemicals, and electronic devices are among the most globally competitive industries of Japan).

Dozens of different products exist within each of the three main applications (notebooks, monitors, and TVs), but all of them can be produced using the same fab and equipment as long as the physical sizes of input glass and output panels are compatible. This flexibility stems from the fact that most components and materials are common across products. The only binding constraint is that large panels cannot be cut out of a small sheet glass. Hence, a fab's physical capacity and technological generation are defined by the size of the input glass ("mother glass") that it can handle. The most advanced fabs at the beginning of 2001 used the fourth-generation (4G) technology and its variant (4.5G), which process 730mm×920mm input glass and could produce up to 40-inch panels. Subsequently, the frontier technology shifted to 10G, which uses 2,850mm×3,250mm input glass, by the end of our sample period (2011:Q4).

2.3 Definition of Innovation

Following Schumpeter (1934) and many other studies, we use the most basic definition of innovation as "new combination of productive means" (p. 66). We focus on the first two of his five categories of innovation: (i) "the introduction of a new good or of a new quality of a good" and (ii) "the introduction of a new method of production."[11] Even though our empirical context is clearly high-tech and involves cutting-edge technologies of the time, we would like to remind the readers that these economic definitions of innovation are not predicated on either scientifically new discoveries or the legal formalities of obtaining patents. Hence, our analysis is agnostic about the exact source of new goods and methods (e.g., whether LCD innovations should be labeled as "invention" or "technology adoption").[12]

[11] The other three are: (iii) "the opening of a new market," (iv) "the conquest of a new source of supply of raw materials or half-manufactured goods," and (v) "the carrying out of the new industrial organization of any industry." Our empirical context features some elements of them as well, such as the "upstream innovation" that we discuss at the end of this subsection closely relates to (iv). But we consider the precise measurement of (i) and (ii) as our primary contribution.

[12] We emphasize this point because many new LCD products and processes are *not* patented inventions, unlike new drugs, for example.

We operationalize the notion of product innovation by organizing it into two subcategories: physically larger products and other new products. We distinguish between size and other observed characteristics because certain sizes require newer generations of fabs and are, therefore, clearly tied to specific investments. By contrast, other product characteristics have no direct connections to tangible assets.

Similarly, we separately identify two channels of process innovation, vintage capital and learning by doing, both of which drive cost reductions. First, the "vintage" effect is rooted in the fact that unit costs of manufacturing are lower at newer fabs. A larger sheet of glass can be cut into a larger number of panels of a given size. Because the fixed cost of handling a sheet glass increases less than proportionally to its surface area, the average unit cost per panel decreases with a larger mother glass. Second, the "learning" effect is underpinned by the fact that the average unit cost decreases as yield improves, that is, as the fraction of defective products decreases. This process takes many months because production engineers can experiment with only a limited number of technical configurations within a given time interval. As in other capital-intensive industries such as chemical processing and semiconductors, "learning primarily results from the fine-tuning of production techniques" (Benkard 2000, p. 1036).[13] Learning by doing in the LCD context is a matter of searching for optimal parameters of manufacturing equipment.

Finally, we acknowledge the fact that the costs of raw materials and components tend to decrease over time due to innovations in the upstream industries (fine chemicals and other materials). This mechanism is not attributable to LCD-panel manufacturers, which is the main focus of our study. Hence, we do not include this factor as a subcategory of process innovation. Nevertheless, it is a major contributor to the overall cost reductions. We call it "upstream innovation" and report its effects in Appendix section A.5.2.2.

3 Data

This section explains our data, including their source, preprocessing, and salient patterns. Our main source is *Display Search*, a specialized data provider for flat display panels. Their information is widely used as a key reference by both buyers and sellers of LCD panels in the global wholesale market. The original dataset consists of three components: sales (section 3.1), costs (section 3.2), and investments (section 3.3).

[13] By contrast, in labor-intensive industries such as aircraft and shipbuilding, "learning primarily results from workers becoming more efficient at the task they perform through multiple repetitions" (Benkard 2000, p. 1036).

3.1 Prices, Quantities, and Product Characteristics

The average sales price and total shipment volume are recorded at quarterly frequency between 2001:Q1 and 2011:Q4 at the level of product, which is finely defined as a combination of (i) supplier, (ii) application, (iii) size, (iv) resolution, and (v) backlight. For example, an LCD panel made by LG for notebook PCs, with 14.1-inch diagonal length, 1280×800 pixels, and light-emitting-diode (LED) backlights is a unique product. Based on this definition, the total number of unique products is 1,081. Even if we ignore supplier identity (i) and exclusively focus on physical characteristics (ii)–(v), as many as 302 products appear on record.

Despite this product variety, LCD panels are traded as commodities in the global wholesale market. Product specifications are standardized to promote technical compatibility throughout the IT supply chain. In terms of demand, only a handful of products are popular at any point in time. In terms of technology, a single fab can manufacture all different varieties using the same equipment as long as its input-glass size is compatible (see section 2.2). As a result, most of the mainstream products are supplied by multiple firms. Products with the same physical characteristics are nearly perfect substitutes for each other regardless of supplier identities.

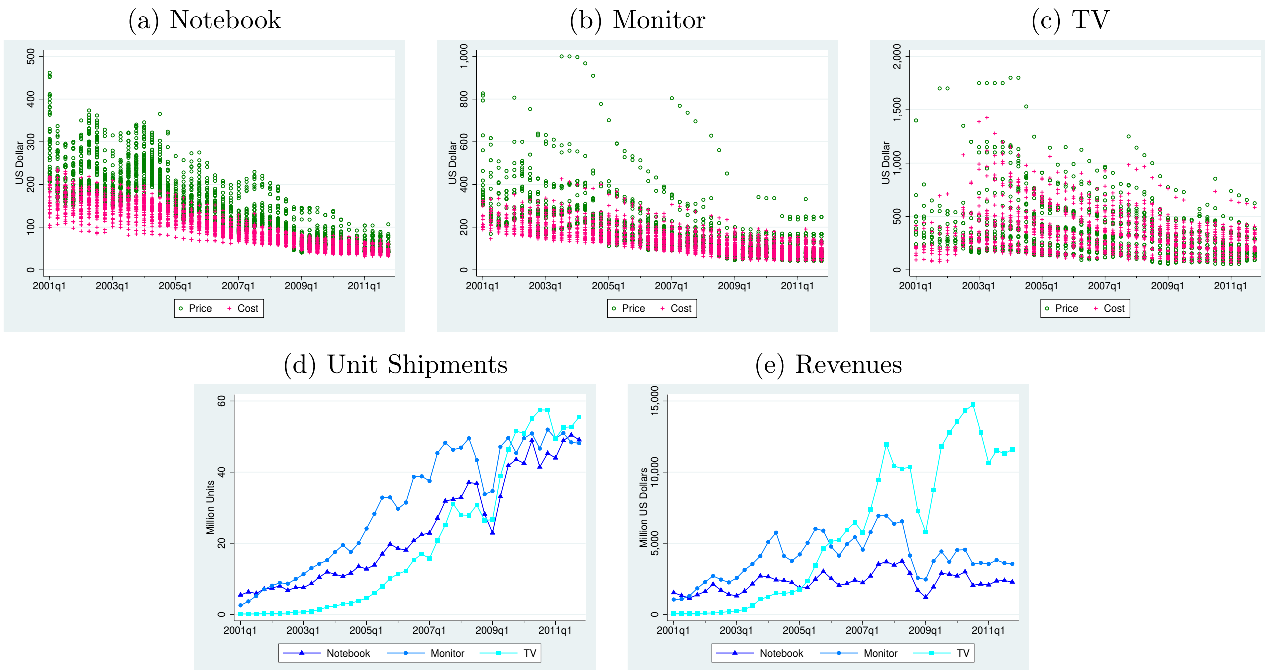
Figure 2 plots prices, costs, and sales, from which five patterns emerge. First, prices and costs tend to decrease over time. Second, prices show some cyclical movements along the downward trend, whereas costs do not.[14] Third, the price-cost margin seems to decrease over time, presumably because the cartel existed only in the first half of the data (2001:Q4–2006:Q1). Fourth, the shipment volume grew rapidly over time, as LCD panels became mainstream products in all applications. Fifth, the Great Recession manifested itself in 2008:Q4–2009:Q2 as negative shocks to both prices and quantities. For summary statistics of sales data, including product characteristics, see Table 14 in Appendix A.3.1.

3.2 Manufacturing Costs

The second database records the average unit cost of manufacturing LCD panels at a quarterly frequency between 2000:Q2 and 2016:Q4. Information is available at the level of products as physically defined by (ii)–(v) in the sales data. This database is designed to replicate how their unit costs vary with the age of a fab, technological generation of manufacturing equipment, geographical location (Japan, Korea, and Taiwan), and other technical details.

[14] The cyclical nature of IT demand seems responsible. The purchasing behavior of PCs and their peripherals tends to follow multi-year cycles. See Matthews (2005) for a detailed account of the "crystal cycles," in which small shifts in demand can lead to larger swings in prices.

Figure 2: Prices, Costs, and Sales



Note: Panels (a), (b), and (c) plot the global, industry-wide average prices and costs by physically defined product. Panels (d) and (e) plot aggregate sales quantities by application.

Thus, precise cost data are available at the level of product-fab-quarter triplets.[15] We focus on the "cash cost" part of the data and exclude the "depreciation" part because the latter is an accrual-based accounting measure of capital cost and does not constitute economic marginal cost. Such fine-tuning is made possible by the availability of an extremely detailed cost breakdown. For summary statistics of cost data, see Table 15 in Appendix A.3.2.

3.3 Investments in New Fabs

The third database contains a comprehensive record of all major firms' investments in new fabs at a monthly frequency between December 1994 and July 2024 (including planned future investments). For each of the few hundred fabs, we observe its technological generation of manufacturing equipment, production capacity, and the timing of investment. The timing record includes monthly time stamps in three stages of fab investments: equipment purchase order, delivery and installation, and mass-production ramp. The average wait time between

[15]Such detailed engineering estimates are available because LCD panels have a highly modular architecture and a relatively straightforward manufacturing process. Information is available on the prices of key materials and components (e.g., glass, color filter, polarizer, liquid crystal, driver integrated circuit, and backlight). As a result, "LCD manufacturers have nowhere to hide profit margins," according to our interview with a staff analyst at *Display Search*.

order and full-scale production is approximately 12 months.

4 Demand Estimation

We use the data on sales and costs for 2001:Q1–2011:Q4 to estimate a random-coefficient nested-logit model of demand for differentiated products (section 4.1). Based on the estimated demand model, we calculate the implied equilibrium prices under monopoly and Bertrand competition (section 4.2). We compare the actual prices in the data against these theoretical predictions to assess the extent of market power during the sample period. These estimates lay the foundation for our welfare analysis in sections 5 and 6.

4.1 Model and Estimates

We specify buyer i's utility from LCD panel j in period t as

$$u_{ijt} = \alpha_i p_{jt} + \sum_s \beta^s \mathbb{1}\{size_j = s\} + \beta^r \ln ppi_j + \beta^b led_j + \xi_{jt} + \zeta_{ist} + (1-\rho)\varepsilon_{ijt}, \quad (1)$$

where p_{jt} is price, $\mathbb{1}\{size_j = s\}$ is an indicator for size-s product, $\ln ppi_j$ is picture resolution measured by the natural logarithm of pixels per square inch (PPI), led_j is a dummy variable for LED-based backlights, ξ_{jt} represents other product qualities that are not observed, and ζ_{ist} and ε_{ijt} are buyer-specific preference shocks.[16] We assume that ε_{ijt} is i.i.d. Gumbel and that ζ_{ist} has the unique distribution such that $\varepsilon^*_{ijt} \equiv \zeta_{ist} + (1-\rho)\varepsilon_{ijt}$ is i.i.d. Gumbel as well. β^s, β^r, and β^b are coefficients of size, resolution, and backlight type, respectively. We incorporate heterogeneity in the price coefficient as $\alpha_i = \alpha / y_i$, where y_i is i's income level drawn from the income distribution in the relevant mid-to-high-income countries.[17]

Three considerations guide this specification. First, we incorporate all observable product characteristics, including size, PPI, and backlight type, to ensure proper accounting of product innovations. Second, we allow as much flexibility as possible in capturing contributions of lower prices and larger sizes, which are the primary channels through which process and product innovations increase welfare, respectively. Obtaining reasonable estimates of α and

[16] The *Display Search* sales data focus on wholesale transactions of LCD panels, which become key components of final products. We abstract from the downstream supply chain and model it as a collection of individual buyers and their representatives.

[17] We use data from the World Bank on the population and income levels of the Organisation for Economic Co-operation and Development (OECD) member countries for which complete time series are available. We abstract from the details of the supply chain and sales channels between the LCD-panel manufacturers and final users.

β^s is critical for our purposes.[18] Third, we abstract from the durable-good aspect for three reasons.[19] One is that LCD panels were relatively new in 2001–2011; replacement demand played a limited role relative to first-time buyers. Another reason is data availability—we are not aware of reliable data on product ownership with a global coverage for our sample period. The final and most important reason is that we are deliberately keeping our model simple and static to fully exploit the unusually detailed data and generate findings that are data-driven and transparent.

We address the endogeneity concern that prices p_{jt} and within-nest market shares might be correlated with unobserved quality ξ_{jt} by using four types of instrumental variables (IVs): (i) the unit cost of production c_{jt}, (ii) a dummy variable indicating the existence of the cartel in 2001:Q4–2006:Q1, (iii) the number of products in each category—defined by size, resolution, backlight type, and their combinations—, and (iv) the measures of product differentiation proposed by Gandhi and Houde (2023). We use the estimation algorithm of Berry, Levinsohn, and Pakes (1995) in Conlon and Gortmaker's (2020) *PyBLP* Python implementation.[20]

Table 1 reports our demand estimates for each of the three applications (notebook, monitor, and TV). All price coefficients are negative, but their magnitude varies from notebook (more negative) to TV (less negative). The median own-price elasticities are -6.78 (notebook), -9.73 (monitor), and -4.31 (TV).[21] These estimates suggest lower prices significantly increase utility, thereby leaving ample room for process innovation (cost reduction) to improve welfare. The nest parameter values are 0.629 (notebook), 0.805 (monitor), and 0.725 (TV), highlighting the importance of size categories in buyers' decisions. The size-bin coefficients show that certain sizes, such as 14"–16" (notebook), 18"–24" (monitor), and 32"–55" (TV), are particularly popular. The appeal of these products means ample room exists for product innovation to improve welfare as well. The coefficients on the two other physical characteristics (PPI and LED) are also positive, as expected.[22]

[18] This specification follows Berry, Levinsohn, and Pakes (1999). Its combination with the size-bin nests is similar to the specification used by Brenkers and Verboven (2006) for European car markets. We experimented with additional nests and/or additional random coefficients led to counter-intuitive estimates due to multicollinearity problems. As Grigolon and Verboven (2014) show, adding random coefficients and nests on other (continuous) product characteristics leads to imprecise or unreasonable estimates due to multicollinearity when these variables are correlated with the main ones (i.e., prices and sizes in our case).

[19] We refer readers interested in durability to Conlon (2012).

[20] *PyBLP* can automatically construct and include two categories of differentiation IVs: (a) the Euclidean distance between a focal product and all other products—in each of the continuous product characteristics—and (b) their interactions. We use both of them. We thank Jeff Gortmaker for sharing these details.

[21] The median of all products' own-price elasticities across three applications is -6.69. We interpret these relatively high elasticities as reflecting the fact that multiple similar products existed within most of the narrowly defined product categories.

[22] The only exception is $\hat{\beta}^b < 0$ for monitors. Many CCFL-based products remained popular in this appli-

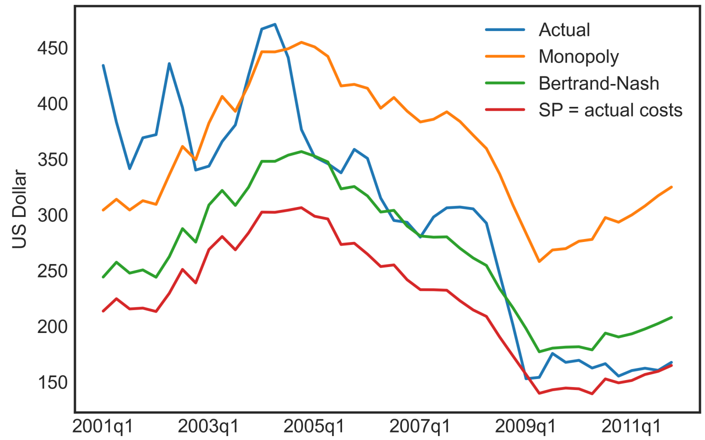
Table 1: Demand Estimates

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−309.6	27.9	−155.6	5.6	−41.5	2.5
Size nests (ρ)	0.629	0.025	0.805	0.016	0.725	0.020
Size = 12" (β^{12})	1.596	0.076	–	–	–	–
Size = 13" (β^{13})	1.929	0.088	–	–	–	–
Size = 14" (β^{14})	2.906	0.095	–	–	1.892	0.185
Size = 15" (β^{15})	3.291	0.129	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	2.920	0.103	–	–	–	–
Size = 16" (β^{16})	3.006	0.114	4.872	0.080	2.821	0.156
Size = 17" (β^{17})	2.629	0.112	–	–	–	–
Size = 18" (β^{18})	0.525	0.164	6.159	0.089	1.917	0.176
Size = 20" (β^{20})	–	–	7.230	0.106	4.135	0.176
Size = 22" (β^{22})	–	–	6.753	0.110	3.979	0.194
Size = 24" (β^{24})	–	–	6.276	0.110	3.360	0.183
Size = 26" (β^{26})	–	–	–	–	4.691	0.194
Size = 27" (β^{27})	–	–	5.856	0.134	–	–
Size = 28" (β^{28})	–	–	–	–	3.822	0.266
Size = 30" (β^{30})	–	–	–	–	5.302	0.261
Size = 32" (β^{32})	–	–	–	–	6.464	0.209
Size = 40" (β^{40})	–	–	–	–	6.135	0.228
Size = 45" (β^{45})	–	–	–	–	5.997	0.233
Size = 50" (β^{50})	–	–	–	–	6.066	0.253
Size = 55" (β^{55})	–	–	–	–	6.248	0.287
Size = 60" (β^{60})	–	–	–	–	5.548	0.358
Size $\geq$ 65" (β^{65})	–	–	–	–	6.074	0.389
Resolution (β^r)	1.416	0.192	3.025	0.273	0.190	0.072
LED (β^b)	0.124	0.045	−0.134	0.040	0.259	0.039
Firm = Samsung	0.195	0.051	0.113	0.044	0.250	0.045
Firm = LG	0.091	0.053	0.186	0.039	0.094	0.037
Firm = CMO	−0.127	0.059	−0.161	0.041	0.072	0.044
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.476	0.073	−0.078	0.059	−0.067	0.042
Firm = CPT	−0.251	0.068	−0.123	0.048	−0.281	0.064
Firm = HS	−0.540	0.083	−0.062	0.055	−0.822	0.089
Firm = Others	−0.248	0.052	−0.089	0.042	−0.354	0.046
Constant	−7.580	0.582	−17.973	1.163	−10.819	0.388
Time dummies	Yes		Yes		Yes	
Own elasticity	−6.78		−9.73		−4.31	
1st-stage R^2: price	0.941		0.893		0.920	
1st-stage R^2: share	0.378		0.370		0.453	
Number of obs.	4,140		3,374		3,582	

Note: The sample period is 2001:Q1–2011:Q4. "Price" is measured in current US dollars. "Size nests" refers to the nest parameter. The omitted size categories are 11", 14", and 12" for notebook, monitor, and TV applications, respectively. "Resolution" is measured in the natural logarithm of pixels per square inch (PPI). "LED" is an indicator for LED-based backlights, where the omitted category is CCFL-based ones. AUO is the omitted category for firm dummies. "Own elasticity" is the median own-price elasticity across all observations within each application. We report the R^2s of the regressions of prices and within-nest market shares on all IVs and other regressors as "1st-stage R^2" to demonstrate their relevance, even though the BLP procedure does not involve first-stage regressions as in two-stage least squares.

cation despite the influx of LED-based ones. This product feature is not directly related to fab investments and does not play any major role in our subsequent analysis.

Figure 3: Comparison of Actual Price with Theoretical Benchmarks



Note: This graph compares the average price in the data with three theoretical benchmarks: (i) monopoly, (ii) Bertrand-Nash, and (iii) social planner. See Appendix A.4.2 for similar plots by application.

4.2 Monopoly, Bertrand-Nash, and Social-Planner Benchmarks

We assess the extent of market power by comparing the actual average price in the data with three theoretical benchmarks: (i) monopoly, (ii) Bertrand-Nash, and (iii) social planner. Monopoly means all firms' all products are priced at high levels as if the entire industry maximized producer surplus (PS); social planner would instead maximize consumer surplus (CS) with marginal-cost pricing, thereby maximizing social welfare (SW) as well. The Bertrand-Nash prices are based on the actual product-ownership pattern across firms, each of which unilaterally maximizes its firm-level profit.

Figure 3 shows the actual price was relatively close to the monopoly level in 2001:Q1–2004:Q3, which is broadly consistent with the existence of the cartel in the first half of our data. Some of the price spikes in these years are known to have been caused by a combination of positive demand shocks and industry-wide capacity constraints, which our model abstracts from. The actual price fluctuated around the Bertrand-Nash benchmark since 2004:Q4, which suggests the LCD cartel became less effective in its last several quarters of operation. Finally, the negative impact of the Great Recession (2008:Q4–2009:Q2) and its aftermath is evident in the last three years of our data as the actual price fell below the Bertrand-Nash level.

The main takeaway from this price-comparison graph is that monopoly pricing and Bertrand-Nash prices offer reasonable approximation to the data in 2001:Q1–2004:Q3 and 2004:Q4–2011:Q4, respectively. Accordingly, we use this combination (sequence) of conduct assumptions in our subsequent analyses in sections 5–8.[23]

[23] We also compute some of the key results in sections 5 under an alternative assumption of Bertrand-Nash

5 Welfare Gains from Innovations

This section quantifies the welfare impact of LCD innovations. Sections 5.1 and 5.2 focus on product innovation and process innovation, respectively. Section 5.3 reorganizes their findings by interpreting each new generation of fabs as a bundle of specific types of product and process innovations.

5.1 Product Innovation

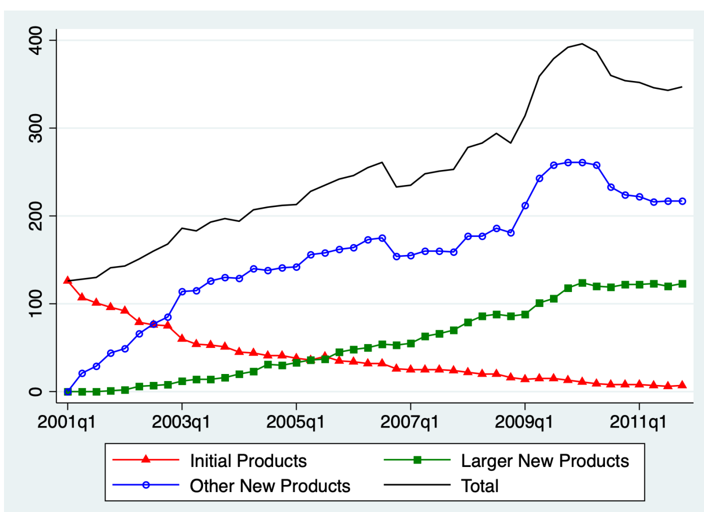
This subsection measures the welfare impact of product innovation. We first explain two kinds of product innovation that we study (section 5.1.1) and then conduct counterfactual simulations to quantify their welfare effects (section 5.1.2).

5.1.1 Two Types of Product Innovation

We distinguish between two types of product innovation: (i) larger products and (ii) other new products. We briefly explain each of them in the following.

The industry introduced LCD panels of ever larger sizes by using newer, larger manufacturing equipment and fabs. The largest available products in 2001:Q1 (the beginning of our data) were 15.7-inch notebooks, 24-inch monitors, and 28-inch TVs. Any products larger than these sizes were new in this sense.

Figure 4: Number of Products



Note: This graph counts the number of products defined by all observable characteristics on record, that is, (i)–(v) in section 3.1 including supplier identity. Appendix A.5.1.1 reports the same information by application.

throughout the sample period in Appendix A.5.3.

Not all new products were larger than the existing ones, but they represented new combinations of size, resolution, and backlight type. Newer products tended to feature higher resolution (PPI) and better backlights (LED), but many of them offer size-resolution combinations that are simply different from—not necessarily physically superior to—the existing ones.

Figure 4 plots the numbers of larger new products and other new products, respectively, alongside the count of existing products as of 2001:Q1 ("initial products"). Appendix A.5.1 provides further details, including by-application versions of Figure 4, the visualization of all products' locations in the product-characteristics space, and product-level statistics.

5.1.2 Counterfactual: No Product Innovation

We quantify the effects of the two types of product innovation by simulating counterfactual market equilibria without new products.

Table 2 compares the welfare performance of the actual product portfolio with three counterfactual simulations: (i) without larger panels that did not exist in 2001:Q1, (ii) without other new products that did not exist in 2001:Q1, and (iii) their combination. The results are quite heterogeneous between IT (notebooks and monitors) and TV.

Table 2: Welfare Impact of Product Innovation, 2001–2011

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
Baseline	57.9	(±0)	27.5	(±0)	85.4	(±0)
(i) Without larger products	52.7	(−9.0)	25.5	(−7.5)	78.1	(−8.5)
(ii) Without other new products	32.6	(−43.6)	19.0	(−31.0)	51.6	(−39.6)
(i) + (ii)	24.7	(−57.3)	15.6	(−43.5)	40.3	(−52.8)
B. Monitor						
Baseline	157.3	(±0)	73.7	(±0)	231.0	(±0)
(i) Without larger products	153.2	(−2.6)	72.4	(−1.8)	225.6	(−2.3)
(ii) Without other new products	75.3	(−52.1)	43.8	(−40.6)	119.1	(−48.4)
(i) + (ii)	70.7	(−55.0)	42.1	(−42.9)	112.8	(−51.2)
C. TV						
Baseline	186.0	(±0)	54.7	(±0)	240.7	(±0)
(i) Without larger products	45.1	(−75.7)	13.2	(−75.8)	58.4	(−75.8)
(ii) Without other new products	148.4	(−20.2)	46.4	(−15.1)	194.8	(−19.1)
(i) + (ii)	6.1	(−96.7)	4.4	(−91.9)	10.5	(−95.6)
D. All applications						
Baseline	401.2	(±0)	156.0	(±0)	557.1	(±0)
(i) Without larger products	251.0	(−37.4)	111.1	(−28.8)	362.1	(−35.0)
(ii) Without other new products	256.3	(−36.1)	109.2	(−30.0)	365.6	(−34.4)
(i) + (ii)	101.5	(−74.7)	62.1	(−60.2)	163.6	(−70.6)

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

The contributions of (ii) are much greater than those of (i) in the relatively mature markets of notebooks and monitors. For notebooks, Panel A shows the total welfare impact of (i) is 8.5%, whereas that of (ii) is an order of magnitude larger at 39.6%. The reason is that the largest initial product size in 2001:Q1 (15.7 inch) already covered most of the popular sizes. Hence, most of the new products in high demand fell under category (ii). Similarly, the largest initial size of monitors (24 inch) was sufficiently large to cover most popular products. Panel B shows the impact of eliminating (i) is only 2.3%. Other new products play a much bigger role (48.4%). Their combined welfare contribution is 52.8% and 51.2% for notebooks and monitors, respectively.

By contrast, larger products were much more important than other new products in the TV segment, and their combined welfare contribution was truly remarkable. The elimination of larger TVs above 28 inch and other new varieties would have reduced SW by 75.8% and 19.1%, respectively, for a combined impact of 95.6%. The magnitude is staggering yet reasonable because only 11 products of relatively small sizes existed in 2001:Q1; most of the popular sizes (e.g., 32 inch and 40 inch) did not. Hence, Panel C is effectively quantifying the welfare impact of the emergence of LCD-TVs an entirely new class of products.

The overall welfare impact of product innovations across all three applications is 70.6% (Panel D). The relative contributions of larger products (35.0%) and other new products (34.4%) are nearly identical at this aggregate level. The main takeaway is that product innovation matters a lot and that the relative importance of different types of product innovation varies with the lifecycle-stage of each product category.

5.2 Process Innovation

This subsection measures the welfare impact of process innovation. We first identify multiple channels of process innovation by running a regression of cost data on various determinants (section 5.2.1). We then simulate counterfactual trajectories of costs and market outcomes by hypothetically eliminating each channel of process innovation at a time (section 5.1.2).

5.2.1 Determinants of Manufacturing Cost

One of the main advantages of our empirical setting is that we have detailed cost data, which we derived from the widely used engineering model of unit cost by *Display Search*. Its precision and reliability are externally validated by the fact that both the buyers and sellers of LCD panels extensively use it as a key reference for their actual commercial transactions (see section 3.2). We use this dataset to estimate the relationship between manufacturing cost and its many determinants.

We specify the cost of manufacturing product j in fab k at time t as

$$\ln c_{jkt} = \underbrace{\sum_g \theta^g \mathbb{1}\{gen_k = g\} + \sum_a \theta^a \mathbb{1}\{age_{kt} = a\} + \theta^{odf} odf_k}_{\text{process innovations}} + \theta^{cf} cf_{f(k)t}$$
$$+ \sum_c \theta^c \mathbb{1}\{capa_{kt} = c\} + \underbrace{\tilde{\delta}_t + \tilde{\delta}_{f(k)} + \tilde{\delta}_j}_{\text{time, firm, \& product dummies}} + \eta_{jkt}, \quad (2)$$

where $\mathbb{1}\{gen_k = g\}$ is an indicator for generation-g fab, $\mathbb{1}\{age_{kt} = a\}$ is an indicator for age-a fab, odf_k is a dummy variable for the one-drop-fill (ODF) method of putting liquid crystal between glass sheets,[24] $cf_{f(k)t}$ is a dummy for the in-house manufacturing of color filters (CFs),[25] $\mathbb{1}\{capa_{kt} = c\}$ is an indicator for capacity-utilization-level bin c, $\tilde{\delta}_t$ is a time dummy, $\tilde{\delta}_{f(k)}$ is a firm dummy, $\tilde{\delta}_j$ is a product dummy, and η_{jkt} captures all other non-systematic factors and measurement error (i.e., the gap between the engineering estimate and the actual cost).[26] Coefficients θ^g, θ^a, θ^{odf}, θ^{cf}, and θ^c represent the effects of the five technological determinants.

For our analysis of process innovation, the most important parameters are θ^g (the effects of different capital vintages), θ^a (the effects of fab's age/experience), and θ^{odf} (the effect of the ODF process). They are directly related to firms' fab investments, that is, conscious decisions taken by the LCD manufacturers. By contrast, we do not interpret θ^{cf} (the cost saving from in-house CFs) and θ^c (the effect of capacity utilization) as process innovation.[27] The time fixed effects $\tilde{\delta}_t$ capture changes in the input costs of raw materials and key components, some of which reflect process innovations and other changes in the upstream industries, including glass and other materials, fine chemicals, and electronic devices.[28] The fixed effects for firms and products, $\tilde{\delta}_{f(k)}$ and $\tilde{\delta}_j$, may contain some technological elements as well, but they are not directly related to process innovation.

Table 3 reports the result of cost regressions across columns in an increasing order of flexibility. Column 1 uses a linear functional form for all regressors, whereby we replace the

[24] This method improved productivity by reducing the time and steps required for the "cell" process as well as the amount of wasted liquid crystal. It was first introduced by Hitachi Industries, a leading equipment manufacturer, in 2002 and commercialized in 5G fabs. See Akabane (2014) for the technical details.

[25] CFs are one of the key components that can be either externally sourced or internally manufactured.

[26] In principle, the gap between the engineering estimate (our data) and the actual economic cost may contain a systematic difference, which could bias the mean of η_{jkt} away from zero. In practice, the intuitive patterns in Figure 3, as well as the reasonable fit between the theoretically predicted prices (based on the cost data) and the actual price, suggest no systematic biases.

[27] θ^{cf} reflects the internalization of an upstream industry's rent, not any physical improvement; capacity utilization is not a technological choice but an equilibrium object that reflects many factors including demand shocks and rivals' reactions.

[28] Appendix A.5.2.2 measures their welfare contributions.

dummies for θ^g, θ^a, and θ^c with linear terms, $\tilde{\delta}_t$ with a time trend, and $\tilde{\delta}_j$ with observed product characteristics. Column 2 adds quadratic terms of three fab-level variables (gen_k, age_{kt}, and $capa_{kt}$) and time. Column 3 adds back $\tilde{\delta}_t$ for each period. Column 4 is our preferred specification with a full set of dummies (i.e., equation 2), which we use in all of our subsequent analyses.

Table 3: Determinants of Manufacturing Cost

Specification	(1)		(2)		(3)		(4)	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
A. Fab specs								
Tech. gen.	−0.045	(0.000)	−0.208	(0.002)	−0.178	(0.002)	–	(–)
Tech. gen. squared	–	(–)	0.012	(0.000)	0.010	(0.000)	–	(–)
Fab age	−0.003	(0.000)	−0.015	(0.000)	−0.015	(0.000)	–	(–)
Fab age squared	–	(–)	0.000	(0.000)	0.000	(0.000)	–	(–)
ODF method (θ^{odf})	−0.102	(0.001)	−0.005	(0.001)	−0.011	(0.001)	−0.006	(0.001)
In-house CF (θ^{cf})	−0.022	(0.001)	0.011	(0.001)	−0.011	(0.001)	0.003	(0.001)
Capa. util.	−0.213	(0.004)	−0.244	(0.032)	−1.171	(0.037)	–	(–)
Capa. util. squared	–	(–)	0.038	(0.021)	0.596	(0.025)	–	(–)
B. Firm specs								
Tier-1	−0.194	(0.003)	−0.105	(0.003)	−0.108	(0.003)	−0.085	(0.003)
Korea	−0.107	(0.001)	−0.111	(0.001)	−0.111	(0.001)	–	(–)
Taiwan	−0.286	(0.003)	−0.192	(0.003)	−0.196	(0.003)	–	(–)
C. Product specs								
Surface area	0.925	(0.001)	0.932	(0.001)	0.932	(0.001)	–	(–)
Monitor	−0.106	(0.001)	−0.109	(0.001)	−0.108	(0.001)	–	(–)
TV	0.086	(0.002)	0.077	(0.002)	0.074	(0.002)	–	(–)
LED (edge)	0.060	(0.001)	0.064	(0.001)	0.064	(0.001)	–	(–)
LED (direct)	−0.132	(0.001)	−0.127	(0.001)	−0.126	(0.001)	–	(–)
D. Time and others								
Time	−0.030	(0.000)	−0.092	(0.002)	–	(–)	–	(–)
Time squared	–	(–)	0.000	(0.000)	–	(–)	–	(–)
Constant	13.533	(0.013)	20.133	(0.153)	9.193	(0.027)	5.175	(0.018)
Tech. gen. dummy (θ^g)	No		No		No		Yes	
Fab age dummy (θ^a)	No		No		No		Yes	
Capa. util. dummy (θ^c)	No		No		No		Yes	
Firm dummy ($\tilde{\gamma}_f$)	No		No		No		Yes	
Product dummy ($\tilde{\nu}_j$)	No		No		No		Yes	
Time dummy ($\tilde{\mu}_t$)	No		No		Yes		Yes	
Number of obs.	341,216		341,216		341,216		341,216	
R^2	0.963		0.966		0.969		0.984	
Adjusted R^2	0.963		0.966		0.969		0.984	

Note: The dependent variable is the natural logarithm of the unit cash cost of producing an LCD panel. Standard errors are in parentheses. See the main text for the explanation of the regressors. All estimates are based on the ordinary-least-squares (OLS) regressions and meant to summarize the engineering cost estimates underlying the data.

Let us review the results in column 1 because its simplicity helps us understand how these factors affect cost. First, the estimates in section A (fab-level characteristics) suggest: (i) a new-generation technology reduces cost by 4.5%, (ii) an extra quarter of operation reduces cost by 0.3%, (iii) the introduction of the ODF method reduces cost by 10.2%, (iv) in-house CFs reduce cost by 2.2%, and (v) changing capacity utilization from 0% to 100% reduces cost by 21.3%. Second, section B (firm-level characteristics) shows that the indicators for "tier-1," Korean, and Taiwanese firms (the reference category is "tier-2" Japanese firms) are associated with approximately 10%–30% cost advantages.[29] Third, section C (product characteristics) suggests: (i) a 1% increase in the size of the panel (measured by surface area in m^2) leads to a less-than-proportional increase in cost (0.93%); (ii) monitor panels are 10.6% less costly than notebook panels (reference category), whereas TV panels are 8.6% costlier; (iii) the cost performance of LED backlights could be either inferior or superior to CCFL ones (reference category) depending on the exact type and layout ("edge" or "direct"). Finally, the time-trend estimate in section D suggests the input cost decreases by 3% per quarter on average. These linear estimates are missing certain important heterogeneity and nonlinearity (see below) but still achieves the adjusted R^2 of 0.963 because we observe and control for literally everything that goes into the engineering cost model that generated our data.

Figure 5 visualizes the heterogeneity and nonlinearity that become evident in the most flexible specification (column 4 of Table 3). Panel (a) shows heterogeneous impacts of technological generations, whereby G5, G6, and G8.5 led to larger cost reductions than other vintages. Likewise, Panel (b) reveals that more than half of learning by doing occurs within the first two quarters of volume production. Yield improvement continues until year six, but subsequently stops and moves into reverse as physical depreciation (e.g., wear and tear) starts to kick in.[30] The maximum productivity gain from each of these two channels is close to 30%. Hence, both vintage capital and learning by doing are quantitatively important and comparable in magnitude.

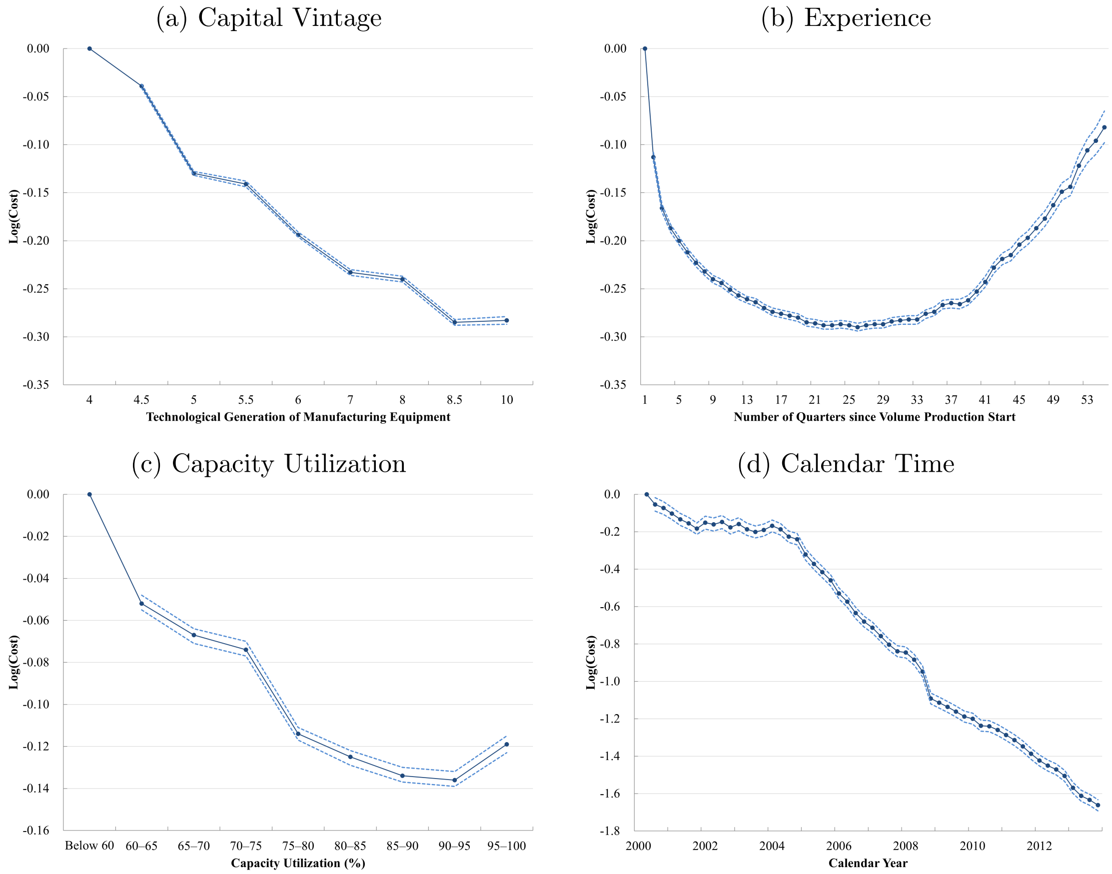
Panel (c) of Figure 5 suggests the presence of discontinuity in the effect of capacity utilization. Unit cost does not vary by more than 2% if a fab operates within the 75%–100% range, which is almost always the case in our sample period except for the Great Recession.[31] However, operating below 75% (and then below 60%) results in disproportionate cost disadvantages because of the lumpiness in the typical labor schedule, whereby four groups of workers take turns to perform three 8-hour shifts per day (the fourth shift is a break). Finally, Panel (d) plots the estimates of the calendar-time effects, which reflect the secular decreasing trend in the cost of raw materials and key components. Relatively little

[29]The tier-1 category applies to only several firms in Japan and Korea based on their historical status as the leaders of the LCD technology, which reflects their technological expertise and preferential treatment by key suppliers.

[30]The shape of the experience curve—including the upward-sloping part—is common across all vintages of fabs, and hence is not an artifact of the right-censoring of data (i.e., the sample period ends before newer-vintage fabs gain experience).

[31]The mean and standard deviation of capacity utilization in our data are 83% and 10%, respectively. The median is 85%. See Appendix A.3.2 for more summary statistics.

Figure 5: How Unit Cost Declines with Vintage, Experience, Capacity Utilization, and Time



Note: These graphs visualize our preferred estimates of the nonlinear effects of selected factors on column 4 of Table 3. The solid lines with markers plot coefficient estimates of the dummy variables for (a) technological generations of manufacturing equipment, (b) fab's age since the beginning of volume production, (c) capacity-utilization bins, and (d) calendar quarters, respectively. The dashed lines represent their 95% confidence intervals.

improvement occurred until 2004, but the subsequent advances led to an industry-wide cost reduction by more than an order of magnitude.[32]

5.2.2 Counterfactual: No Process Innovation

We measure the welfare impact of process innovation by simulating "but-for" costs and then computing "but-for" equilibrium outcomes based on these costs. First, we hypothetically eliminate the vintage-capital effects by setting $\theta^g = 0$, which means firms can no longer invest in new-generation fabs and equipment.[33] Second, we turn off learning by doing by

[32] The timing of acceleration around 2004 roughly coincides with the takeoff of LCD-TVs as mainstream household goods in East Asia. The entire supply chain attracted investments around this period.

[33] We bundle the effect of the ODF process θ^{odf} with this category because it was typically adopted in the installation of 5G fabs, forming part of newer vintages.

setting $\theta^a = 0$, which means production engineers can no longer reoptimize the production lines or the equipment's parameters to improve yield. Based on these counterfactual histories of costs, we recompute equilibrium prices, sales, and welfare outcomes in each t.

Table 4: Welfare Impact of Process Innovation, 2001–2011

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
Baseline	57.9	(±0)	27.5	(±0)	85.4	(±0)
(i) No vintage capital	51.3	(−11.3)	24.8	(−10.0)	76.1	(−10.9)
(ii) No learning by doing	38.2	(−34.0)	18.2	(−33.8)	56.4	(−33.9)
(i) + (ii)	33.2	(−42.7)	16.1	(−41.6)	49.3	(−42.3)
B. Monitor						
Baseline	157.3	(±0)	73.7	(±0)	231.0	(±0)
(i) No vintage capital	138.4	(−12.0)	68.5	(−7.0)	207.0	(−10.4)
(ii) No learning by doing	102.6	(−34.8)	47.1	(−36.1)	149.8	(−35.2)
(i) + (ii)	87.8	(−44.2)	42.9	(−41.8)	130.7	(−43.5)
C. TV						
Baseline	186.0	(±0)	54.7	(±0)	240.7	(±0)
(i) No vintage capital	167.0	(−10.2)	48.9	(−10.6)	215.9	(−10.3)
(ii) No learning by doing	139.8	(−24.8)	41.2	(−24.7)	181.0	(−24.8)
(i) + (ii)	124.3	(−33.2)	36.4	(−33.4)	160.7	(−33.2)
D. All applications						
Baseline	401.2	(±0)	156.0	(±0)	557.1	(±0)
(i) No vintage capital	356.7	(−11.1)	142.2	(−8.8)	498.9	(−10.5)
(ii) No learning by doing	280.6	(−30.0)	106.5	(−31.7)	387.2	(−30.5)
(i) + (ii)	245.2	(−38.9)	95.4	(−38.8)	340.6	(−38.9)

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

Table 4 reports CS, PS, and SW. We discuss our main findings based on the aggregate numbers in Panel D because all three applications are similarly impacted. The absence of (i) vintage-capital effects would have reduced SW by 10.5%; the elimination of (ii) learning by doing would have had a larger impact of 30.5%. This difference stems from the fact that (i) affects only newer fabs, whereas (ii) affects all fabs. The combination of (i) and (ii) would have led to a welfare loss of 38.9%.[34]

5.3 New-Generation Fabs as Bundles of Innovations

Sections 5.1–5.2 presented unusually detailed evidence on the impact of innovation, but treating various types of innovations as separate phenomena would be a misrepresentation of the LCD technology. An important subset of them arrived in "bundles"—embodied by new generations of fabs. Accordingly, we reorganize some of the preceding results by the technological generation of fabs, each of which encapsulates a combination of specific product

[34] Appendix A.5.2.2 reports additional results related to the time effects in Figure 5 (d), which we attribute to the effects of upstream innovation.

and process innovations.Because fab investments are well measured in our data, the findings in this subsection will be directly useful in section 6 and later.

Exactly which subcategories of product and process innovations belong to such a bundle? Of the two types of product innovation, the first one (larger new products) is closely connected to new-generation fabs. Larger panels require larger mother-glass sheets, which only larger equipment and fabs can handle. The newest fab generation at the beginning of our data (2001:Q1) was 4.5G, which could produce notebook and monitor panels of all sizes but not TV panels above 40 inches.[35] Hence, no LCD-TVs above 40 inches would have existed without the post-4.5G technologies.[36] By contrast, the second type of product innovation (other new products) does not rely on new-generation fabs. Of the two channels of process innovation, vintage capital is synonymous with new-generation fabs, whereas learning by doing applies to all generations. In summary, new-generation fabs represent a bundle of larger new products and vintage-capital effects.

We assess the welfare contribution of each technological generation as follows. First, we hypothetically eliminate all capital vintages beyond 4.5G, along with any larger new products and cost advantages due to vintage-capital effects that rely on them. This counterfactual scenario forms the basis for measuring the contributions of all post-4.5G technologies. Second, we add back the 5G technology. The difference between this simulation and the previous 4G–4.5G-only simulation reflects the marginal contribution of the 5G fabs. Subsequently, we cumulatively add back each of the 5.5G, 6G, 7G, 8G, 8.5G, and 10G technologies at a time, the comparisons of which reveal their respective contributions.

Table 5 summarizes the welfare contribution of each technological generation and conveys two findings. First, new vintages increased welfare, but their marginal contributions tend to diminish in later generations. The 5G fabs had by far the largest impact because its productivity effect is large—see Figure 5 (a) in section 5.2.1—and because a host of popular new products (45"–55" TVs) relied on this vintage. By contrast, the marginal contribution of 10G is negligible.[37]

Our second finding is that the impact of new-generation fabs is much larger for TVs (Panel C) than for IT applications (Panels A and B). For example, 5G fabs increased SW by 32.3% for TVs, but only by 9.3% and 9.7% for notebooks and monitors, respectively. Larger-

[35] The supply of 45"–55" TV panels had to wait until 5G fabs began mass production, and 60"–65" TV panels until 5.5G fabs.

[36] Note this definition of "larger new products" is slightly different from the one we used in section 5.1, which was not precisely connected to the physical size limit of each fab generation. In this subsection, only TVs above 40 inches are considered "larger new products" because they could not be manufactured by a 4.5G fab, the newest available technology as of 2001:Q1.

[37] In fact, it is slightly negative because its cost structure is slightly inferior to 8.5G according to our cost regression in Table 3 and Figure 5. Only Sharp invested in 10G during our sample period.

Table 5: Welfare Impact of New Technologies, 2001–2011

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
4G–4.5G only (baseline)	51.3	(±0)	24.8	(±0)	76.1	(±0)
4G–5G only	56.2	(+9.6)	26.9	(+8.7)	83.2	(+9.3)
4G–5.5G only	56.9	(+10.9)	27.2	(+9.6)	84.1	(+10.5)
4G–6G only	57.4	(+11.9)	27.3	(+10.4)	84.8	(+11.4)
4G–8G only	57.8	(+12.6)	27.5	(+10.9)	85.2	(+12.0)
4G–10G	57.9	(+12.7)	27.5	(+11.1)	85.4	(+12.2)
B. Monitor						
4G–4.5G only (baseline)	138.4	(±0)	68.5	(±0)	207.0	(±0)
4G–5G only	154.1	(+11.4)	72.9	(+6.3)	227.0	(+9.7)
4G–5.5G only	154.2	(+11.4)	72.9	(+6.3)	227.0	(+9.7)
4G–6G only	156.0	(+12.7)	73.3	(+7.0)	229.4	(+10.8)
4G–8G only	157.0	(+13.4)	73.6	(+7.4)	230.6	(+11.4)
4G–10G	157.3	(+13.7)	73.7	(+7.6)	231.0	(+11.6)
C. TV						
4G–4.5G only (baseline)	131.3	(±0)	36.6	(±0)	167.8	(±0)
4G–5G only	172.1	(+31.1)	49.9	(+36.5)	222.0	(+32.3)
4G–5.5G only	174.6	(+33.0)	51.1	(+39.7)	225.7	(+34.5)
4G–6G only	182.6	(+39.1)	53.5	(+46.3)	236.1	(+40.7)
4G–8G only	185.2	(+41.1)	54.4	(+48.8)	239.7	(+42.8)
4G–10G	186.0	(+41.7)	54.7	(+49.6)	240.7	(+43.4)
D. All applications						
4G–4.5G only (baseline)	321.0	(±0)	129.9	(±0)	450.9	(±0)
4G–5G only	382.5	(+19.2)	149.7	(+15.3)	532.2	(+18.0)
4G–5.5G only	385.7	(+20.2)	151.1	(+16.3)	536.8	(+19.1)
4G–6G only	396.1	(+23.4)	154.2	(+18.7)	550.2	(+22.0)
4G–8G only	400.0	(+24.6)	155.5	(+19.7)	555.5	(+23.2)
4G–10G	401.2	(+25.0)	156.0	(+20.1)	557.1	(+23.6)

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting. Rows for "4G–7G only" and "4G–8.5G only" are omitted because their outcomes are nearly identical to "4G–8G only" and "4G–10G," respectively. See Appendix A.5.3 for a robustness check with respect to the assumption on competitive conduct.

product innovation was a major driving force in the nascent market for LCD-TVs and heavily relied on the new vintages of capital investment. By contrast, the panels for notebooks and monitors had limited room for product innovation with larger-product innovation by 2001:Q1. This contrast conforms to the characterization of typical product life cycles (e.g., Klepper 1996): product innovation matters relatively more in earlier stages of a new market, whereas process innovation becomes essential in later stages once the industry converges on a "dominant design" of popular products.

These subtleties notwithstanding, the main message is simple: new-generation fabs made substantial contributions to welfare. However, whether these benefits exceeded the huge costs of fab investments is a separate question, which we investigate in section 6.

6 Social and Private Returns on Investment

The welfare analysis in section 5 showed sizeable social benefits from fab investments in the order of billions of dollars per calendar quarter. However, whether these investments generated a positive return is not obvious because the industry spent more than a hundred billion dollars on new fabs during the sample period. This section incorporates the cost of fab investments and measures their returns.

Section 6.1 calculates the realized return on investment (ROI) evaluates the aggregate ROI under the actual market structure (i.e., seven major firms and fringe). Section 6.2 evaluates ROI under hypothetical monopoly. Section 6.3 incorporates more realistic, strategic considerations and measures oligopolistic firms' individual incentives innovate, which forms the basis for our analysis of competition and innovation in sections 7 and 8.

6.1 High Social Returns, Low Private Returns

This subsection introduces the cost of fab investments and measures their returns. We define suitable measures of social and private ROI along the way.

Table 6 lists the total dollar amount of fab investments by firm. Samsung and LG of Korea lead the industry with \$28.6 billion and \$27.1 billion, respectively, followed by CMO (\$25.1 billion) and AUO (\$19.9 billion) of Taiwan. Their smaller rivals, CPT (\$5.3 billion) and HS (\$2.3 billion), lag behind as they stopped investing in new fabs in the mid-2000s. Sharp (\$9.8 billion) is the only Japanese firm with comparable footprints. "Others" are mostly fringe firms in Japan, with only \$5.5 billion of collective investments.

Table 6: Cost of Fab Investments by Firm, 2001–2011

Firm	Location	Total fab investment (\$)
Samsung	South Korea	28.598
LG	South Korea	27.106
CMO	Taiwan	25.149
AUO	Taiwan	19.925
Sharp	Japan	9.813
CPT	Taiwan	5.289
HS	Taiwan	2.296
Others	Mostly Japan	5.526
Industry total	–	123.703

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

Figure 6 compares the aggregate social benefits and costs in (undiscounted) time series. "Social benefits" plot the difference between the actual SW with all generations of fabs (4G–

10G) and the counterfactual SW with only 4G–4.5G fabs,[38]

$$\Delta SW_t(a, \tilde{a}) \equiv SW_t(a) - SW_t(\tilde{a}), \tag{3}$$

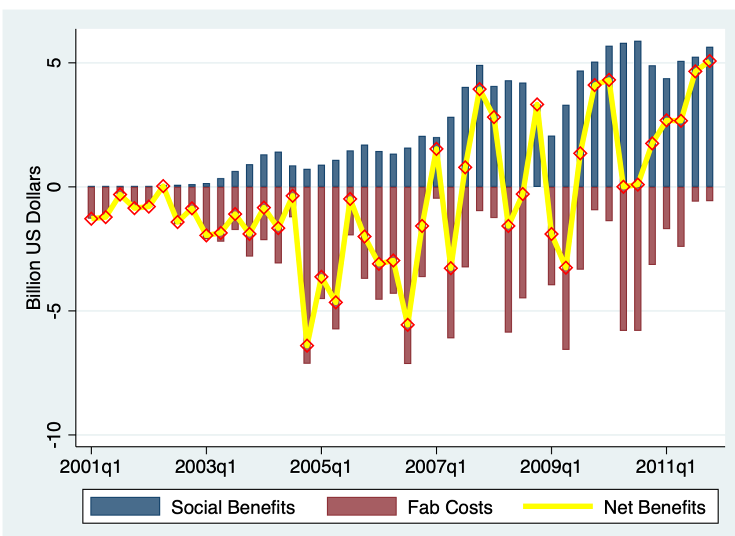
and "fab costs" plot the industry's total investment in each period,

$$\Delta FC_t(a, \tilde{a}) \equiv FC_t(a) - FC_t(\tilde{a}), \tag{4}$$

where $a \equiv (a_f)_{f=1}^F$ and $\tilde{a} \equiv (\tilde{a}_f)_{f=1}^F$ denote the actual and counterfactual profiles of investment strategies ("actions") for F oligopolistic firms, respectively.

For simplicity, we denote each firm's entire history of fab investments in a lump-sum manner as $a_f \in \{0, 1\}$, where $a_f = 1$ summarily represents all of firm f's actual investments in 2001:Q1–2011:Q4, and $a_f = 0$ indicates no investment during the same period (i.e., no progress beyond the initial technology with 4G–4.5G fabs). The no-investment counterfactual of this subsection sets $\tilde{a}_f = 0$ for all f. By treating the actual course of investments a as a fixed, lump-sum choice, we are implicitly interpreting the entire sample period within a static framework akin to a two-period model.

Figure 6: Social Benefits and Costs of Fab Investments (Undiscounted)



Note: "Social benefits" aggregate all new-generation (5G–10G) fabs' welfare contribution in each quarter, ΔSW_t, which corresponds to our analysis in section 5.3. "Fab costs" aggregate the industry-wide total investment costs in each quarter, ΔFC_t, shown as negative numbers in the graph for intuitive visualization. "Net benefits" show their difference in each quarter, $NB_t \equiv \Delta SW_t - \Delta FC_t$. See the main text for more precise definitions.

[38]This definition is exactly the same as in section 5.3. We keep using the same assumptions on firms' conduct based on the results in section 4.2: monopoly pricing in 2001:Q1–2004:Q3 followed by Bertrand-Nash pricing in 2004:Q4–2011:Q4.

Figure 6 shows the costs were larger than the benefits in period-by-period comparisons until around 2007, at which point ΔSW_t started to exceed ΔFC_t. This picture is intuitive but incomplete for an analysis of long-term investments. A more comprehensive evaluation must incorporate time discounting as well as continuation values after the sample period.

Table 7 shows the benefit-cost analysis with time discounting at the annual rates of 1%, 2.5%, 5%, and 10%, respectively. Regarding the post-sample period, we simply assume that the incremental social benefit remains constant at its 2011:Q4 level (i.e., $\Delta SW_t = \Delta SW_T$ for all $t > T$, where T is 2011:Q4) and that no new fab investments would take place (i.e., $\Delta FC_t = 0$ for all $t > T$).

Table 7: Social and Industry Returns on Fab Investments

Annual discount rate	1%	2.5%	5%	10%
1. Change in consumer surplus, $DPV(\Delta CS)$	1,645.7	594.1	250.2	88.7
2. Change in producer surplus, $DPV(\Delta PS)$	477.0	173.8	74.5	27.4
3. Change in social welfare ($= 1 + 2$), $DPV(\Delta SW)$	2,122.7	767.9	324.7	116.1
4. Fab investment cost, $DPV(\Delta FC)$	116.6	106.7	92.1	68.9
5. Change in net social value ($= 3 - 4$), ΔNSV	2,006.1	661.2	232.5	47.2
6. Change in net producer value ($= 2 - 4$), ΔNPV	360.4	67.1	−17.7	−41.4

Note: All discounted present values (DPVs) are in billion US dollars as of 2001:Q1 unless otherwise noted.

Rows 1–3 report the discounted present values (DPVs) of the changes in CS, PS, and SW as of 2001:Q1, respectively; row 4 reports the DPV of total fab costs. DPV is defined as $DPV(\Delta X(a, \tilde{a})) \equiv \sum_{t=0}^{\infty} \delta^t \Delta X_t(a, \tilde{a})$, where $\delta \equiv \frac{1}{1+r}$ is the discount factor, $r > 0$ is the discount rate, $t = 0$ corresponds to 2001:Q1, and $\Delta X \in \{\Delta CS, \Delta PS, \Delta SW, \Delta FC\}$. Based on these measures, we define the change in net social value as

$$\Delta NSV(a, \tilde{a}) \equiv DPV(\Delta SW(a, \tilde{a})) - DPV(\Delta FC(a, \tilde{a})). \tag{5}$$

Row 5 shows that the net benefit is positive even at a relatively high discount rate of 10%. Thus, the investments in 5G–10G technologies were socially valuable.

Whether these investments made commercial sense is another story. Row 6 reports the industry-wide net present value (NPV), defined as the change in the net producer value,

$$\Delta NPV(a, \tilde{a}) \equiv DPV(\Delta PS(a, \tilde{a})) - DPV(\Delta FC(a, \tilde{a})). \tag{6}$$

Even though $\Delta NPV(a, \tilde{a}) > 0$ at low r, it is clearly negative at 5% and above. The industry-wide internal rate of return (IRR)—the break-even discount rate—is 4.05%. This level of return is not appealing from financial perspectives because it barely covers the lowest-possible cost of capital (risk-free rates). Moreover, the true return is likely to be even lower because the cost of fab is only a component of the overall costs for developing and implementing new technologies.[39] In short, the industry as a whole represented only a mediocre investment opportunity at best.

Table 8: Realized Private Return by Firm

Annual discount rate	1%	2.5%	5%	10%
A. Change in producer surplus, $DPV(\Delta PS_f)$				
Samsung	173.9	64.8	28.8	11.4
LG	189.1	70.0	30.9	12.3
CMO	39.3	13.6	5.3	1.6
AUO	51.4	18.8	8.1	2.9
Sharp	61.1	21.7	8.9	2.9
CPT	−2.0	−1.1	−0.8	−0.6
HS	0.5	0.3	0.2	0.2
Others	−36.2	−14.2	−6.9	−3.2
B. Fab investment cost, $DPV(\Delta FC_f)$				
Samsung	26.9	24.6	21.1	15.7
LG	25.4	23.2	19.8	14.5
CMO	23.7	21.6	18.5	13.6
AUO	18.9	17.4	15.2	11.6
Sharp	9.2	8.4	7.2	5.2
CPT	5.1	4.8	4.4	3.6
HS	2.2	2.1	1.9	1.5
Others	5.2	4.7	4.1	3.1
C. Change in net producer value ($= A - B$), ΔNPV_f				
Samsung	147.0	40.3	7.7	−4.3
LG	163.6	46.8	11.1	−2.2
CMO	15.7	−8.0	−13.2	−12.0
AUO	32.5	1.4	−7.1	−8.7
Sharp	51.9	13.3	1.7	−2.4
CPT	−7.1	−6.0	−5.2	−4.2
HS	−1.8	−1.8	−1.7	−1.4
Others	−41.4	−19.0	−11.0	−6.3

Note: All DPVs are in billion US dollars as of 2001:Q1 unless otherwise noted.

Despite low aggregate returns, some firms were much more profitable than others. Table 8 decomposes the realized returns in Table 7 into individual firms. Panels A, B, and C report $DPV(\Delta PS_f)$, $DPV(\Delta FC_f)$, and ΔNPV_f, respectively. Panel C shows Samsung and LG as clear winners of the investment race, with positive ΔNPV_f at $r = 5\%$. The performances of CMO, AUO, and Sharp are less stellar. Even worse, CPT, HS, and Others suffered negative returns even at 1% discount rate; they would have been better off had the industry not moved on to the post-4.5G technologies.[40] Innovations did not "lift all boats."[41]

[39] Other costs (e.g., R&D efforts behind new products and processes) are not precisely measured and could not be used in our analysis.

[40] Some readers might wonder why such unprofitable firms did not exit. We propose three interpretations. First, CPT and HS did stop investing in new fabs by the mid 2000s, dropping out of the investment race, and many fringe firms in Others did exit the industry altogether. Second, their revenues and expenditures were an order of magnitude smaller than those of the top-five firms, which means even minor errors (e.g., due to misspecification or mismeasurement) could change the sign of their ROI estimates. Third, government subsidies might have helped them survive.

[41] Some readers might wonder why the price-fixing cartel did not extend the scope of cooperation to

6.2 Greater Appropriability under Monopoly

The preceding analysis highlights relatively low realized returns. Competition reduces firms' ability to appropriate social returns. Could less competitive market structure, such as monopoly, have helped promote innovation by improving private ROI?

We repeat the analysis of Table 7 under a counterfactual market structure with monopoly. First, we simulate equilibrium prices and sales in each period under the assumption that all products were sold by a monopolist.[42] Second, we eliminate all fabs with the post-4.5G technologies and recompute another trajectory of monopoly prices and sales. Third, we calculate the difference in welfare outcomes between these two situations.

Table 9: Industry-wide Returns under Monopoly

Annual discount rate	1%	2.5%	5%	10%
1. Change in consumer surplus, $DPV(\Delta CS)$	889.6	322.4	136.8	49.3
2. Change in producer surplus, $DPV(\Delta PS)$	749.2	271.6	115.3	41.6
3. Change in social welfare $(= 1 + 2)$, $DPV(\Delta SW)$	1,638.9	594.1	252.1	90.9
4. Fab investment cost, $DPV(\Delta FC)$	116.6	106.7	92.1	68.9
5. Change in net social value $(= 3 - 4)$, ΔNSV	1,522.3	487.3	160.0	22.0
6. Change in net producer value $(= 2 - 4)$, ΔNPV	632.6	164.9	23.2	−27.2

Note: All DPVs are in billion US dollars as of 2001:Q1 unless otherwise noted.

Table 9 reports ROI results under monopoly. Rows 1–3 show that monopoly reduces the positive impact of innovations on CS by approximately 45% compared with the actual/oligopoly case in Table 7, increases the gains in PS by approximately 55%, and reduces the total welfare gain by approximately 22% (at all levels of r). Consequently, ΔNSV decreases by between 24.1% (at $r = 1\%$) and 53.4% (at $r = 10\%$), whereas ΔNPV significantly improves. Hence, monopoly increases PS at the expense of CS and SW, which is one of the most basic lessons in economics.

This basic lesson notwithstanding, some readers might be tempted by the positive impact of monopoly on $\Delta NPV(a, \tilde{a})$ to infer that monopoly would be good for innovation. However, that is not a foregone conclusion for two reasons. First, innovation is not the ultimate social goal in its own right but only a means to achieve it. Rows 3 and 5 of Table 9 show massive decreases in $DPV(\Delta SW)$ and ΔNSV relative to the actual oligopoly. Thus, monopoly cannot be socially desirable in the current context. Second, these negative welfare results may still understate monopoly's true negative impact on SW. Industry reports routinely characterized the behavior of the oligopolistic firms as an investment arms race, which suggests

investments. The results in panel C suggest that the winners of the investment race (e.g., Samsung and LG) would not have agreed to reduce investments.

[42] Section 6.1 assumed monopoly pricing (only) in 2001:Q1–2004:Q3 to mimic the cartel's influence in reality, whereas ection 6.2 assumes monopoly for the entire sample period (including 2004:Q4–2011:Q4).

that monopoly might have invested much less aggressively.

6.3 Competitive Pressure under Oligopoly

The preceding analyses compared outcomes *with* and *without* all/any fab investments. The latter, no-investment ($\tilde{a} = 0$) counterfactual is equivalent to an industry-wide ban on investments. However, no single firm had the ability to impose such a ban in reality. Hence, even though section 6.1 presented valid measures of aggregate returns and their firm-level decomposition, they fail to capture individual firms' strategic incentives, which this subsection properly measures.

We investigate whether each firm could have increased profits by unilaterally deviating from $a = 1$ and not investing in any new fabs. Let $\breve{a}(f) \equiv (\breve{a}_{f'})_{f'=1}^{F}$ denote such a counterfactual profile of investments, where $\breve{a}_f = 0$ and $\breve{a}_{f'} = 1$ for all $f' \neq f$. Then the difference in focal firm f's NPV between a and $\breve{a}(f)$,

$$\Delta NPV_f(a, \breve{a}(f)) \equiv DPV(\Delta PS_f(a, \breve{a}(f))) - DPV(\Delta FC_f(a, \breve{a}(f))), \tag{7}$$

represents its incentive to invest in this strategic environment.

Table 10: Returns Relative to Unilateral No-Investment Deviation

Annual discount rate	1%	2.5%	5%	10%
A. Change in producer surplus, $DPV(\Delta PS_f)$				
Samsung	244.7	91.7	41.2	16.7
LG	245.4	92.3	41.9	17.5
CMO	85.3	30.3	12.4	4.2
AUO	88.7	32.7	14.2	5.4
Sharp	68.6	24.8	10.5	3.7
CPT	1.4	0.7	0.4	0.2
HS	2.2	1.1	0.7	0.4
Others	1.2	0.4	0.2	0.0
B. Fab investment cost, $DPV(\Delta FC_f)$				
	(Omitted: same as in Table 8)			
C. Change in net producer value (= $A - B$), ΔNPV_f				
Samsung	217.8	67.2	20.1	1.0
LG	219.9	69.2	22.1	3.0
CMO	61.7	8.8	−6.1	−9.4
AUO	69.8	15.3	−1.0	−6.3
Sharp	59.4	16.4	3.3	−1.5
CPT	−3.7	−4.1	−4.0	−3.4
HS	0.0	−0.9	−1.2	−1.1
Others	−4.0	−4.3	−3.9	−3.0
Sum of positive changes	628.6	176.8	45.4	4.0
Sum of negative changes	−7.7	−9.4	−16.1	−24.8
Sum of all changes, SII	620.9	167.4	29.4	−20.8

Note: All DPVs are in billion US dollars as of 2001:Q1 unless otherwise noted.

Table 10 shows that most firms had positive incentives to invest at $r = 2.5\%$ and that Samsung and LG had positive incentives even at $r = 10\%$. The weakest firms' (CPT, HS, and Others) incentives are still non-positive at any r, but the magnitude of losses is now much smaller than in Table 8. The differences between Tables 10 and 8 reflect the effects of strategic incentives in a racing environment. The rewards and threats from business stealing seem to have created sufficient incentives for most firms to keep investing.[43] No-investment was not an attractive alternative for them.

Regarding the overall impact of competition on innovation, we find that the aggregate incentive to innovate under the actual, seven-firm oligopoly was similar to (or greater than) that under monopoly. Let us define the sum of individual incentives to innovate (SII) as

$$SII \equiv \sum_f \Delta NPV_f. \tag{8}$$

The bottom row of Table 10 shows that SII is \$620.9 billion, \$167.4 billion, \$29.4 billion, and \$$-20.8$ billion, at 1%, 2.5%, 5%, and 10% discount rates, respectively. These sums are similar to or greater than their monopoly counterparts in row 6 of Table 9. This result suggests that the positive incentive effect of business stealing (competitive pressure) can offset the negative incentive effect of the relative lack of appropriability under oligopoly. We investigate this theme more systematically in sections 7 and 8.

7 Market Structure and the Incentive to Innovate

This section broadens the preceding analysis of market structure. Section 6 compared the incentive to innovate under the actual oligopoly (with seven major firms and Others) and hypothetical monopoly, but did not study any intermediate levels of concentration. We now consider all possible combinations of firms and the resulting market structures.

Section 7.1 studies the impacts of seven-to-six mergers. Section 7.2 further investigates the impacts of all possible mergers that would lead to more concentrated market structures with five, four, three, two, and one firm(s). Section 7.3 examines several specific mergers to gain further insights. Section 7.4 assesses the merit of "failing firm" defense by simulating firm exits.

[43] CPT, HS, and Others mostly stopped investments in the first half of the sample period, which is consistent with their non-positive ΔNPV_f in Table 10 as well.

7.1 Seven-to-Six Mergers

This subsection measures the effects of seven-to-six mergers on welfare and the incentive to innovate. Our welfare measure continues to be the DPV of SW, but our analytical focus is different from sections 5 and 6, which measured the gains from innovations in terms of $\Delta SW(a, \tilde{a})$. In this section, we calculate the levels of SW under different market structures Ω—by which we denote the identity of the owner of each and every product—while holding fixed the actual history of fab investments a. Likewise, we measure the effects of mergers on the incentive to innovate by comparing SII under different Ω given the actual a.

The idea behind this counterfactual design is to go as far as we can with the simple static model of BLP-style demand and supply, fully exploiting the richness of data with product-and-fab-level details. The main benefits of this "static" approach are its simplicity, its capacity to incorporate hundreds of differentiated products, and its direct connection to the current practice in merger simulations for antitrust purposes. Its main drawback is that we cannot allow the timing and amount of investments in a to change in response to the change in Ω, which would require a multi-period dynamic model.[44]

Table 11: List of All Possible Seven-to-Six Mergers and Their Impacts

Rank	Acquirer	Target	Welfare effect		Incentive effect	
			$\Delta DPV(SW)$	(% change)	ΔSII	(% change)
1	Samsung	LG	−17.7	(−1.4)	0.2	(0.8)
2	LG	AUO	−7.6	(−0.6)	1.5	(5.1)
3	LG	CMO	−6.8	(−0.5)	1.2	(4.0)
4	Samsung	CMO	−6.7	(−0.5)	0.1	(0.3)
5	Samsung	AUO	−6.5	(−0.5)	0.1	(0.2)
6	Samsung	Sharp	−4.6	(−0.4)	1.2	(4.0)
7	CMO	AUO	−4.2	(−0.3)	0.6	(2.0)
8	LG	Sharp	−1.6	(−0.1)	0.4	(1.3)
9	CMO	Sharp	−0.9	(−0.1)	−0.1	(−0.3)
10	AUO	Sharp	−0.9	(−0.1)	0.1	(0.3)
11	LG	CPT	−0.3	(−0.0)	−0.2	(−0.7)
12	Samsung	CPT	−0.3	(−0.0)	−0.1	(−0.4)
13	LG	HS	−0.2	(−0.0)	0.0	(0.0)
14	CMO	CPT	−0.2	(−0.0)	−0.0	(−0.1)
15	AUO	CPT	−0.2	(−0.0)	−0.0	(−0.1)
16	Samsung	HS	−0.1	(−0.0)	0.0	(0.1)
17	AUO	HS	−0.1	(−0.0)	0.0	(0.1)
18	CMO	HS	−0.1	(−0.0)	0.0	(0.1)
19	Sharp	CPT	−0.0	(−0.0)	−0.0	(−0.0)
20	CPT	HS	−0.0	(−0.0)	0.0	(0.0)
21	Sharp	HS	−0.0	(−0.0)	−0.0	(−0.0)

Note: The 21 possible mergers are sorted and ranked by the magnitude of (negative) welfare effect, $\Delta DPV(SW)$. All DPVs are in billion US dollars as of 2001:Q1 at $r = 5\%$. The designation of "acquirer" and "target" firms is purely illustrative and does not affect our simulation results—we list whichever merging party with a larger amount of fab investment in Table 6 as the former and the other party as the latter.

[44] Our companion paper (Igami, Qiu, and Sugaya 2023) pursues this approach.

Table 11 lists all of the 21 possible seven-to-six mergers in the descending order of the magnitude of (negative) welfare effect, $\Delta DPV(SW)$ at $r = 5\%$.[45] The top five mergers involve Samsung, LG, CMO, and AUO (i.e., four largest firms by the amount of fab investments) and lead to sizeable reductions in SW.[46] Mergers 6–10 are less powerful combinations that often include Sharp, the fifth largest firm. Finally, the bottom half (ranks 11–21) lists mergers involving CPT and HS, the two smallest firms, with negligible impacts on SW. These results are straightforward and intuitive.

By contrast, mergers' impact on the incentive to innovate is much more nuanced. Mergers 2, 3, and 6–8 lead to substantial increases in SII (1.3%–5.1%), whereas mergers 1, 4, and 5 have limited impacts (0.2%–0.8%). Thus, the magnitude of incentive effects is not closely correlated with that of welfare effect. Another interesting finding is that seven out of the 21 mergers (9, 11, 12, 14, 15, 19, and 21) reduce SII, which makes them unambiguously bad from social perspectives because $\Delta DPV(SW) < 0$ for all mergers. Curiously, these seven cases involve Sharp, CPT, and/or HS, the three smallest firms. To the extent that smaller firms are easier acquisition targets (e.g., because they are cheaper and attract less antitrust scrutiny), they are more "realistic" mergers than others near the top of Table 11.

In summary, mergers' impact on innovation incentives is quite heterogeneous and could be positive or negative depending on the specific combination of firms, which suggests the antitrust evaluation of innovation effects must be merger-specific. Because ΔSII could be either positive or negative, the degree of required case-specificity is greater than that of a more conventional, short-run welfare analysis (in which $\Delta DPV(SW)$ is always negative). Appendix A.7.1 compares these results with the cases of firm exit to assess the merit of "failing firm" defense.

7.2 All Other Mergers and Market Structures

This subsection extends our merger simulations to include all possible combinations of firms. We simulate all of the 140 five-firm market structures (i.e., there are 140 possible combinations of the seven original firms into five new entities). Likewise, there are 350 four-firm, 301 three-firm, and 63 two-firm configurations, as well as one quasi-monopoly situation ("quasi"

[45] We do not consider mergers with Others until section 7.2 because it s a collection of many small firms. We conduct a sensitivity analysis with different discount rates in section 8.2.

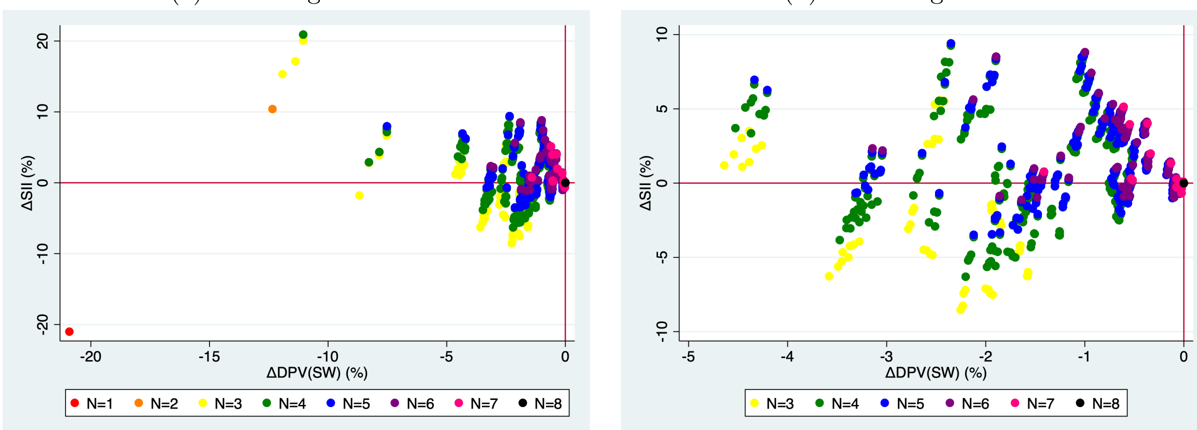
[46] A note on magnitude is in order. As in sections 5 and 6, we compute the entire sequence of equilibrium outcomes in 2001:Q1–2011:Q4 (and beyond) under each simulated ownership structure Ω. However, because we keep assuming that the cartel was fully effective (i.e., monopoly pricing prevailed) until 2004:Q3, the impact of changing Ω manifests itself only in $t >$2004:Q3. Thus, even though $\Delta DPV(SW)$ and ΔSII might appear relatively small, it could be an artifact of time-discounting; the actual impact in each $t >$2004:Q3 could be much larger.

because we keep Others independent); we simulate all of them. Finally, we also simulate perfect monopoly in which all seven major firms and Others are consolidated.[47]

Figure 7: Effects of Market Structure on Social Welfare and Innovation Incentives

(a) Including Outliers

(b) Excluding Outliers



Note: Each dot represents a specific configuration of firms, Ω, and color-coded by the number of active firms (including Others). Both welfare and incentive effects are calculated as DPVs in billion US dollars as of 2001:Q1 at $r = 5\%$ and then expressed in terms of percentage changes from Ω_0, the baseline (actual) market structure with seven firms and Others. See Appendix A.7.2 for a detailed examination of the outliers, and section 8 for sensitivity analyses.

Figure 7 visualizes all merger simulations. Each data point represents a specific configuration of firms (i.e., a product-ownership structure Ω that arises from specific combinations of firms), with its impact on welfare on the horizontal axis and its incentive effect on the vertical axis. The reference point $(0, 0)$ is the original market structure Ω_0 with seven major firms and Others, shown as a black dot (and labeled as $N = 8$ in the legend to acknowledge the presence of Others as an independent firm). The effects of all other configurations are expressed relative to $DPV(SW)$ and SII under this initial state Ω_0.

Pink dots visually represent the 21 six-firm market structures that we examined in section 7.1 (labeled as $N = 7$ in the legend), most of which are near $(0, 0)$. Likewise, purple dots plot the 140 five-firm situations ($N = 6$). Their distribution is slightly more dispersed in both horizontal and vertical dimensions and left-shifted relative to the pink dots. Table 12 confirms these impressions with more precise statistics (compare rows "6 + Others" and "5 + Others").

Similar but more nuanced patterns arise as we visually inspect the blue dots ($N = 5$), green dots ($N = 4$), yellow dots ($N = 3$), and an orange dot ($N = 2$). Several outliers in the top-center part of the plot might create an impression that industry consolidation

[47]This last setup is identical to that of section 6.2. Its comparison with all other mergers gives it a useful context to understand the mechanism underlying our findings.

Table 12: Summary of All Possible Market Structures and Their Effects

Number of firms	Possible config.	Welfare effect, $\Delta DPV(SW)$ (%) Mean	Stdev	Min	Max	Incentive effect, ΔSII (%) Mean	Med	Stdev	Min	Max	Frac < 0
7 + Others	1	± 0	± 0	± 0	± 0	± 0	± 0	± 0	± 0	± 0	0.00
6 + Others	21	−0.2	0.3	−1.4	−0.0	0.8	0.1	1.6	−0.7	5.1	0.33
5 + Others	140	−0.5	0.6	−3.1	−0.0	1.5	0.4	2.1	−1.1	8.8	0.31
4 + Others	350	−1.0	0.8	−7.5	−0.1	1.8	1.1	2.6	−3.5	9.4	0.30
3 + Others	301	−1.7	1.3	−11.0	−0.5	1.3	0.6	3.6	−6.3	20.9	0.42
2 + Others	63	−3.4	2.4	−11.9	−1.6	−1.2	−2.8	5.9	−8.5	0.1	0.65
1 + Others	1	−12.3	–	−12.3	−12.3	10.4	10.4	–	10.4	10.4	0.00
No Others	1	−20.9	–	−20.9	−20.9	−21.0	−21.0	–	−21.0	−21.0	1.00

Note: Both welfare and incentive effects are calculated as DPVs in billion US dollars as of 2001:Q1 at $r = 5\%$ and then expressed in terms of percentage changes from Ω_0, the original market structure with seven firms and Others. The bottom row (No Others) is a perfect monopoly that consolidates Others as well.

would encourage innovation, but Table 12 shows that both the mean and median of ΔSII decrease between $N = 5$ (four firms and Others) and $N = 3$ (two firms and Others), whereas its variability increases—in terms of both standard deviation and min-max range. Meanwhile, the fraction of market structures with $\Delta SII < 0$ (in the right-most column) drastically increases from 0.30 to 0.65. The orange dot (only one major firm and Others) is a clear exception but would seem a risky target for public policy. Thus, the vast majority of mergers results in steady shifts toward south-west, that is, reductions in both welfare and innovation incentives. In Appendix A.7.2, we closely examine each of the outliers and find that all of them are unrealistic cases.

The red dot ($N = 1$) in the lower-left corner of Figure 7 represents perfect monopoly, which corresponds to the simulation in section 6.2. Its outcomes are strictly worse than under any other market structures, with $\Delta DPV(SW) = -20.9\%$ and $\Delta SII = -21.0\%$. Even though its greater market power helps monopoly appropriate more returns, the total lack of business-stealing incentives makes it a lazy innovator.

Table 13: Summary of All Possible Mergers and Their Effects

Merger from/to	Possible mergers	Welfare effect, $\Delta DPV(SW)$ (%) Mean	Stdev	Min	Max	Incentive effect, ΔSII (%) Mean	Med	Stdev	Min	Max	Frac < 0
7 to 6	21	−0.2	0.3	−1.4	−0.0	0.8	0.1	1.6	−0.7	5.1	0.33
6 to 5	315	−0.3	0.5	−2.6	−0.0	0.7	0.0	1.7	−3.5	6.4	0.48
5 to 4	1,400	−0.5	0.8	−6.4	−0.0	0.4	−0.1	2.1	−6.2	9.2	0.59
4 to 3	2,100	−1.0	1.3	−9.7	−0.0	−0.4	−0.5	3.2	−7.7	25.3	0.67
3 to 2	903	−2.3	2.6	−10.5	−0.0	−1.3	−2.7	6.4	−9.4	24.6	0.74
2 to 1	63	−9.2	2.4	−10.9	−0.5	12.1	13.6	6.2	−8.0	20.7	0.05
No Others	1	−9.8	–	−9.8	−9.8	−28.4	−28.4	–	−28.4	−28.4	1.00

Note: Both welfare and incentive effects are calculated as DPVs in billion US dollars as of 2001:Q1 at $r = 5\%$ and then expressed in terms of percentage changes from the immediately preceding market structure of each merger. The bottom row (No Others) is a merger to perfect monopoly that consolidates Others as well.

Table 13 examines the impacts of mergers more closely by focusing on the changes in

$DPV(SW)$ and SII between the market structures immediately before and after each possible merger. Both the mean and median of ΔSII are positive for seven-to-six and six-to-five mergers. However, the median incentive effect of five-to-four mergers is -0.1%, with 59% of them resulting in negative changes. Even the mean—which tends to be influenced by positive outliers—becomes negative (-0.4%) with four-to-three mergers. Two-to-one mergers are an exception to this negative tendency, but any positive change at this stage is overshadowed by the large negative impact of perfect monopoly in the last row.

In summary, two messages emerge from these results. One is that the much-debated positive incentive effects of mergers do exist, but positive outcomes are far from being guaranteed because both their direction and magnitude are highly merger-specific. The other message is that their direction becomes predominantly negative once the number of major firms reaches five or four. Hence, even if the regulators are willing to permit mergers with the hope of fostering innovation, their justification would become increasingly more difficult.

8 Sensitivity Analysis

The relationship between competition and innovation is complex and known to depend on the parameters that govern demand, cost, and investment (e.g., Marshall and Parra 2019; Lefouili and Madio 2024). Hence, our analysis would be incomplete without an assessment of exactly how their relationship changes with these parameters. Section 8.1 shows the robustness of our findings to small, plausible changes in parameter values, whereas Section 8.2 investigates the consequences of extremely large changes.

8.1 Robustness to Small Changes in Parameter Values

This subsection examines the robustness of our findings to small changes in three parameters: price coefficient α, "quality" coefficients $\beta \equiv (\beta^s, \beta^r, \beta^b)$, and discount rate r.[48] We perturb α and β by their respective standard errors in Table 1; we set $r \in \{4\%, 6\%\}$ instead of 5%.

Table 24 in Appendix A.8 shows the results are broadly similar to the baseline ones in Table 13 (section 7.2). Mergers' static-welfare effects barely change in these six alternative settings. As in our main result, mergers' innovation-incentive effects become negative in the majority of five-to-four mergers (or whenever $N \leq 6$ if we count Others as another firm).[49]

[48] We also show robustness with respect to the sunk cost of fab investments, FC, in section 8.2.

[49] This "tipping point" shifts to six-to-five mergers (or $N \leq 7$ if we count Others) under two settings, $\beta = \hat{\beta} + SE(\hat{\beta})$ and $r = 6\%$, which suggests even more stringent merger control would be desirable. See panels (c) and (e) of Table 24.

Thus, the competition-innovation relationship that we documented in section 7 is robust to statistically plausible changes in parameter values due to sampling errors.

8.2 Conditions for Qualitatively Different Results

This subsection experiments with much larger changes in parameter values to determine the conditions under which qualitatively different results could emerge. First, we multiply α and β by 1.5 and 0.5, respectively, which are order-of-magnitude larger changes than those in section 8.1. Second, we try $r \in \{2.5\%, 10\%\}$. Third, we multiply the sunk cost of fabs, FC, by 1.5 and 0.5 as well.

Results (reported in Appendix A.8) suggest the overall pattern is robust to most of these large changes. Only two of the eight results exhibit qualitatively different patterns. First, drastically lower price-sensitivity ($\alpha = 0.5 \times \hat{\alpha}$) makes mergers more pro-innovation. Second, drastically lower quality-sensitivity ($\beta = 0.5 \times \hat{\beta}$) makes mergers generally anti-innovation.

The mechanism behind these results is straightforward. Lower price-sensitivity means higher ROI for innovating firms because they can charge higher prices for new products and expect larger incremental profits from productivity growth. Mergers increase market power, which further reinforces these higher expected returns. The same mechanism works in reverse under lower β: lower quality-sensitivity means lower ROI for innovating firms because buyers' willingness to pay (WTP) is generally lower. Under such circumstances, greater market power would not encourage investment and instead translate into the ability to forgo innovations without a fear of losing business to competitors. Thus, both of these special cases highlight the critical role of buyers' WTP in incentivizing innovation.

The policy implication of these findings is that the innovation-based justification for mergers deserves serious attention only when the price-sensitivity of demand is low. All other cases—including our baseline results—suggest mergers tend to reduce the incentive to innovate when the number of major firms is five or smaller.

9 Conclusion

Our analysis of the LCD industry conveys four messages. First, both product and process innovations led to massive welfare improvements, the relative contributions of which varied across market segments in different stages of product life cycle. Second, the sunk costs of technological investments were so large that some firms' realized financial returns were low, even though their social returns were high. Third, some mergers among the seven major firms could have increased their collective incentive to innovate. However, both the direction and magnitude of such effects are highly merger-specific, and the majority of mergers entails negative consequences when the number of major firms is less than or equal to five. Fourth, this competition-innovation relationship is robust to almost any variations in the key parameters. For mergers' incentive effects to become clearly positive, the price-sensitivity of demand must be extremely low.

The unique strength of this study is in our unusually detailed data. To make our findings as data-driven and transparent as possible, we deliberately kept our model simple—static demand and supply without any "frills." Results suggest rich data and a simple model can shed new light on one of the most difficult and intriguing questions in IO and innovation. Nevertheless, such a static framework has obvious limitations. One is that it cannot allow the timing and amount of investments to change in response to the competitive environment. Another is that it cannot allow market structure to evolve with endogenous mergers, innovations, and entry-exit dynamics (e.g., as in Igami and Uetake 2020). Finally, a static model cannot disentangle the relationship between collusion and innovation, both of which are present in our sample period. We are currently developing a dynamic-game model of collusion and innovation in a companion paper (Igami, Qiu, and Sugaya 2023) to supplement some of these fornoe dynamics.

Appendix

The section numbers of the Appendix sections have gaps because they reflect those of the related main-text sections, not all of which have corresponding supplementary materials.

A.3.1 Summary Statistics of Sales Data

Table 14: Summary Statistics (Sales)

Variable	Unit	Mean	Std. dev.	Minimum	Median	Maximum	Num. of obs.
A. Notebook							
Shipment	1,000 units	252.28	605.88	0.017	75.00	7,447.19	4,140
Price	US dollar	136.32	75.69	38.50	118.00	481.67	4,140
Cost	US dollar	97.32	45.95	25.73	84.74	235.48	4,140
Size	Inch	14.35	1.72	10.40	14.10	20.00	4,140
Resolution	PPI	111.37	16.13	83.00	110.00	171.00	4,140
LED	Indicator	0.26	0.44	0.00	0.00	1.00	4,140
B. Monitor							
Shipment	1,000 units	403.90	592.70	0.011	123.00	4,028.00	3,374
Price	US dollar	241.03	269.06	42.00	145.68	2,084.44	3,374
Cost	US dollar	156.56	88.91	42.33	136.41	664.71	3,374
Size	Inch	19.42	3.44	12.10	19.00	31.50	3,374
Resolution	PPI	92.94	12.14	65.00	91.00	204.00	3,374
LED	Indicator	0.11	0.31	0.00	0.00	1.00	3,374
C. TV							
Shipment	1,000 units	252.34	460.63	0.009	84.00	4,776.00	3,582
Price	US dollar	457.47	579.19	42.00	268.00	5,303.38	3,582
Cost	US dollar	390.82	354.84	47.29	285.36	3,995.51	3,582
Size	Inch	30.21	12.76	10.00	26.00	80.00	3,582
Resolution	PPI	61.28	18.86	28.00	57.00	102.00	3,582
LED	Indicator	0.16	0.37	0.00	0.00	1.00	3,582
D. All applications							
Shipment	1,000 units	298.40	563.10	0.009	86.45	7,447.19	11,096
Price	US dollar	271.84	388.18	38.50	158.75	5,303.38	11,096
Cost	US dollar	210.08	244.93	25.73	136.16	3,995.51	11,096
Size	Inch	21.01	10.09	10.00	17.00	80.00	11,096
Resolution	PPI	89.60	26.38	28.00	91.00	204.00	11,096
LED	Indicator	0.18	0.39	0.00	0.00	1.00	11,096

Note: See the main text of section 4.1 for the details of the variables.

A.3.2 Summary Statistics of Cost Data

Table 15: Summary Statistics (Costs)

Variable	Unit	Mean	Std. dev.	Minimum	Median	Maximum	Num. of obs.
Cash cost	US dollar	253.19	268.30	19.82	153.21	5,900.14	340,471
A. Fab specs							
Tech. gen.	Generation	5.83	1.38	4.00	5.50	10.00	340,471
Fab age	Quarter	19.05	11.58	1.00	18.00	55.00	340,471
ODF method	Indicator	0.89	0.32	0.00	1.00	1.00	340,471
In-house CF	Indicator	0.37	0.48	0.00	0.00	1.00	340,471
Capa. util.	Fraction	0.83	0.10	0.37	0.85	1.00	340,471
B. Firm specs							
Tier-1	Indicator	0.48	0.50	0.00	0.00	1.00	340,471
Japan	Indicator	0.19	0.10	0.00	0.00	1.00	340,471
Korea	Indicator	0.30	0.46	0.00	0.00	1.00	340,471
Taiwan	Indicator	0.51	0.50	0.00	1.00	1.00	340,471
C. Product specs							
Notebook	Indicator	0.23	0.42	0.00	0.00	1.00	340,471
Monitor	Indicator	0.30	0.46	0.00	0.00	1.00	340,471
TV	Indicator	0.47	0.50	0.00	0.00	1.00	340,471
Surface area	m^2	0.29	0.26	0.03	0.16	1.35	340,471
Resolution	PPI	76.57	26.95	31.00	85.00	135.00	340,471
LED (edge)	Indicator	0.47	0.50	0.00	0.00	1.00	340,471
LED (direct)	Indicator	0.04	0.20	0.00	0.00	1.00	340,471

Note: See the main text of section 5.2.1 for the details of the variables.

A.4.1 Unobserved Quality, Outside Goods, and Welfare Adjustment

Unobserved Product Quality and the Value of Outside Goods

As part of our investigation into product innovation, we closely examine the evolution of unobserved product quality. A well-known problem in any discrete-choice demand models is that the mean unobserved quality of the inside goods is not separately identified from the mean value of the outside good. The existing literature offers two solutions. One is to assume away any systematic change in the value of the outside good ($u_{i0t} = \varepsilon_{i0t}$), which is what we do in our baseline analysis in the main text. The other approach is to impose additional restrictions on the unobserved quality of the inside goods, which is what we pursue in this Appendix section as a sensitivity analysis.

Specifically, we allow utility from the outside option (i.e., not buying any LCD panel) to change over time: $u_{i0t} = \gamma_t + \varepsilon_{0it}$. Moreover, we decompose ξ_{jt} into three terms,

$$\xi_{jt} = \tau_t + \phi_{f(j)} + \tilde{\xi}_{jt}, \tag{9}$$

where τ_t is the mean utility of the choice set in time t relative to the initial period, $\phi_{f(j)}$ is a dummy for firm f (the owner of product j), and $\tilde{\xi}_{jt}$ is the product-time-specific unobserved quality term. We assume $E[\tilde{\xi}_{jt}|\mathbf{z}_{jt}] = 0$, where $\mathbf{z}_{jt}$ is a set of instruments. To separately identify the mean (unobserved) quality of the inside goods, τ_t, from the mean value of the outside goods, γ_t, we follow Pakes, Berry, and Levinsohn (1993) to assume

$$\forall j \in \mathcal{C}_t : E[\xi_{jt} - \xi_{j,t-1}] = E[(\tau_t - \tau_{t-1}) + (\tilde{\xi}_{jt} - \tilde{\xi}_{j,t-1})] = 0 \tag{10}$$

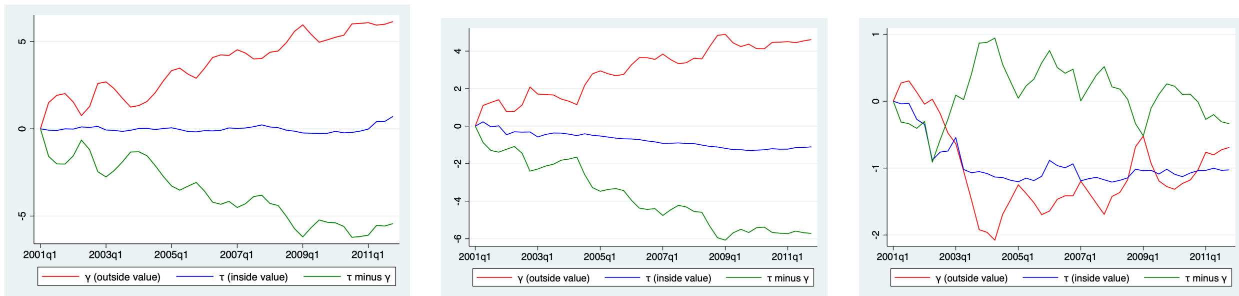
where $\mathcal{C}_t$ is the set of continuing products offered in both time t and $t-1$. In words, even though unobserved product characteristics ξ_{jt} can change over time within the same continuing product j, its mean change is assumed to be zero.

Figure 8 plots the net appeal of the inside goods ($\tau_t - \gamma_t$) and its two components. In the notebook and monitor markets, the net appeal follows a downward trend, which suggests the inside goods became less attractive over time vis-à-vis the outside option. Its decomposition into the mean unobserved quality of inside goods (τ_t) and that of the outside goods (γ_t) shows that most of the downward trend stems from the increasing attractiveness of the latter. Meanwhile, the former exhibits either negligible changes (in notebooks) or a slightly decreasing trend (in monitors). These patterns are inconsistent with the fact that the physical quality of LCD panels improved over time.[50]

[50] Examples of unrecorded product characteristics, such as the range of possible brightness, sharpness, response speed, viewing angle, and other determinants of picture quality. Meanwhile, final-product-level

Figure 8: Mean Values of Inside and Outside Goods

(a) Notebook (b) Monitor (c) TV



Note: See the main text of section A.4.1 for the underlying decomposition of the unobserved quality term.

Results are qualitatively different in the TV market. The net appeal of the inside goods ($\tau_t - \gamma_t$) does not follow any clear trend but fluctuates in a vaguely cyclical pattern. Its decomposition suggests the mean unobserved quality of inside goods decreased in the first few years and never recovered afterward. This result is counter-intuitive and difficult to reconcile with the generally improving quality of LCD-TVs in reality.

In summary, the identifying assumption of Pakes, Berry, and Levinsohn (1993) has led to uninterpretable results regarding the unobserved quality of inside goods in all segments. One possibility is that assumption (10) might not be innocuous in the current high-tech context. Another possibility is that unobserved quality changes were either relatively unimportant, highly collinear with observed quality, or both.

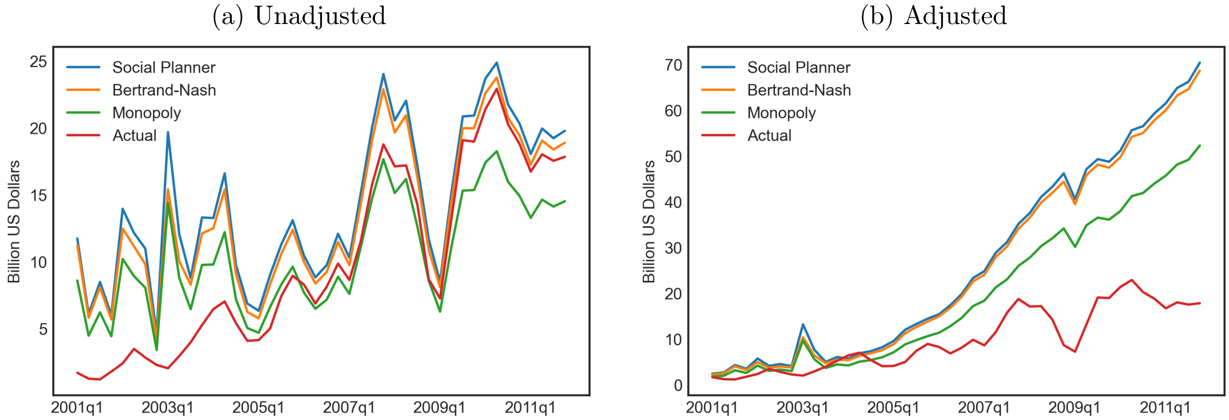
Adjusting Welfare Measures Relative to the Outside Option

A standard measure of CS is the compensating variation of the product set relative to the outside good in the same period. Hence, we denote the CS at time t given the outside-good value γ_t by $CS_t(\gamma_t)$. Adjusting for this factor is potentially important when we want to compare CS across time. For example, CS would seem to decrease during the economic downturn because the value of the outside option (i.e., holding onto cash) increases due to income shocks, even if the quality of inside goods stays constant. PS and SW can be similarly affected by this factor.

To be consistent with the way we handle the value of the outside good in the above, we follow Grieco, Murry, and Yurukoglu (2023) to adjust our welfare measures for the changes in γ_t. First, we calculate the CS for each t using the outside good's value for some other period t', $CS_t(\gamma_{t'})$. Then, we average over the outside-good values in all sample periods to

characteristics (e.g., design aesthetics and user interface) are not relevant in our analysis because the dataset focuses on the business-to-business markets of panels and not the business-to-consumer markets of final goods.

Figure 9: Comparison of Social Welfare



Note: See the main text of section A.4.1 for the details of "adjustment."

construct the adjusted measure as

$$CS_t = \frac{1}{T}\sum_{t'=1}^{T} CS_t(\gamma_{t'}), \tag{11}$$

which removes changes in the value of outside goods. By using this measure, we may directly compare the welfare values of product sets from different periods.

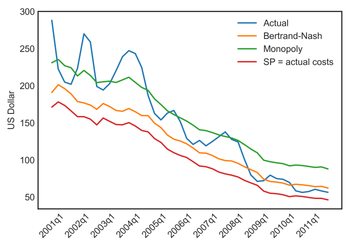
Figure 9 plots the unadjusted and adjusted versions of SW. The adjusted SW tends to be larger than the unadjusted SW, especially in the later years, because the value of the outside goods tends to increase over time in our estimates (see Figure 8 in section 4.1). Whereas the unadjusted welfare plot closely reflects the price-comparison plot in Figure 3 (section 4.2) and is therefore reasonable, the adjusted welfare plot fails to capture the actual path within a range of economically plausible values (i.e., between the planner's and monopolist's solutions). For these reasons, we have chosen to stick with the unadjusted welfare measure (and the assumption of $u_{i0t} = \varepsilon_{i0t}$) in the main text and to regard the results in this Appendix section as a sensitivity analysis.

Even if we completely switch to the adjusted welfare measures, we find that our numerical results concerning the welfare gains from innovation in section 5 do not materially change in terms of percentage change. By contrast, the welfare adjustment nontrivially affects the results of our benefit-cost analysis in section 6. Welfare numbers are much larger across the board after the adjustment, which mechanically increases the implied benefits of innovation as well. Meanwhile, our measure of the sunk cost of fab investments directly comes from the database and remains unchanged. The difference between benefits and costs becomes larger as a result.

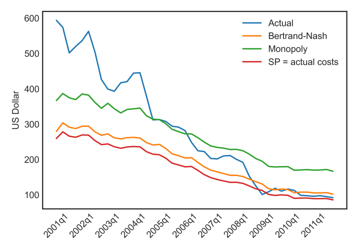
A.4.2 Price Comparison by Application

Figure 10: Comparison of Prices by Application

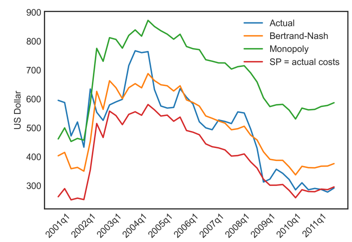
(a) Notebook



(b) Monitor



(c) TV



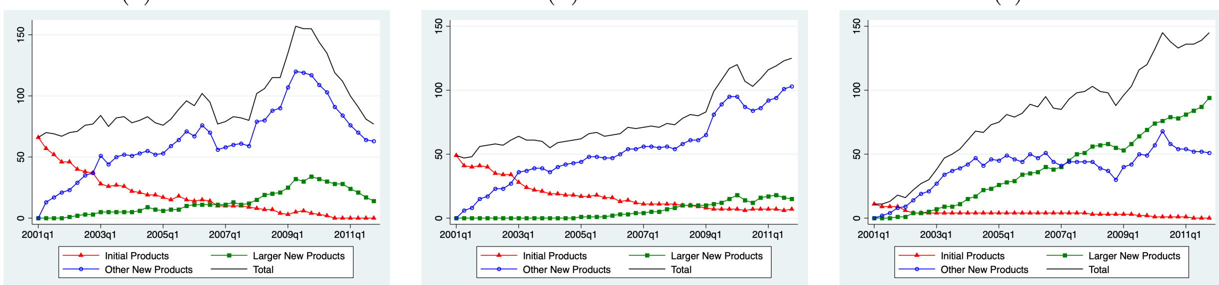
Note: Each graph compares the average price in the data with three theoretical benchmarks: (i) monopoly, (ii) Bertrand-Nash, and (iii) social planner.

A.5.1.1 Product-Level Plots and Statistics by Survival Cohort

This Appendix section presents additional plots and detailed statistics of product-level data by survival cohort. That is, we split all products into three or four categories based on their presence at the beginning and end of our sample period (2001:Q1–2011:Q4): (i) initial, (ii) middle, (iii) end, and (iv) all-time products.

Figure 11: Number of Products by Application

(a) Notebook (b) Monitor (c) TV



Note: These graphs count the number of products defined by all observable characteristics on record, that is, (i)–(v) in section 3.1 including supplier identity.

Figure 11 is a detailed version of Figure 4 that shows the evolution of the number of products by application. Initial products are present in 2001:Q1. Relatively few products belong to this category (66 notebook, 42 monitor, and 11 TV panels) as the top rows of Tables 16–18 show. Middle products are those that appear between 2001:Q2–2011:Q3 but not in the initial or final period. The largest number of products belong to this category (269, 126, and 220 products, respectively), but their median duration (i.e., the number of periods in which a product appears on record) is only seven calendar quarters in all applications. This rapid turnover suggests firms were actively introducing and terminating new products. End products are present in 2011:Q4, including 77 notebook, 118 monitor, and 145 TV panels. Finally, we separately categorize seven monitor panels that appear in both 2001:Q1 and 2011:Q4 as all-time products, and exclude them from the first and third categories to avoid double-counting.[51] No such product exists for notebooks or TVs.

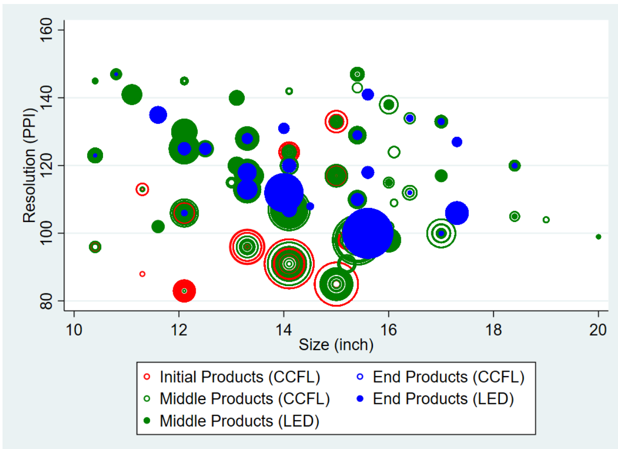
Figure 12 visualizes the positions of all products in the space of three main product characteristics—size (horizontal axis), resolution (vertical axis), and backlight type (hollow vs. filled circles)—again by application and survival cohort. As briefly described in section 5.1.1, newer products tend to feature larger size, higher resolution, and better backlights (LED) as a general trend, but many of them seem to fill in the empty space with new

[51]The addition of the fourth category is the only difference relative to Figures 4 and 11, in which we count category-(iv) monitor panels as part of category (i), for ease of exposition.

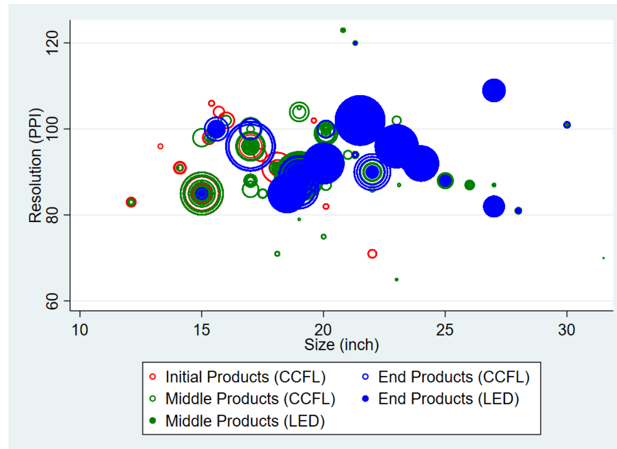
size-resolution combinations that are not necessarily physically superior to the existing ones. Detailed product-level statistics are reported in Tables 16, 17, and 18.

Figure 12: Evolution of Industry-wide Product Portfolios

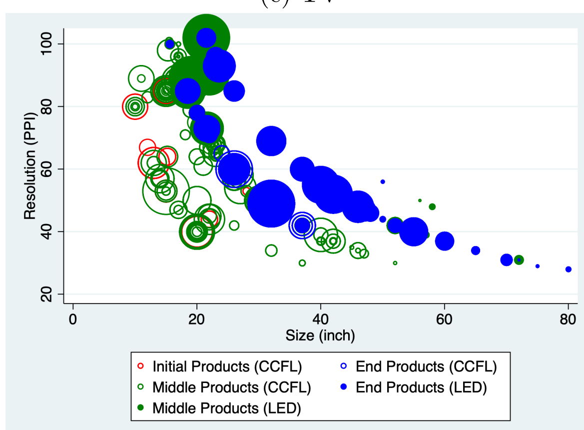
(a) Notebook



(b) Monitor



(c) TV



Note: Each circle represents a product, which is defined as a supplier-application-size-resolution-backlight combination. Circle size reflects total unit shipments across all periods. "Initial products" are those that existed in 2001:Q1, the first period of our sales data. "Middle products" are those that entered the sample after 2001:Q1 and exited before 2011:Q4, the final period of our sales data. "End products" are those that existed in 2011:Q4. A small fraction of monitor products are both "initial" and "end" products; we have chosen to display them as part of initial products (and not end products) for ease of exposition.

Table 16: Summary Statistics by Product Cohort (1): Notebooks

Variable	Unit	Cohort	Mean	Stdev	Min	Med	Max	Num. products
Duration	Quarter	Initial	11.8	10.0	1.0	9.0	35.0	66
Duration	Quarter	Middle	9.6	8.4	1.0	7.0	34.0	269
Duration	Quarter	End	10.0	3.8	1.0	11.0	16.0	77
Revenue	Million US dollar	Initial	26.8	42.2	0.1	12.6	292.2	66
Revenue	Million US dollar	Middle	22.2	45.3	0.0	8.2	495.7	269
Revenue	Million US dollar	End	27.7	49.0	0.1	10.7	321.3	77
Share	Percent	Initial	1.48	2.30	0.00	0.72	18.27	66
Share	Percent	Middle	0.91	1.76	0.00	0.29	15.02	269
Share	Percent	End	1.17	2.23	0.00	0.42	15.17	77
Shipment	1,000 units	Initial	145	235	0	66	1,797	66
Shipment	1,000 units	Middle	204	472	0	60	5,266	269
Shipment	1,000 units	End	524	1,037	1	180	7,447	77
Price	US dollar	Initial	198	66	86	190	482	66
Price	US dollar	Middle	139	71	39	123	407	269
Price	US dollar	End	64	21	39	61	206	77
Cost	US dollar	Initial	138	39	39	142	235	66
Cost	US dollar	Middle	98	42	27	88	232	269
Cost	US dollar	End	52	11	26	50	96	77
Size	Inch	Initial	13.8	1.3	10.4	14.1	15.7	66
Size	Inch	Middle	14.5	1.8	10.4	15.0	20.0	269
Size	Inch	End	14.4	1.8	10.4	14.1	18.4	77
Resolution	PPI	Initial	103	16	83	96	133	66
Resolution	PPI	Middle	112	16	83	110	171	269
Resolution	PPI	End	118	11	100	118	147	77
LED	Indicator	Initial	0.00	0.00	0.00	0.00	0.00	66
LED	Indicator	Middle	0.13	0.34	0.00	0.00	1.00	269
LED	Indicator	End	0.98	0.15	0.00	1.00	1.00	77

Note: "Duration" is the number of periods in which a product appears on record. "Share" is market share within all inside goods. The unit of observation is product-quarter.

Table 17: Summary Statistics by Product Cohort (2): Monitors

Variable	Unit	Cohort	Mean	Stdev	Min	Med	Max	Num. products
Duration	Quarter	Initial	11.5	9.5	1.0	9.0	41.0	42
Duration	Quarter	Middle	9.0	7.1	1.0	7.0	39.0	126
Duration	Quarter	End	12.5	9.8	1.0	10.0	43.0	118
Duration	Quarter	All-time	41.6	3.2	37.0	44.0	44.0	7
Revenue	Million US dollar	Initial	26.8	45.0	0.0	7.7	319.4	42
Revenue	Million US dollar	Middle	28.0	45.2	0.0	8.6	321.8	126
Revenue	Million US dollar	End	70.3	92.6	0.0	38.1	576.9	118
Revenue	Million US dollar	All-time	96.2	138.4	0.1	33.9	750.0	7
Share	Percent	Initial	1.17	1.99	0.00	0.25	12.22	42
Share	Percent	Middle	0.62	1.14	0.00	0.17	10.16	126
Share	Percent	End	1.57	1.91	0.00	0.92	12.92	118
Share	Percent	All-time	2.86	4.11	0.00	0.61	19.31	7
Shipment	1,000 units	Initial	120	215	0	24	1,302	42
Shipment	1,000 units	Middle	192	339	0	40	2,581	126
Shipment	1,000 units	End	629	680	0	382	3,574	118
Shipment	1,000 units	All-time	560	793	1	227	4,028	7
Price	US dollar	Initial	389	313	47	278	1,652	42
Price	US dollar	Middle	301	307	46	189	2,084	126
Price	US dollar	End	139	136	42	92	1,300	118
Price	US dollar	All-time	282	338	44	165	1,778	7
Cost	US dollar	Initial	216	81	65	198	467	42
Cost	US dollar	Middle	184	92	46	161	665	126
Cost	US dollar	End	115	61	42	97	517	118
Cost	US dollar	All-time	165	110	45	136	571	7
Size	Inch	Initial	16.9	2.5	12.1	15.4	22.0	42
Size	Inch	Middle	19.6	3.5	12.1	19.0	31.5	126
Size	Inch	End	20.4	3.1	15.0	19.0	30.0	118
Size	Inch	All-time	17.8	3.3	15.0	17.0	24.0	7
Resolution	PPI	Initial	91	13	71	88	192	42
Resolution	PPI	Middle	95	17	65	94	204	126
Resolution	PPI	End	92	6	81	90	120	118
Resolution	PPI	All-time	91	5	85	94	96	7
LED	Indicator	Initial	0.00	0.00	0.00	0.00	0.00	42
LED	Indicator	Middle	0.02	0.15	0.00	0.00	1.00	126
LED	Indicator	End	0.23	0.42	0.00	0.00	1.00	118
LED	Indicator	All-time	0.00	0.00	0.00	0.00	0.00	7

Note: "Duration" is the number of periods in which a product appears on record. "Share" is market share within all inside goods. The unit of observation is product-quarter.

Table 18: Summary Statistics by Product Cohort (3): TVs

Variable	Unit	Cohort	Mean	Stdev	Min	Med	Max	Num. products
Duration	Quarter	Initial	14.8	16.1	1.00	5.00	41.0	11
Duration	Quarter	Middle	8.3	6.5	1.0	7.0	30.0	220
Duration	Quarter	End	11.0	8.4	1.0	8.0	32.0	145
Revenue	Million US dollar	Initial	13.5	14.1	0.1	10.3	72.5	11
Revenue	Million US dollar	Middle	30.4	67.5	0.0	9.5	716.3	220
Revenue	Million US dollar	End	124.6	159.0	0.0	65.5	966.6	145
Share	Percent	Initial	5.47	8.00	0.00	2.01	47.62	11
Share	Percent	Middle	0.85	1.21	0.00	0.37	9.70	220
Share	Percent	End	1.23	1.68	0.00	0.59	9.60	145
Shipment	1,000 units	Initial	67	61	0	54	266	11
Shipment	1,000 units	Middle	95	155	0	34	1,125	220
Shipment	1,000 units	End	452	615	0	227	4,776	145
Price	US dollar	Initial	266	286	55	179	1,899	11
Price	US dollar	Middle	501	565	46	270	5,303	220
Price	US dollar	End	427	496	42	280	4,901	145
Cost	US dollar	Initial	200	130	47	179	703	11
Cost	US dollar	Middle	416	399	61	291	3,996	220
Cost	US dollar	End	381	308	47	298	2,536	145
Size	Inch	Initial	16.0	3.4	10.0	15.0	28.0	11
Size	Inch	Middle	26.9	12.2	10.0	22.0	72.0	220
Size	Inch	End	35.5	11.6	15.6	32.0	80.0	145
Resolution	PPI	Initial	60	16	40	53	85	11
Resolution	PPI	Middle	64	21	30	60	102	220
Resolution	PPI	End	59	17	28	55	102	145
LED	Indicator	Initial	0.00	0.00	0.00	0.00	0.00	11
LED	Indicator	Middle	0.03	0.16	0.00	0.00	1.00	220
LED	Indicator	End	0.33	0.47	0.00	0.00	1.00	145

Note: "Duration" is the number of periods in which a product appears on record. "Share" is market share within all inside goods. The unit of observation is product-quarter.

A.5.2.2 Impact of Upstream Innovation

Table 19: Welfare Effects of Upstream Innovation, 2001–2011

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
Baseline	57.9	(±0)	27.5	(±0)	85.4	(±0)
(iii) No upstream innovation	20.3	(−64.9)	12.5	(−54.5)	32.8	(−61.5)
(i) + (ii) + (iii)	9.8	(−83.0)	6.5	(−76.4)	16.3	(−80.9)
B. Monitor						
Baseline	157.3	(±0)	73.7	(±0)	231.0	(±0)
(iii) No upstream innovation	71.5	(−54.6)	46.4	(−37.0)	117.9	(−49.0)
(i) + (ii) + (iii)	35.8	(−77.3)	25.9	(−64.9)	61.6	(−73.3)
C. TV						
Baseline	186.0	(±0)	54.7	(±0)	240.7	(±0)
(iii) No upstream innovation	28.1	(−84.9)	9.5	(−82.6)	37.6	(−84.4)
(i) + (ii) + (iii)	14.5	(−92.2)	5.0	(−90.8)	19.5	(−91.9)
D. All applications						
Baseline	401.2	(±0)	156.0	(±0)	557.1	(±0)
(iii) No upstream innovation	119.9	(−70.1)	68.5	(−56.1)	188.4	(−66.2)
(i) + (ii) + (iii)	60.1	(−85.0)	37.4	(−76.0)	97.5	(−82.5)

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

A.5.3 Welfare Results under Alternative Assumption on Conduct

Our baseline assumption on firms' competitive conduct in sections 5–8 is the combination of monopoly pricing (2001:Q1–2004:Q3) and Bertrand-Nash prices (2004:Q4–2011:Q4). This specification is empirically motivated by our markup-comparison results in section 4.2. Nevertheless, because it is not the most typical setup in the context of demand-estimation literature, we conduct a robustness check with respect to this specification here.

We report our results in sections 5.3 (welfare impact of new technologies) under an alternative assumption of Bertrand-Nash throughout the sample period in Table 20. We focus on this table because all of our subsequent analyses in sections 6–8 directly rely on these numbers. In the notebook and monitor segments, the levels of CS, PS, and SW are meaningfully different for obvious reasons (i.e., higher CS, lower PS, and higher SW under the always-Bertrand assumption relative to the baseline first-monopoly-then-Bertrand assumption). However, these different assumptions only mildly affect the percentage-change results (i.e., up to a few percentage points of difference in CS and PS); the percentage-change numbers for SW are almost identical to the ones in Table 5. In the TV segment, even the levels of welfare outcomes almost remain unchanged. Because its market size was small in the first few years of the sample period, the difference in conduct assumptions regarding 2001:Q1–2004:Q3 hardly matters. In summary, our main findings regarding the changes in welfare outcomes are robust.

Table 20: Welfare Impact of New Technologies under Always-Bertrand Assumption

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
4G–4.5G only (baseline)	63.6	(±0)	20.2	(±0)	83.8	(±0)
4G–5G only	69.5	(+9.2)	22.3	(+10.3)	91.7	(+9.5)
4G–5.5G only	70.2	(+10.3)	22.5	(+11.4)	92.7	(+10.6)
4G–6G only	70.8	(+11.2)	22.7	(+12.3)	93.4	(+11.5)
4G–8G only	71.1	(+11.8)	22.8	(+13.0)	93.9	(+12.1)
4G–10G	71.2	(+11.9)	22.8	(+13.2)	94.1	(+12.2)
B. Monitor						
4G–4.5G only (baseline)	192.8	(±0)	57.3	(±0)	229.1	(±0)
4G–5G only	192.8	(+9.7)	57.3	(+7.3)	250.1	(+9.2)
4G–5.5G only	192.8	(+9.7)	57.3	(+7.3)	250.1	(+9.2)
4G–6G only	194.6	(+10.7)	57.8	(+8.3)	252.4	(+10.2)
4G–8G only	195.5	(+11.3)	58.1	(+8.8)	253.6	(+10.7)
4G–10G	195.8	(+11.4)	58.2	(+9.1)	254.0	(+10.9)
C. TV						
4G–4.5G only (baseline)	131.8	(±0)	36.7	(±0)	168.5	(±0)
4G–5G only	172.4	(+30.8)	50.2	(+36.7)	222.6	(+32.1)
4G–5.5G only	174.9	(+32.7)	51.3	(+39.9)	226.2	(+34.2)
4G–6G only	182.8	(+38.7)	53.8	(+46.5)	236.6	(+40.4)
4G–8G only	185.4	(+40.7)	54.7	(+49.1)	240.1	(+42.5)
4G–10G	186.2	(+41.2)	55.0	(+49.8)	241.2	(+43.1)
D. All applications						
4G–4.5G only (baseline)	371.1	(±0)	110.3	(±0)	481.4	(±0)
4G–5G only	434.6	(+17.1)	129.7	(+17.6)	564.3	(+17.2)
4G–5.5G only	437.8	(+18.0)	131.1	(+18.9)	569.0	(+18.2)
4G–6G only	448.1	(+20.7)	134.3	(+21.7)	582.4	(+21.0)
4G–8G only	452.0	(+21.8)	135.6	(+23.0)	587.6	(+22.1)
4G–10G	453.1	(+22.1)	136.1	(+23.4)	589.2	(+22.4)

Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting. Rows for "4G–7G only" and "4G–8.5G only" are omitted because their outcomes are nearly identical to "4G–8G only" and "4G–10G," respectively.

A.7 Additional Results of Merger/Market-Structure Simulations

A.7.1 Failing-Firm Defense

This subsection investigates the merit of the so-called "failing firm" defense of mergers. When a firm is likely to exit and be liquidated along with its products, should the regulators permit its "rescue" by a merger? Our results suggest the answer is "yes."

Table 21 shows that the negative welfare effect of exit is an order of magnitude larger than that of a merger in Table 11 (section 7.1). Hence, any seven-to-six merger is strictly preferable to the exit of a firm and its products in terms of static welfare.

Table 21: How Exits Affect Welfare and Innovation Incentives

Case	Exit by	Welfare effect		Incentive effect	
		$\Delta DPV(SW)$	(% change)	ΔSII	(% change)
1	Samsung	-126.2	(-10.1)	-3.5	(-9.6)
2	LG	-108.6	(-8.7)	-5.7	(-15.6)
3	CMO	-54.0	(-4.3)	0.9	(2.6)
4	AUO	-48.7	(-3.9)	1.1	(2.9)
5	Sharp	-28.2	(-2.3)	-2.6	(-7.2)
6	CPT	-2.8	(-0.4)	0.0	(0.0)
7	HS	-1.6	(-0.1)	0.0	(0.0)
8	Others	-71.4	(-5.7)	0.1	(0.2)

Note: All DPVs are in billion US dollars as of 2001:Q1 at $r = 5\%$. All changes are relative to Ω_0, the original market structure with seven firms and Others.

The innovation-incentive effect of exit is more complicated but does not overturn the advantage of a merger-as-rescue. First, the exit of Samsung, LG, or Sharp would have reduced SII by 7%–16% as they were the main innovators with clearly positive incentives. Second, eliminating CMO or AUO would have increased SII by approximately one billion dollars, which is comparable to the impact of the most innovation-friendly mergers in Table 11 (e.g., LG-AUO, LG-CMO, and Samsung-Sharp mergers). Third, SII hardly changes with the exit of CPT, HS, or Others. In summary, merger seems preferable to exit in terms of incentive effects as well because ΔSII of most seven-to-six mergers dominate their exit counterparts—sometimes by wide margins.

A.7.2 Case Studies

This Appendix section closely examines the "outliers" in Figure 7 and several other market structures. Our goal is to assess whether outliers should be taken seriously for public-policy purposes and to gain further insights into the mechanism behind our findings in section 7.

Outliers. Table 22 lists the outliers in Figure 7, with $\Delta DPV(SW) < -5\%$, in the ascending order of $\Delta DPV(SW)$. The column labeled "market structure configuration" shows the exact ownerwhip structure Ω by presenting merged firms within a bracket. The full-monopoly case in the top row is a true outlier with massively negative outcomes in terms of both welfare and incentive effects, as we have already discussed in the main text.

Table 22: Case Studies of "Outlier" Market Structures

Case	Market structure configuration	Num. firms (N)	$\Delta DPV(SW)$ (% change)	ΔSII (% change)
1	$\{Samsung, LG, CMO, AUO, Sharp, CPT, HS, Other\}$	1	−20.9	−21.0
2	$\{Samsung, LG, CMO, AUO, Sharp, CPT, HS\}, Other$	2	−12.3	10.4
3	$\{Samsung, LG, CMO, AUO, Sharp, CPT\}, HS, Other$	3	−11.9	15.3
4	$\{Samsung, LG, CMO, AUO, Sharp, HS\}, CPT, Other$	3	−11.4	17.2
5	$\{Samsung, LG, CMO, AUO, Sharp\}, \{CPT, HS\}, Other$	3	−11.1	20.1
6	$\{Samsung, LG, CMO, AUO, Sharp\}, CPT, HS, Other$	4	−11.1	20.9
7	$\{Samsung, LG, CMO, AUO, CPT, HS\}, Sharp, Other$	3	−8.7	−1.8
8	$\{Samsung, LG, CMO, AUO, CPT\}, \{Sharp, HS\}, Other$	3	−8.3	2.8
9	$\{Samsung, LG, CMO, AUO, CPT\}, Sharp, HS, Other$	4	−8.3	2.9
10	$\{Samsung, LG, CMO, AUO, HS\}, \{Sharp, CPT\}, Other$	3	−7.9	3.9
11	$\{Samsung, LG, CMO, AUO, HS\}, Sharp, CPT, Other$	4	−7.8	4.4
12	$\{Samsung, LG, CMO, AUO\}, \{Sharp, CPT, HS\}, Other$	3	−7.5	6.7
13	$\{Samsung, LG, CMO, AUO\}, \{Sharp, CPT\}, HS, Other$	4	−7.5	7.5
14	$\{Samsung, LG, CMO, AUO\}, \{CPT, HS\}, Sharp, Other$	4	−7.5	7.2
15	$\{Samsung, LG, CMO, AUO\}, \{Sharp, HS\}, CPT, Other$	4	−7.5	7.9
16	$\{Samsung, LG, CMO, AUO\}, Sharp, CPT, HS, Other$	5	−7.5	8.0

Note: This table lists the outliers in Figure 7 with $\Delta DPV(SW) < -5\%$ in the ascending order of $\Delta DPV(SW)$. Firms in the same brackets are merged and maximize joint profits. Other definitions follow Table 12.

More interesting results arise in cases 2–6, where the incentive effects are large and positive, with $\Delta SII > 10\%$. Case 2 is the quasi-monopoly with consolidation of the seven major firms, which definitely enhances their market power (and the appropriability of social returns) but falls short of totally eliminating competition and business-stealing incentives for innovation. Whether the fringe firms in Others could exert such competitive pressure in reality is questionable because these firms lack the physical capacity to drastically increase outputs in the short run even if the quasi-monopoly engages in monopoly-like pricing. The BLP-style static model abstracts from such capacity constraints, which is why the presence of Others could matter so much in these simulations.

Cases 3–6 entail the largest positive incentive effects above 15%. They commonly feature mergers of the top-five firms (Samsung, LG, CMO, AUO, and Sharp) while leaving out CPT and HS—the weakest of the seven major firms, with low brand power, little investment, and negligible or negative incentive to innovate (see Tables 1, 6, and 10, respectively). They are unlikely to contribute to SII even if they are merged with other, stronger firms. Meanwhile, their existence as independent competitors preserves the room for business stealing and helps motivate the dominant player to invest. As in Case 2, whether CPT and HS in reality could put such competitive pressure on the coalition of the stronger firms is questionable due to capacity constraints. Nevertheless, the finding that the incentive to innovate hinges on a delicate balance between strong appropriability and business-stealing opportunities is general and fundamental.

Cases 7–16 leave out Sharp as well and follow similar patterns albeit in smaller magnitude. Note all of the 16 outliers (except cases 1–2) involve consolidation of the top-four firms while leaving out weaker firms as independent competitors. We would like to point out that such market structures are unlikely to emerge in a typical process of industry consolidation, in which weaker (rather than stronger) players tend to become acquisition targets. Hence, we regard these outliers as more of theoretical curiosities than relevant policy targets.

More Symmetric Cases with "National Champions." Table 23 lists four cases of more symmetric market structures than those in the "outliers." Our purpose is to develop intuition about the determinants of merger's effects.

Table 23: Case Studies of "National Champion" Market Structures

Case	Market structure configuration	Num. firms (N)	$\Delta DPV(SW)$ (% change)	ΔSII (% change)
17	$\{CMO, AUO, CPT, HS\}, Samsung, LG, Sharp, Others$	5	-0.4	1.5
18	$\{Samsung, LG\}, CMO, AUO, CPT, HS, Sharp, Other$	7	-1.4	0.8
19	$\{Samsung, LG\}, \{CMO, AUO, CPT, HS\}, Sharp, Other$	4	-1.9	-4.3
20	$\{Samsung, LG\}, \{CMO, AUO, CPT, HS, Sharp\}, Other$	3	-2.2	-7.2

Note: Firms in the same brackets are merged and maximize joint profits. Other definitions follow Table 12.

Cases 17 and 18 show positive incentive effects. Case 17 consolidates the four Taiwanese firms (CMO, AUO, CPT, and HS) into a single "national champion." This case would seem highly anti-competitive as it reduces the number of firms—including Others—from eight to five. However, $DPV(SW)$ decreases by only 0.4% and SII increases by 1.5% from the original market structure. Case 18 creates a national champion in Korea by merging Samsung with LG. Even though $N = 7$ appears more competitive than $N = 5$, its performances fall short of case 17.

By contrast, cases 19 and 20 entail negative incentive effects. Case 19 creates two national champions, in Taiwan and Korea respectively. Case 20 further accelerates industry consolidation by letting Sharp of Japan join the Taiwanese national champion. The 7.2% decrease in SII is close to the worst performance under $N = 3$ (see Table 12 in section 7.2).

These case studies suggest that the determinants of the incentive effects of mergers include not only the number of firms—and the degrees of concentration and asymmetry among them—but also the investment profile of all major players, both inside and outside mergers. This observation further confirms our finding in section 7 that incentive effects are much more merger-specific than static welfare effects.

A.8 Details of Sensitivity Analysis

This Appendix section presents results of the sensitivity analyses in section 8.

Robustness to Small Changes. Table 24 reports detailed statistics for the six sensitivity analyses in section 8.1. The welfare effects of mergers show only minor quantitative variation. The innovation-incentive effects exhibit larger variation, but the general tendency of the median outcomes and the fraction of cases with $\Delta SII < 0$ is remarkably similar to the baseline result in Table 13 (section 7.2).

Larger Changes in Demand-Side Parameters. Figure 13 (a) and (b) show that greater (lesser) price-sensitivity of demand induces two changes. First, it makes the incentive effect of mergers more negative (positive), as represented by a downward (upward) shift of data points. This result is intuitive because firms cannot increase prices when buyers are highly price-sensitive, which reduces the ROI for innovating firms. Second, the slope of the relationship between competition and innovation becomes flatter (steeper), that is, ΔSII exhibits no visible change (a tendency to increase) as N decreases—with the exception of $N = 1$. The reason is that more concentrated market structure does not translate into much higher markups when buyers are highly price-sensitive. Overall, greater price-sensitivity makes most mergers socially undesirable. By contrast, lesser price-sensitivity opens the possibility that positive ΔSII might partially offset negative $\Delta DPV(SW)$ in the long run. The policy implication of this finding is that an innovation-based justification of mergers has potential merit only when the demand is not very price-sensitive.

In Figure 13 (c), greater sensitivity to product quality does not seem to change the baseline pattern. By contrast, subfigure (d) shows that lesser quality-sensitivity makes the impact of most mergers small and negative (note the narrow range of the vertical scale). We interpret these results as follows. When buyers are ready to pay for higher product quality, the greater appropriability under more concentrated market structure could sometimes encourage firms' investments. Conversely, when their willingness to pay (WTP) for product innovation is low, the lack of competition means firms could slack off by simply reducing innovative efforts. Thus, any innovation-based justification of mergers has potential merit only when the demand-side truly appreciates product innovations.

Larger Changes in Supply-Side Parameters. We now proceed to the two supply-side parameters. Both of them affect the cost of LCD production, as r relates to the cost of capital to finance investments, and FC is the upfront cost of investments.

Table 24: Sensitivity (1)—Small Changes in Parameters

Merger from/to	Possible mergers	Welfare effect, $\Delta DPV(SW)$ (%) Mean	Stdev	Min	Max	Incentive effect, ΔSII (%) Mean	Med	Stdev	Min	Max	Frac < 0
(a) *Greater price-sensitivity*, $\alpha = \hat{\alpha} - SE(\hat{\alpha})$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	1.2	0.2	2.4	−1.1	8.0	0.33
6 to 5	315	−0.3	0.5	−2.6	−0.0	1.0	0.0	2.6	−5.8	9.2	0.49
5 to 4	1,400	−0.5	0.8	−6.5	−0.0	0.3	−0.2	3.2	−10.2	13.2	0.60
4 to 3	2,100	−1.0	1.3	−9.8	−0.0	−1.1	−1.1	4.9	−12.8	37.4	0.70
3 to 2	903	−2.3	2.6	−10.6	−0.0	−3.3	−5.0	9.7	−15.6	36.2	0.78
2 to 1	63	−9.2	2.4	−11.0	−0.5	16.5	18.8	9.5	−12.3	30.6	0.05
No Others	1	−9.8	–	−9.8	−9.8	−47.0	−47.0	–	−47.0	−47.0	1.00
(b) *Lesser price-sensitivity*, $\alpha = \hat{\alpha} + SE(\hat{\alpha})$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	0.6	0.1	1.3	−0.5	3.9	0.38
6 to 5	315	−0.3	0.5	−2.6	−0.0	0.6	0.0	1.3	−2.4	5.2	0.50
5 to 4	1,400	−0.5	0.8	−6.4	−0.0	0.4	−0.1	1.6	−4.3	7.5	0.58
4 to 3	2,100	−1.0	1.3	−9.7	−0.0	−0.0	−0.3	2.5	−5.4	20.3	0.65
3 to 2	903	−2.3	2.6	−10.5	−0.0	−0.4	−1.7	5.0	−6.6	19.9	0.70
2 to 1	63	−9.1	2.4	−10.9	−0.5	10.4	11.5	4.8	−6.0	16.9	0.05
No Others	1	−9.7	–	−9.7	−9.7	−20.0	−20.0	–	−20.0	−20.0	1.00
(c) *Greater quality-sensitivity*, $\beta = \hat{\beta} + SE(\hat{\beta})$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	0.2	0.0	0.6	−0.8	1.5	0.43
6 to 5	315	−0.3	0.5	−2.6	−0.0	0.1	0.0	0.7	−3.0	1.7	0.55
5 to 4	1,400	−0.5	0.7	−6.2	0.0	−0.2	−0.1	1.0	−4.1	1.7	0.65
4 to 3	2,100	−0.9	1.3	−8.9	0.0	−0.9	−0.5	1.4	−5.2	6.6	0.78
3 to 2	903	−2.1	2.4	−9.7	−0.0	−2.1	−2.2	2.2	−6.3	6.2	0.88
2 to 1	63	−8.6	2.3	−10.3	−0.6	1.0	1.2	1.8	−4.7	4.6	0.25
No Others	1	−11.0	–	−11.0	−11.0	−16.8	−16.8	–	−16.8	−16.8	1.00
(d) *Lesser quality-sensitivity*, $\beta = \hat{\beta} - SE(\hat{\beta})$											
7 to 6	21	−0.2	0.4	−1.4	−0.0	0.6	0.0	1.1	−0.3	3.4	0.43
6 to 5	315	−0.4	0.5	−2.6	−0.0	0.6	0.0	1.2	−1.0	5.3	0.46
5 to 4	1,400	−0.6	0.8	−6.6	−0.0	0.7	−0.0	1.4	−2.8	9.8	0.51
4 to 3	2,100	−1.0	1.4	−10.4	−0.0	0.7	−0.1	2.2	−3.5	17.6	0.53
3 to 2	903	−2.5	2.7	−11.3	−0.0	1.3	−0.3	4.4	−4.0	17.4	0.55
2 to 1	63	−9.7	2.5	−11.5	−0.3	10.7	12.0	4.1	−4.3	15.1	0.05
No Others	1	−9.2	–	−9.2	−9.2	−13.3	−13.3	–	−13.3	−13.3	1.00
(e) *Higher discount rate*, $r = 6\%$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	1.4	0.1	3.9	−3.8	11.5	0.48
6 to 5	315	−0.3	0.5	−2.6	−0.0	1.1	−0.0	4.2	−12.1	13.7	0.57
5 to 4	1,400	−0.5	0.7	−6.2	−0.0	0.0	−0.4	5.1	−17.8	18.5	0.64
4 to 3	2,100	−0.9	1.3	−9.4	−0.0	−2.4	−2.1	7.6	−23.3	61.3	0.71
3 to 2	903	−2.2	2.5	−10.2	−0.0	−6.1	−8.4	14.7	−28.5	59.4	0.81
2 to 1	63	−8.9	2.3	−10.6	−0.5	23.7	26.8	15.6	−18.3	53.8	0.05
No Others	1	−9.6	–	−9.6	−9.6	−70.8	−70.8	–	−70.8	−70.8	1.00
(f) *Lower discount rate*, $r = 4\%$											
7 to 6	21	−0.2	0.4	−1.4	−0.0	0.6	0.1	1.1	−0.3	3.4	0.33
6 to 5	315	−0.3	0.5	−2.7	−0.0	0.6	0.0	1.2	−2.1	4.4	0.44
5 to 4	1,400	−0.5	0.8	−6.7	−0.0	0.5	−0.0	1.4	−3.9	8.1	0.55
4 to 3	2,100	−1.0	1.4	−10.1	−0.0	0.2	−0.2	2.2	−4.8	18.3	0.61
3 to 2	903	−2.4	2.7	−10.9	−0.0	−0.1	−1.2	4.5	−5.7	17.9	0.68
2 to 1	63	−9.4	2.5	−11.3	−0.5	9.5	10.7	4.3	−4.9	14.8	0.05
No Others	1	−10.0	–	−10.0	−10.0	−17.2	−17.2	–	−17.2	−17.2	1.00

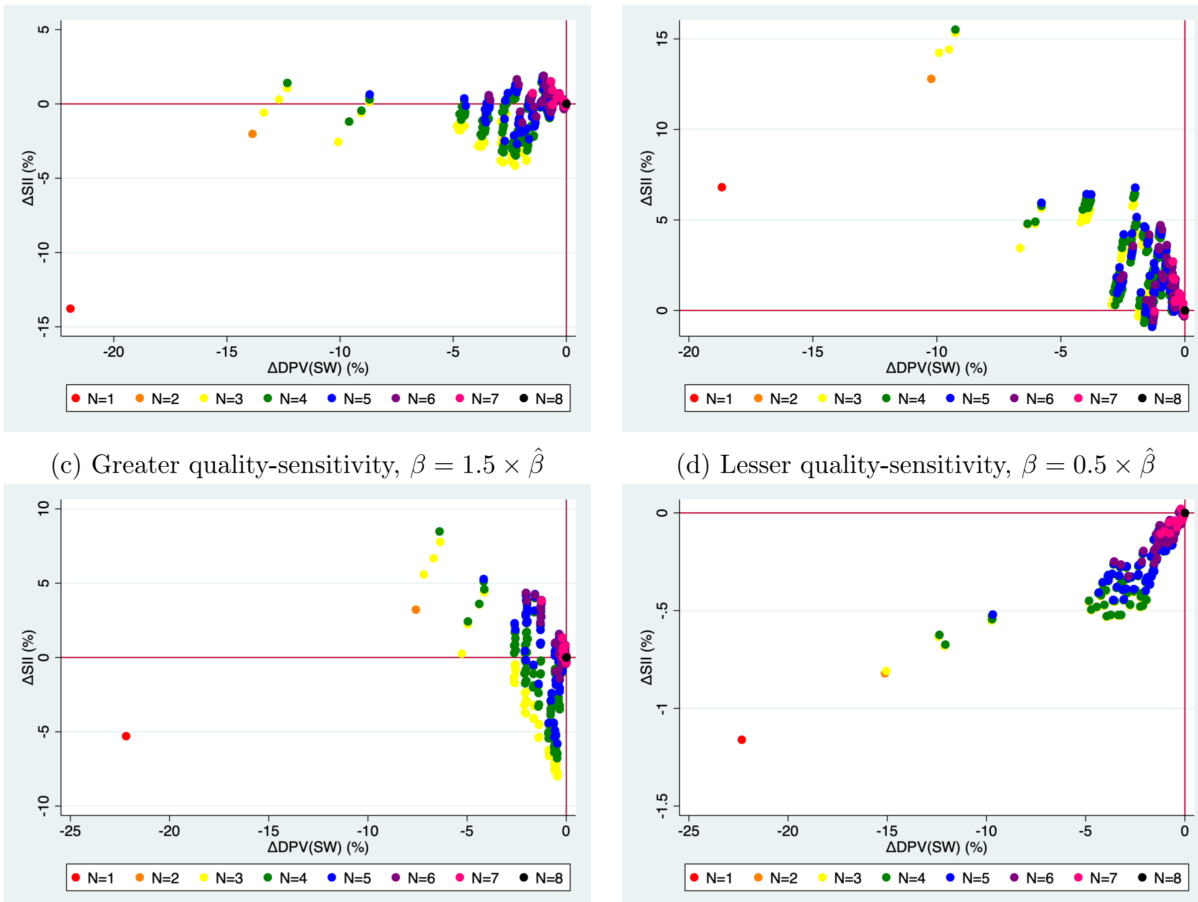
Note: See the note to Table 13 for definitions and explanations.

Figure 14 (a) and (b) show that a higher (lower) discount rate (i) reduces (increases) the incentive to innovate across the board and (ii) makes the slope of the competition-innovation

Figure 13: Sensitivity of Market-Structure Effects to Demand-Side Parameters

(a) Greater price-sensitivity, $\alpha = 1.5 \times \hat{\alpha}$ (b) Lesser price-sensitivity, $\alpha = 0.5 \times \hat{\alpha}$

(c) Greater quality-sensitivity, $\beta = 1.5 \times \hat{\beta}$ (d) Lesser quality-sensitivity, $\beta = 0.5 \times \hat{\beta}$

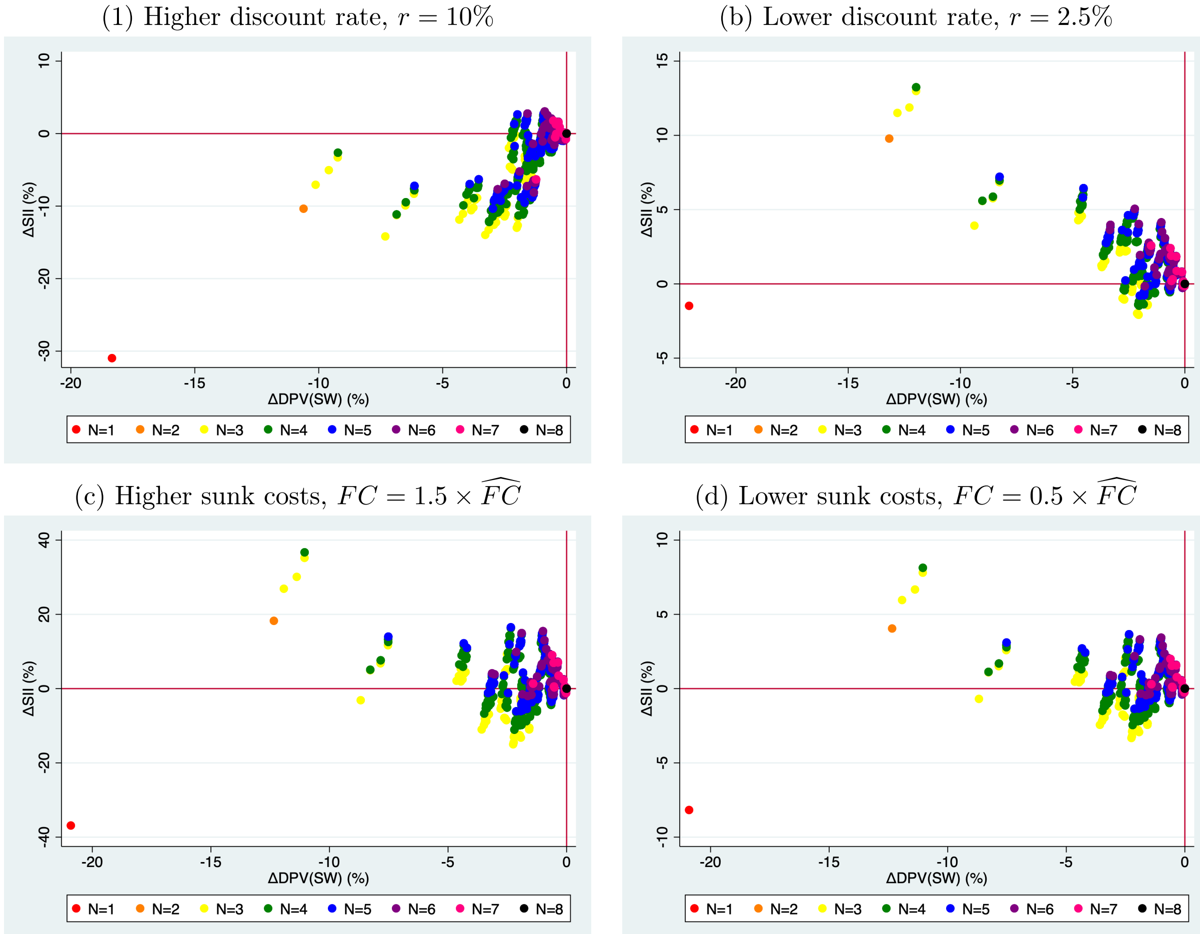


Note: These plots are constructed in the same way as Figure 7 under alternative parameter values. Their summary statistics are reported in Table 25 below.

relationship flatter (steeper). The first effect is obvious because, as r increases (decreases), the long-run benefits from investments become less (more) important relative to their short-run costs. The second effect is more complicated but resembles some of the patterns in section 8.1. When the gains from innovations are small, firms will not invest in them unless competitive pressure forces them to do so. By contrast, when the gains are large, greater market power could sometimes inflate these gains and encourage investment.

What are the policy implications? The mostly negative ΔSII under $r = 10\%$ suggests that most mergers are clearly harmful when the cost of capital is realistically high (and/or the promise of future benefits is uncertain). Conversely, the results under $r = 2.5\%$ suggests mergers could sometimes help increase innovation when the cost of financing is low (and/or the level of uncertainty is low)—with the caveat that the majority of four-to-three and three-to-two mergers, as well as $N = 1$, is still unambiguously bad (see their underlying statistics

Figure 14: Sensitivity of Market-Structure Effects to Supply-Side Parameters



Note: These plots are constructed in the same way as Figure 7 under alternative parameter values. Their summary statistics are reported in Table 26.

in Table 25 below).[52]

Finally, Figure 14 (c) and (d) show total lack of sensitivity with respect to FC. Their vertical scales vary, but the relative positions of all data points are exactly the same as in Figure 7. Despite FC's major role in benefit-cost calculations, this term cancels out when we compare SII under different market structures.[53]

[52] Whether these values of r are realistic is a different question. In our view, $r = 10\%$ seems a plausible level of capital cost for most private enterprises operating in a rapidly changing world of global high-tech industries. By contrast, $r = 2.5\%$ seems unrealistically low because it could be well below the risk-free rate of return, which means the latter result becomes relevant only under extraordinary circumstances. Given that the incentive effects of mergers are mostly negative under $r = 5\%$ and 10% (especially when $N \leq 5$), defending mergers on the grounds of incentive to innovate seems difficult.

[53] Recall that we take the timing and amount of fab investments, a, in the data as given and fixed. Endogenizing them requires an explicitly multi-period model, which is beyond the scope of this paper.

Table 25: Sensitivity (2)—Larger Changes in Demand-Side Parameters

Merger	Possible	Welfare effect, $\Delta DPV(SW)$ (%)				Incentive effect, ΔSII (%)					
from/to	mergers	Mean	Stdev	Min	Max	Mean	Med	Stdev	Min	Max	Frac < 0
					(a) *Greater price-sensitivity*, $\alpha = 1.5 \times \hat{\alpha}$						
7 to 6	21	-0.2	0.4	-1.5	-0.0	0.2	0.0	0.4	-0.2	1.5	0.48
6 to 5	315	-0.4	0.5	-2.8	-0.0	0.1	-0.0	0.5	-1.8	1.5	0.52
5 to 4	1,400	-0.6	0.8	-7.5	-0.0	-0.1	-0.0	0.7	-3.3	1.9	0.63
4 to 3	2,100	-1.1	1.5	-10.9	-0.0	-0.7	-0.4	1.1	-3.8	4.0	0.82
3 to 2	903	-2.6	3.0	-11.9	-0.0	-1.8	-1.8	1.6	-4.5	3.7	0.91
2 to 1	63	-10.4	2.7	-12.3	-0.6	0.4	0.6	1.2	-3.1	2.1	0.35
No Others	1	-9.3	–	-9.3	-9.3	-11.5	-11.5	–	-11.5	-11.5	1.00
					(b) *Lesser price-sensitivity*, $\alpha = 0.5 \times \hat{\alpha}$						
7 to 6	21	-0.2	0.3	-1.2	-0.0	0.4	-0.0	0.8	-0.2	2.7	0.57
6 to 5	315	-0.3	0.4	-2.2	-0.0	0.5	-0.0	0.9	-0.5	3.6	0.50
5 to 4	1,400	-0.4	0.6	-4.9	-0.0	0.7	0.3	1.1	-0.9	6.1	0.43
4 to 3	2,100	-0.8	1.1	-8.2	-0.0	0.9	0.4	1.6	-1.3	14.4	0.37
3 to 2	903	-1.9	2.1	-8.8	-0.0	1.9	1.0	3.1	-2.2	14.2	0.32
2 to 1	63	-7.5	2.0	-9.1	-0.3	9.0	9.1	3.1	-2.2	13.2	0.05
No Others	1	-9.4	–	-9.4	-9.4	-5.3	-5.3	–	-5.3	-5.3	1.00
					(c) *Greater quality-sensitivity*, $\beta = 1.5 \times \hat{\beta}$						
7 to 6	21	-0.1	0.3	-1.3	0.0	0.4	0.1	0.9	-0.4	3.8	0.19
6 to 5	315	-0.2	0.3	-1.9	0.0	0.3	0.0	1.0	-2.2	4.3	0.36
5 to 4	1,400	-0.3	0.5	-3.8	0.0	-0.0	-0.0	1.4	-6.0	6.8	0.55
4 to 3	2,100	-0.5	0.8	-6.0	0.0	-1.0	-0.5	2.4	-6.7	15.1	0.77
3 to 2	903	-1.3	1.7	-6.8	0.0	-2.8	-4.1	4.7	-7.9	14.5	0.86
2 to 1	63	-5.9	1.6	-7.2	-0.4	7.5	8.1	4.0	-4.2	12.2	0.08
No Others	1	-15.8	–	-15.8	-15.8	-8.2	-8.2	–	-8.2	-8.2	1.00
					(d) *Lesser quality-sensitivity*, $\beta = 0.5 \times \hat{\beta}$						
7 to 6	21	-0.3	0.4	-1.2	-0.0	-0.0	-0.0	0.0	-0.1	0.0	0.95
6 to 5	315	-0.4	0.5	-3.0	-0.0	-0.0	-0.0	0.1	-0.2	0.0	0.96
5 to 4	1,400	-0.6	0.9	-8.4	-0.0	-0.1	-0.0	0.1	-0.3	0.0	0.98
4 to 3	2,100	-1.2	1.6	-10.8	-0.0	-0.1	-0.1	0.1	-0.4	-0.0	1.00
3 to 2	903	-2.8	3.2	-13.4	-0.0	-0.2	-0.3	0.1	-0.5	-0.0	1.00
2 to 1	63	-11.4	2.9	-13.4	-0.1	-0.3	-0.4	0.1	-0.5	-0.0	1.00
No Others	1	-8.5	–	-8.5	-8.5	-0.3	-0.3	–	-0.3	-0.3	1.00

Note: This table corresponds to Figure 13 in section 8.2. See the note to Table 13 for definitions and explanations.

Table 26: Sensitivity (3)—Larger Changes in Supply-Side Parameters

Merger from/to	Possible mergers	Welfare effect, $\Delta DPV(SW)$ (%) Mean	Stdev	Min	Max	Incentive effect, ΔSII (%) Mean	Med	Stdev	Min	Max	Frac < 0
(a) *Higher discount rate*, $r = 10\%$											
7 to 6	21	−0.2	0.3	−1.2	−0.0	−0.1	−0.0	1.6	−6.3	1.8	0.62
6 to 5	315	−0.3	0.4	−2.3	−0.0	−0.4	−0.1	1.9	−9.6	1.9	0.67
5 to 4	1,400	−0.5	0.6	−5.2	−0.0	−0.9	−0.2	2.4	−11.6	1.9	0.73
4 to 3	2,100	−0.8	1.1	−8.1	−0.0	−2.0	−0.9	3.1	−13.0	6.0	0.84
3 to 2	903	−2.0	2.2	−8.9	−0.0	−4.2	−3.4	3.8	−14.4	5.7	0.95
2 to 1	63	−7.8	2.0	−9.4	−0.5	−3.0	−3.7	3.8	−10.2	3.4	0.70
No Others	1	−8.6	–	−8.6	−8.6	−187	−18.7	–	−18.7	−18.7	1.00
(b) *Lower discount rate*, $r = 2.5\%$											
7 to 6	21	−0.2	0.4	−1.5	−0.0	0.5	0.0	0.9	−0.1	2.6	0.33
6 to 5	315	−0.3	0.5	−2.8	−0.0	0.5	0.0	1.0	−1.3	4.2	0.42
5 to 4	1,400	−0.6	0.8	−7.1	−0.0	0.5	0.0	1.1	−2.5	7.4	0.49
4 to 3	2,100	−1.0	1.4	−10.6	−0.0	0.5	−0.1	1.7	−3.0	14.1	0.55
3 to 2	903	−2.5	2.8	−11.4	−0.0	0.7	−0.5	3.4	−3.6	13.9	0.59
2 to 1	63	−9.8	2.6	−11.7	−0.4	7.9	8.4	3.3	−2.8	12.1	0.05
No Others	1	−10.3	–	−10.3	−10.3	−10.3	−10.3	–	−10.3	−10.3	1.00
(c) *Higher sunk costs*, $FC = 1.5 \times \widehat{FC}$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	1.4	0.2	2.8	−1.2	9.0	0.33
6 to 5	315	−0.3	0.5	−2.6	−0.0	1.2	0.0	3.1	−6.8	11.9	0.48
5 to 4	1,400	−0.5	0.8	−6.4	−0.0	0.7	−0.2	3.8	−13.2	15.7	0.59
4 to 3	2,100	−1.0	1.3	−9.7	−0.0	−0.8	−1.0	5.9	−16.5	40.3	0.67
3 to 2	903	−2.3	2.6	−10.5	−0.0	−2.7	−4.6	11.4	−20.0	39.1	0.74
2 to 1	63	−9.2	2.4	−10.9	−0.5	18.9	22.1	10.2	−26.2	28.9	0.05
No Others	1	−9.8	–	−9.8	−9.8	−67.4	−67.4	–	−67.4	−67.4	1.00
(d) *Lower sunk costs*, $FC = 0.5 \times \widehat{FC}$											
7 to 6	21	−0.2	0.3	−1.4	−0.0	0.3	0.0	0.6	−0.3	2.0	0.33
6 to 5	315	−0.3	0.5	−2.6	−0.0	0.3	0.0	0.7	−1.4	2.5	0.48
5 to 4	1,400	−0.5	0.8	−6.4	−0.0	0.2	−0.0	0.8	−2.5	3.6	0.59
4 to 3	2,100	−1.0	1.3	−9.7	−0.0	−0.1	−0.2	1.3	−3.1	9.6	0.67
3 to 2	903	−2.3	2.6	−10.5	−0.0	−0.5	−1.0	2.5	−3.8	9.4	0.74
2 to 1	63	−9.2	2.4	−10.9	−0.5	4.6	5.2	2.3	−3.5	7.6	0.05
No Others	1	−9.8	–	−9.8	−9.8	−11.7	−11.7	–	−11.7	−11.7	1.00

Note: This table corresponds to Figure 14 in section 8.2. See the note to Table 13 for definitions and explanations.

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