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

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December 5, 2024

Abstract

We used unusually detailed data on sales, costs, and investments from the global industry of liquid crystal display (LCD) panels to study the welfare consequences of various types of innovation. Product and process innovations account for 70.6% and 38.9% of total welfare, respectively, with substantial heterogeneity between market segments. The social return on technological investments is unambiguously positive, but the private returns for most firms are negligible because of competition. Simulations suggest the industry-wide incentive to innovate tends to increase with seven-to-six and six-to-five mergers, but the effect becomes mostly negative in subsequent consolidation. We conclude with antitrust policy implications.

Keywords: competition and innovation, market structure, mergers, product innovation, process innovation

*We thank Jo Seldeslachts, Takuo Sugaya, Kevin Bryan, and Kosuke Uetake for reviewing an earlier version of the paper, Naoki Wakamori for advice on demand estimation, Tadashi Uno at *Display Search* (IHS Markit) for sharing industry knowledge, and Isaac Oh and Chise Igami for research assistance. We benefited from many comments at the University of British Columbia, the University of Tokyo, the 2024 IIOC, the NBER-SI 2024 Innovation meeting, the University of North Carolina at Chapel Hill, the University of Toronto, and Kansas State University.

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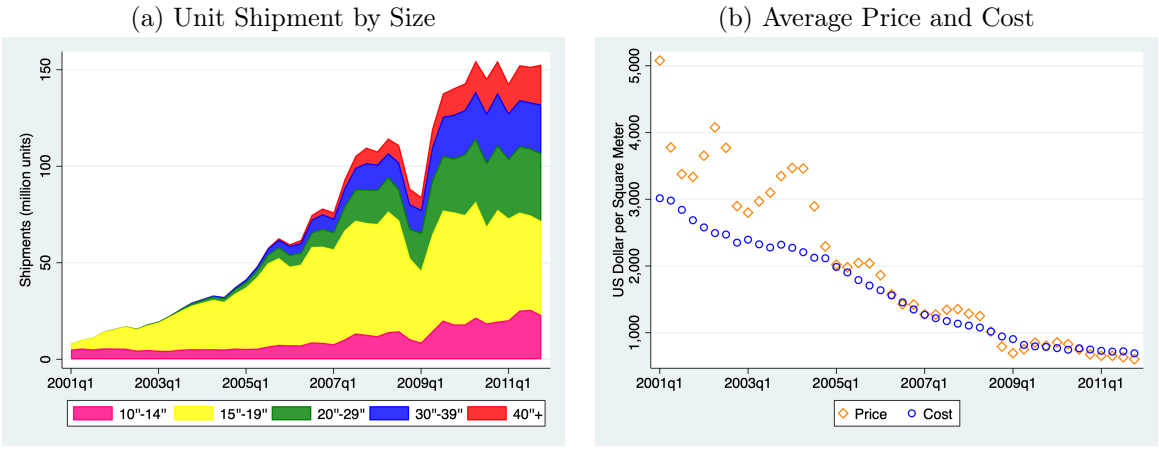
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1 Introduction

Precise measurement of innovation and productivity growth is notoriously difficult, especially on a large scale, such as a global market or an entire industry. Syverson's (2011) literature survey lists multiple determinants of firm-level productivity, including new products, process innovation, and market structure, and concludes that "the relative quantitative importance of each... is still unclear" (p. 358). Progress has been made, but only within a relatively narrow scope, as some of the best empirical works cited therein—Benkard (2000), Levitt, List, and Syverson (2013), and Sinclair, Klepper, and Cohen (2000)—had to focus on a single product (the Lockheed L-1011 aircraft), a single plant (an assembly plant of a major automaker), and a single division of a firm (the specialty chemical division of a Fortune 500 company), respectively. It is unclear how the findings from these specific establishments help us answer broader questions in economics, such as (i) how large the welfare gains from various types of innovation are, (ii) what the relative sizes of the social and private returns on technological investments are, and (iii) how market structure affects the incentive to innovate. We propose to bridge this wide gap by using data from an entire global industry of high-technology products for more than a decade.

Figure 1: Product and Process Innovations in the LCD Industry



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

This paper exploits unusually detailed data from the liquid crystal display (LCD) industry, including sales, manufacturing costs, and investment records of all major firms, all fabrication plants ("fabs"), and all products. This industry provides an ideal setting for studying various types of innovation—larger and better new products became increasingly common, and the average manufacturing cost per square meter of LCD panel decreased by

77% from $3,015 to $692 between 2001 and 2011 (Figure 1). The availability of cost data enables us to estimate not only a demand model but also markups and profits without making assumptions on the firms' competitive conduct: a rare opportunity in the context of industrial organization (IO) literature. Moreover, the combination of cost data and investment record allows us to directly measure the effects of various types of process innovation (i.e., cost-reducing technical changes), including different generations of manufacturing technologies (i.e., the "vintage capital effects" embodied by fab equipment), the time since the start of volume production at each fab (i.e., "learning by doing"), and the use of some specific production methods and inputs. Based on the estimated demand model, the implied conduct of firms, and the cost data, we compute the welfare gains from both product and process innovations by hypothetically eliminating each type of new product and new process at a time, recomputing the counterfactual equilibrium, and comparing the actual and counterfactual welfare outcomes.

The results suggest new products account for a large fraction (62.4%–70.6%) of the total welfare in 2001–2011.[1] Meanwhile, cost reductions due to vintage capital and learning-by-doing are responsible for 38.9%. We find substantial heterogeneity across the three product categories in our data: notebook personal computers (PCs), desktop monitors, and televisions (TVs). Product innovation was quantitatively more important in the nascent market for LCD-TVs, which became mainstream in East Asia circa 2004 and elsewhere since 2007. In contrast, process innovation was the main driver of welfare growth in the more mature markets for notebooks and monitors. Hence, the relative importance of product and process innovations varies depending on the stage of product life cycles. These findings answer our most basic question regarding the magnitude of welfare gains.

To answer our second question (i.e., what the relative sizes of the social and private returns on technological investments are), we reorganize our welfare-gain measures by the generation of fab investments. A new-generation fab achieves two innovations at the same time: the introduction of *larger new products* and the *vintage capital effect* of new equipment. Only newer, larger equipment can handle larger input sheet glass, which is a prerequisite for larger LCD panels; these machines can spread the fixed cost of handling a sheet glass over a larger surface area, reducing the unit cost of producing a panel of a given size. Relative to fourth-generation (4G) technology, which was already available in 2001:Q1, the

[1] Their exact impact depends on whether we exclusively focus on improvements in product quality (62.4%) or also include the contribution of increased product variety (70.6%).

introduction of the 5G–10G fabs increased total welfare by 20.8%–23.6%, or \$95.9–\$106.2 billion.[2] We match these technological-generation-specific welfare gains to the associated sunk costs of investments (the industry as a whole spent \$123.7 billion on new fabs in 2001–2011). Assuming that the post-2011 welfare gains remain constant at their 2011:Q4 level and using the annual discount rate of 5%, we find that these investments generated the net social value of \$232.5 billion, or a 252% return on investment (ROI). However, whether they were commercially successful is a totally different issue. The net producer return was negative (−\$17.7 billion) because only a small fraction of the total gain was appropriated by the manufacturers. The industry-wide internal rate of return (IRR)—the discount rate at which the discounted present values (DPVs) of benefits and costs offset each other—is only 4.05%.[3] Private returns were positive in only three of the seven major firms at a discount rate of 5%.[4]

These findings lead to our third question. Was there "too much competition," as trade publications seem to suggest?[5] We take the following three steps to evaluate the effect of market structure on the firms' incentive to innovate. First, for each of the eight firms in the data (seven major firms and a collection of fringe firms), we calculate its "individual incentive to innovate" as the difference between the DPVs of its profits *with* and *without* its own fab investments in 2001–2011 while fixing the timing and amount of all other firms' fab investments as observed in the data. Second, we measure the industry-wide incentive to innovate by the sum of these individual incentives (SII) across all firms. Third, we compare SIIs under actual and counterfactual market structures to compute the difference, ΔSII.[6] The idea is to measure each firm's incentive based on its gain relative to the unilateral no-investment deviation, aggregate these incentives across firms, and see if a merger increases or decreases this sum. We consider each of the 876 possible combinations of the seven major firms, as well as the creation of a perfect monopoly that consolidates the fringe firms. Because the same market structure can arise from multiple different sequences of mergers,

[2]Here again the range reflects the choice of excluding/including the contribution of product variety.

[3]This estimate represents an "upper bound" in the following sense. On the benefit side, we use our upper-bound estimate of the welfare gain (i.e., including the gains from product variety). On the cost side, our investment cost data focus exclusively on capital expenditure (CAPEX) and do not account for other related costs such as research and development (R&D) expenditures, thereby representing a lower bound of economic sunk costs.

[4]Anecdotal evidence suggests the government subsidies for certain CAPEX and R&D were common in Japan, Korea, and Taiwan, where these firms were located. However, the fact that even the third most profitable firm (Sharp of Japan) struggled to repay its debt in the 2010s highlights their limit.

[5]The industry reports by *Fuji Chimera Research Institute* mention "fierce competition" nearly every year.

[6]We define market structure as the firm-level ownership pattern of all differentiated products.

we are effectively simulating 4,803 possible mergers. The results suggest that the median ΔSIIs in the seven-to-six and six-to-five mergers are marginally positive, but that the effects are negative in most of the subsequent mergers. Furthermore, the innovation incentive effect of a merger is quite heterogeneous and more difficult to predict (based on the change in the Herfindahl-Hirschman index, ΔHHI, and other commonly used statistics) than its effects on prices and static welfare. Thus, the public policy implication of our findings is that any justification of a proposed merger predicated on positive incentive effects must be heavily discounted relative to the potential harm to static welfare.

We have organized the rest of the paper as follows. The remainder of this section reviews the related literature to clarify our contributions. Section 2 explains the institutional/technological background. Section 3 describes our data. Section 4 reports demand estimates and implied conduct. Section 5 quantifies the welfare gains from innovations. Section 6 calculates the social and private returns on technological investments. Section 7 presents merger simulations. Section 8 summarizes our sensitivity analyses with respect to product durability, product variety, and parameter values, respectively. Section 9 concludes.

Related Literature and Contributions. We build on and contribute to various strands of the extensive literature in IO and the economics of innovation. Some are directly related to our three main research questions; others are methodologically similar.

First, the gains from innovation have been extensively studied, but—as noted by Syverson (2011)—none of the existing papers measured both product and process innovations in as much detail as we do at the scale of a global industry. On the one hand, the value of new products has been estimated since at least Griliches (1957) and is one of the main applications of the modern demand analysis.[7] These papers typically use sales data but not cost or investment data, which limits their scope. On the other hand, most of the existing studies on process innovation belong to the productivity literature, in which the use of census-style data is common but welfare analysis is not.[8] Given the large gaps, our primary contribution is to bridge them by incorporating various types of innovation into a unified framework and by providing credible estimates of their welfare contributions at an unprecedented scale.

Second, the literature on the rate of return on technological investments has a similarly

[7]Seminal works include Trajtenberg (1989), Hausman (1996), Petrin (2002), Eizenberg (2014), Ciliberto, Moschini, and Perry (2019), and Grieco, Murry, and Yurukoglu (2024).

[8]See the literature surveys by Syverson (2011) and Thompson (2012).

long tradition. Most research focuses on R&D and patents,[9] but various issues make them less than ideal measures of innovation.[10] We bypass these econometric issues by exploiting detailed data and a convenient technological context in which fab investments are the main vehicle of innovation.[11] Fabs are tangible assets. Accounting data on tangible assets are more straightforward than those on intangible ones. Hence, CAPEX on fabs provides a reliable lower bound on the overall economic cost of innovation.

Third, the relationship between competition and innovation is one of the largest topic areas in economics, even the reviews of which are numerous.[12] Here we focus on highlighting the unique features of our method relative to two prominent approaches in the literature: patent regressions and dynamic structural econometrics. Aghion, Bloom, Blundell, Griffith, and Howitt (2005) epitomize the first approach, in which researchers regress patent count on measures of competition. However, the underlying dynamics of competition and innovation creates a fundamental endogeneity problem.[13] To avoid these issues and to clearly define the incentive to innovate, recent IO papers take the second approach, using micro-founded models that allow researchers to study equilibrium relationships between competition and innovation.[14] However, the computational "curse of dimensionality" limits the granularity of data that such models can incorporate. Because the granularity of data is precisely the main focus and strength of this paper, we take a third approach to fully exploit it: we augment the canonical IO model of demand and supply by Berry, Levinsohn, and Pakes (1995, henceforth BLP) with the detailed data on costs and investments. As its computation has become fast and reliable by Conlon and Gortmaker's (2020) PyBLP package, we can incorporate as many details of new products, manufacturing processes, and mergers between multi-product firms. The measurement of incentive to innovate is not unprecedented in the BLP literature, but has typically been done as a back-of-envelope calculation.[15] In contrast, we propose its

[9] See the literature survey by Hall, Mairesse, and Mohnen (2010).

[10] See Lerner and Seru (2022).

[11] This institutional setting is not as special as it might first appear. Other manufacturing industries in the information technology (IT) sector share similar characteristics, including semiconductor devices, hard disk drives, and other electronic devices.

[12] See Federico, Scott Morton, and Shapiro (2020); Bryan and Williams (2021); Griffith and Van Reenen (2023); and Lefouili and Madio (2024).

[13] Shapiro (2012) points out a related issue that this approach does not distinguish between the current market structure and the expected future profits. Commonly used regressors (e.g., markups, the number of firms, and the HHI) capture only the former, even though the latter is what matters.

[14] See Goettler and Gordon (2011), Conlon (2012), Igami (2017), Björkegren (2019), Marshall and Parra (2019), Yang (2020), Igami and Uetake (2020), Mohapatra and Zhang (2023), Khmelnitskaya (2023), and Qiu (2023).

[15] For example, Petrin (2002) compares the development cost of the minivan with the profits at Chrysler.

systematic analysis.

The following IO papers are closely related as well. First, the use of reliable cost data is a prominent feature of Genesove and Mullin (1998), and Asker, Collard-Wexler, and de Loecker (2018). Second, a growing number of studies examine long-run industry trends, including Collard-Wexler and de Loecker (2015), Ganapati (2021), Miller, Osborne, Sheu, and Sileo (2023), and Grieco, Murry, and Yurukoglu (2024). Third, our predictive regressions in section 7.3 provide new empirical evidence on the usefulness of certain statistics (e.g., ΔHHI) for merger control, along the lines of Miller, Remer, Ryan, and Sheu (2017) and Nocke and Whinston (2022). Whereas all of these papers study mature industries, we focus on competition and innovation in a relatively new, high-technology industry.

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).

2.1 Industry Background

Japanese electronics makers (e.g., Sharp, Panasonic, Sony, Hitachi, and Toshiba) pioneered the development and commercialization of 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 with even lower costs. However, they soon became self-sufficient and marginalized most Japanese firms by 2001.

The dot-com bust in 2001 dampened the demand for many IT products, including LCD panels for notebooks and monitors, the two main applications at the time. The resulting price decreases motivated AU Optronics (AUO), the largest Taiwanese producer, to organize a price-fixing scheme with three other Taiwanese firms (CMO, CPT, and HS) and the two Korean makers. This "crystal cartel" started its monthly price-targeting meetings in October 2001 and lasted until February 2006, when Samsung and LG applied for corporate leniency programs at the US Department of Justice and the European Commission.[16]

[16]We take these developments as given in this paper and leave the task of modeling endogenous collusion and innovation to the companion paper by Igami, Qiu, and Sugaya (2023).

LCD-TVs became mainstream household products first in East Asia circa 2004 and then in North America and the rest of the world since 2007. The Great Recession (2008:Q4–2009:Q2) temporarily reduced the demand for all applications. Samsung and LG expanded market shares during and after this crisis at the expense of weaker rivals in Taiwan.

Most of the once dominant Japanese firms exited these large-area display markets by the end of the 2000s.[17] The only exception was Sharp, which continued to invest in new-generation fabs. Meanwhile, mainland Chinese firms started entering low-end product categories, sometimes by purchasing used equipment from Japan, but their market shares were negligible throughout the 2000s. Thus, we focus on the seven major firms (two Koreans, four Taiwanese, and one Japanese) and treat the rest as a competitive fringe.

2.2 Production Technology

The production process for LCD panels is capital intensive, as firms have to spend billions of dollars on fabs and equipment. Technology is also knowledge-intensive: These physical assets are useless unless production engineers tune their many parameters to improve the "yield," the fraction of defects-free products in all output. Once these physical requirements are satisfied, the costs of more basic inputs such as labor and electricity are critical for the firm's competitiveness, as the exit of (relatively high-cost) Japanese firms demonstrates.

LCD panels contain many different components and materials, including sheet glass, color filters (CFs), 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).

Many 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 as long as the physical size of input sheet glass is larger than that of output panels. Other materials and components are smaller and are mostly common in all products. Hence, both the physical capacity and the technological generation of a fab are determined by the size of the input glass ("mother glass") that it can handle. The most advanced fabs at the beginning of 2001 used fourth-generation (4G) technology and its variant (4.5G), which processes 730mm×920mm input glass and can produce up to 40-inch panels. The frontier technology gradually shifted

[17] The large-area displays are the cutting-edge part of the market, defined by the diagonal length of 10 inches or larger. We do not study the markets for smaller panels, which are more fragmented and populated by many fringe firms with older, smaller fabs.

and reached 10G, which uses 2,850mm×3,250mm input glass, by the end of 2011.

2.3 Definition of Innovation

Following Schumpeter (1934) and many other studies, we use the most basic definition of economic innovation as a "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."[18] We refer to them as product and process innovations, respectively. Although our empirical context is clearly high tech and involves cutting-edge technologies of the time, we emphasize that we focus on *economic innovations* and not scientific discoveries or patented inventions, for two reasons. One is that the former directly contributes to welfare, whereas the latter may not. The other is that new products and processes do not necessarily rely on scientific novelty or its legal recognition.[19] Our welfare analysis is agnostic about the origin and root cause of new goods and methods beyond fabs (i.e., the critical physical assets that embody new technologies).

With respect to product innovation, we operationalize the concept 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. In contrast, other characteristics of the product do not have direct connections to tangible assets.

Regarding process innovation, we separately identify two channels, vintage capital and learning-by-doing, both of which reduce manufacturing cost. The vintage capital effect is rooted in the engineering reality that the unit cost of producing a panel of the same size is lower at newer fabs.[20] The learning-by-doing effect is physically related to yield improvements (i.e., the reduction of defective products) and to the amount of time required to try many different ways of tuning fab equipment.[21] Finally, our data show that the costs

[18]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, which closely relates to (iv). However, we consider the precise measurement of (i) and (ii) as our primary goal.

[19]Whether patents are correlated with these economic innovations is a separate issue that we plan to investigate in the future.

[20]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 cost per square meter decreases with a larger mother glass.

[21]This process takes many months because production engineers can experiment with only a limited

of raw materials and components tend to decrease with time. This trend is not attributable to LCD panel manufacturers, but to innovations in the upstream industries of fine chemicals and other materials.

3 Data

This section explains our data, including their source, pre-processing, 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). We provide further explanations in sections 4–6 when we analyze them in detail.

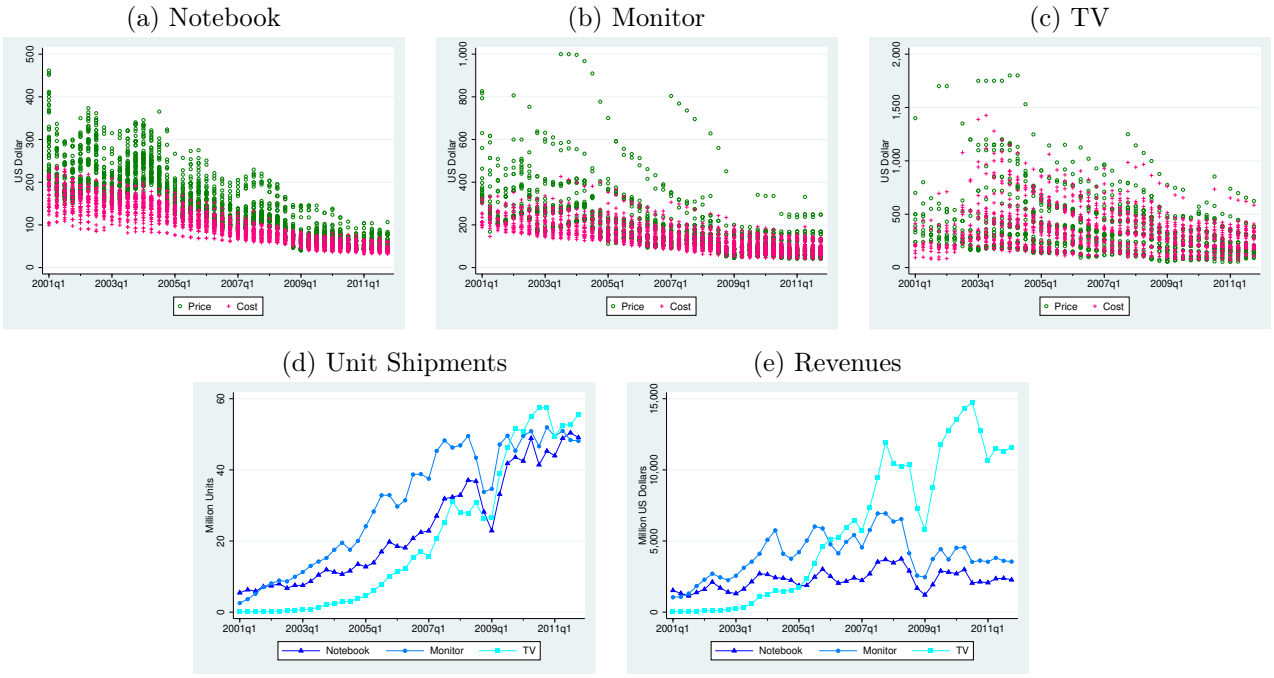
3.1 Prices, Quantities, and Product Characteristics

The average sales price and total shipment volume are recorded quarterly between 2001:Q1 and 2011:Q4 at the product level. Each product is defined as a combination of (i) supplier, (ii) application, (iii) size, (iv) resolution, and (v) backlight—for example, LG's panel for notebooks, 14.1 inches, 1280×800 pixels, and light-emitting diode (LED) backlights. The total number of unique products is 1,081. Even if we ignore supplier identity (i) and exclusively focus on physical dimensions (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 ensure compatibility throughout the IT supply chain. In terms of demand, only a handful of products defined by (ii)–(v) above 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 larger than the output-panel size (see section 2.2). As a result, most of these mainstream products are supplied by multiple firms, and competition is fierce because products with the same physical characteristics are close substitutes for each other.

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). Learning by doing in the LCD context is a matter of searching for optimal parameters of manufacturing equipment. In 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).

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.

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.[22] Third, the price-cost margin seems to decrease over time, presumably because the cartel existed only in the first half of the data. Fourth, the volume of shipment grew rapidly with time, as LCD panels became mainstream products in all applications. Fifth, the Great Recession manifested itself in the second half of the data as negative shocks to both prices and quantities.

3.2 Manufacturing Costs

The second database records the average unit cost of manufacturing each product on a quarterly frequency between 2000:Q2 and 2016:Q4. This database is designed to replicate the cost of any product, at any fab, of any firm, in each quarter. Hence, we can examine it to understand how cost varies with the characteristics of fabs, firms, and products, as well as

[22]The cyclical nature of IT demand seems to cause this pattern, as the purchasing behavior of PCs and their peripherals is known 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.

time. Moreover, the availability of detailed cost breakdown allows us to focus on the "cash cost" part and exclude the "depreciation" part,[23] which is desirable because the latter is an accrual-based accounting measure of capital cost and does not constitute economic marginal cost.

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 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 estimates and the cost data, we calculate the implied equilibrium prices under monopoly, Bertrand competition, and social planner, and compare the actual prices with them to infer the firms' conduct in the data (section 4.2).

4.1 Model and Estimates

Buyer i's utility from product j—defined by (i)–(v) in section 3.1—in period t is

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

[23] 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*. Many of the staff analysts are industry veterans who used to work at these firms or their component suppliers.

where p_{jt} is price, $\mathbb{1}\{size_j = s\}$ is an indicator for size s, $\ln ppi_j$ 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 unobserved product quality, and ζ_{ist} and ε_{ijt} are buyer-specific preference shocks.[24] We assume that ε_{ijt} is i.i.d. Gumbel and that ζ_{ist} has a unique distribution such that $\varepsilon^*_{ijt} \equiv \zeta_{ist} + (1-\rho)\varepsilon_{ijt}$ is i.i.d. Gumbel as well. We allow the value of the outside good (i.e., not buying any LCD panel on the market, denoted by $j = 0$) to vary over time: $u_{i0t} = \gamma_t + \varepsilon_{i0t}$. The coefficients β^s, β^r, and β^b denote the contributions of size, resolution, and backlight type, respectively. We incorporate heterogeneity in the price coefficient as $\alpha_i = \alpha/y_i$, where y_i is the income level of i drawn from the income distribution in the relevant middle to high income countries.[25]

Three considerations guide this specification. First, we try to incorporate the contributions of lower prices and larger sizes with as much flexibility as possible (but without getting counter-intuitive estimates) by using the random coefficient α_i and the size-nest-specific taste ζ_{ist}.[26] These are the primary channels through which process and product innovations increase welfare, respectively. Second, we include all observed characteristics to capture the contributions of all quality improvements.[27] Third, we allow the value of the outside good γ_t to evolve over time because the appeal of the outside options (e.g., conventional monitors and TVs based on cathode ray tube, and new TVs based on the plasma-display technology) seems likely to change.[28] To the extent that LCD products are durable goods, this term could also reflect the utility from previously purchased inside goods.[29]

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

[24] 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.

[25] 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.

[26] The specification of α_i follows Berry, Levinsohn, and Pakes (1999). Its combination with the size-bin nests is similar to Brenkers and Verboven (2006).

[27] We have also experimented with additional random coefficients and nests, but found counter-intuitive estimates, presumably due to multicollinearity problems. Grigolon and Verboven (2014) show that adding random coefficients and nests on multiple product characteristics could lead to imprecise or unreasonable estimates when they are highly correlated with each other.

[28] We separately identify γ_t from the mean of unobserved quality ξ_{jt} (its time-varying component) by using the approach proposed by Pakes, Berry, and Levinsohn (1993). See Appendix A.4.1 for details.

[29] We assess the sensitivity of our results with respect to γ_t and product durability in section 8.1, including a discussion of Conlon's (2012) findings based on his model of durable-good oligopoly.

in 2001:Q4–2006:Q1, (iii) the number of products in each category defined by size, resolution, type of backlight, and their combinations, and (iv) the measures of product differentiation proposed by Gandhi and Houde (2023). We use the BLP estimation algorithm in Conlon and Gortmaker's (2020) *PyBLP* Python implementation.[30]

We estimate the demand parameters separately for each of the three applications as Table 1 shows. 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),[31] which suggest lower prices significantly increase utility. Hence, there is ample room for process innovation to improve welfare. The value of the nest parameter is 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 coefficients on the two other physical characteristics (PPI and LED) are also positive, as expected.[32] Thus, ample room exists for product innovation to improve welfare as well.

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

We assess the extent of market power by comparing the average price in the data p_t with three theoretical benchmarks: (i) monopoly p_t^{mo}, (ii) Bertrand-Nash p_t^{bn}, and (iii) social planner p_t^{sp}. Figure 3 shows p_t was relatively close to p_t^{mo} in 2001:Q1–2004:Q3, which is broadly consistent with the existence of the cartel in the first half of our data.[33] Subsequently, p_t fluctuated around p_t^{bn}, suggesting that the LCD cartel became less effective in its last several quarters. 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 p_t occasionally touched on p_t^{sp}.

The main takeaway is that the monopoly and Bertrand conducts are reasonable approximations to the data in 2001:Q1–2004:Q3 and 2004:Q4–2011:Q4, respectively. A paired t test rejects $p_t < p_t^{mo}$ with probability 0.98 in the former, whereas the means of p_t and p_t^{bn} are sta-

[30] *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. The authors thank Jeff Gortmaker for sharing these details.

[31] The median of all products' own-price elasticities across three applications is −6.69. These relatively high elasticities presumably reflect the presence of multiple similar products within each product category.

[32] The only exception is $\hat{\beta}^b < 0$ for monitors because many cold cathode fluorescent lamp (CCFL) based products remained popular in this application despite the influx of LED-based ones.

[33] 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.

Table 1: Demand Estimates

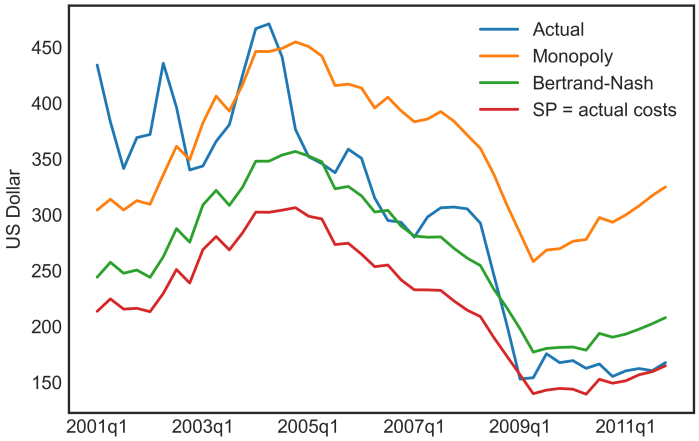
Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−309.6	27.9	−155.6	5.6	−41.5	2.5
Size nests (ρ)	0.629	0.025	0.805	0.016	0.725	0.020
Size = 12" (β^{12})	1.596	0.076	–	–	–	–
Size = 13" (β^{13})	1.929	0.088	–	–	–	–
Size = 14" (β^{14})	2.906	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 PPI. "LED" is an indicator for LED-based backlights, where the omitted category is cold cathode fluorescent lamp (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.

tistically indistinguishable in the latter.[34] Accordingly, we use these supply-side assumptions

[34]See Appendix A.4.2 for details. We thank Chris Conlon and Marco Duarte for helpful discussions.

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.

in our subsequent analyses.[35]

5 Welfare Gains from Innovations

We are now ready to measure the welfare gains from various types of innovation. Sections 5.1 and 5.2 focus on product and process innovations, respectively. Section 5.3 reorganizes these gains by technological generation of fabs to facilitate the benefit-cost analysis later.

5.1 Product Innovation

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

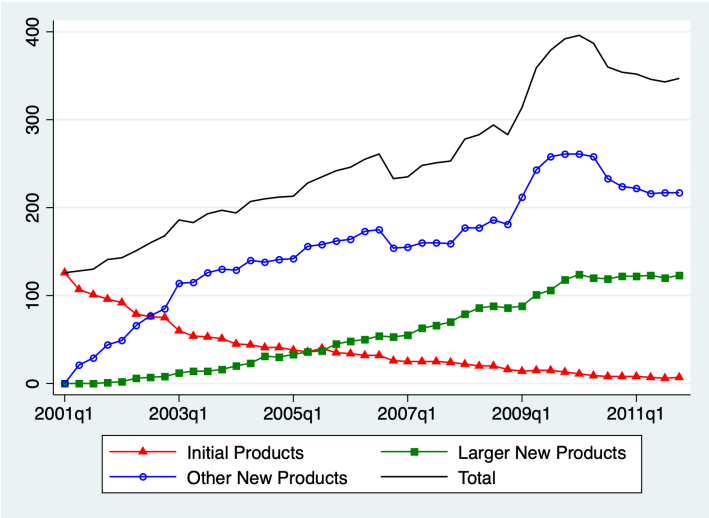
5.1.1 Two Types of Product Innovation

We distinguish between two types of product innovation: (i) larger new products and (ii) other new products. We briefly explain each of them below. The industry introduced ever-larger LCD panels using newer and larger manufacturing equipment and fabs. The largest products available in 2001:Q1 were 15.7-inch notebooks, 24-inch monitors, and 28-inch TVs.

[35] As a robustness check, we also compute some of the key results under a simpler assumption (Bertrand-Nash throughout the sample period) in Appendix A.5.

Any larger products were new in this sense. Other new products embody new combinations of size, resolution, and backlight type. Some of them feature higher resolution (PPI) and better backlights (LED), but many others offer size-resolution combinations that are simply different from—but not necessarily physically superior to—the existing ones. Figure 4 shows the counts of larger and other new products, respectively, as well as the "initial products" (i.e., those available in 2001:Q1).

Figure 4: Number of Products



Note: This graph counts the number of products as defined by (i)–(v) in section 3.1, including supplier identity.

5.1.2 Counterfactual: No Product Innovation

We quantify the welfare effects of new products by simulating counterfactual market equilibria without them. Table 2 compares consumer surplus (CS), producer surplus (PS), and social welfare (SW) in four settings. The first features the full set of actual products, whereas the other three are counterfactuals: (i) without larger new products, (ii) without other new products, and (iii) without any new products.

The results are quite heterogeneous between IT (notebooks and monitors) and TV. In the relatively mature markets of IT applications (panels A and B), the impact of (ii) is much greater than that of (i). The reason is that most of the popular sizes existed in 2001:Q1.

In contrast, panel C shows that larger new products were much more important than other new products in the TV segment. Eliminating TVs larger than 28 inches would have reduced SW by 75.8%. The magnitude is remarkable but reasonable; only 11 products existed in 2001:Q1, and most of the popular sizes (e.g., 32-inch and 40-inch) did not. Without any

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 new 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)
(iii) Without any new products	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 new 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)
(iii) Without any new products	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 new 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)
(iii) Without any new products	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 new 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)
(iii) Without any new products	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. Table 24 in Appendix A.8.2. reports an alternative version that excludes the contribution of increased product variety.

new LCD-TV, SW would have been reduced by 95.6% in total. Hence, we are virtually measuring the welfare impact of the emergence of an entirely new product category.

Panel D shows the overall welfare impact on all applications. The contributions of larger new products (35.0%) and other new products (34.4%) are nearly identical, with the total effect of 70.6%.[36] The main takeaway is that product innovation matters and that the relative importance of different types of product innovation depends on product life cycles.

5.2 Process Innovation

This subsection measures the welfare impact of process innovation. We first identify multiple channels of process innovation by regressing cost on its 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 5.2.2).

[36]These numbers account for both the improvements in product quality and the increases in the number of products. Section 8.2 shows that the total welfare effect is still large (62.4%) even if we ignore the latter.

5.2.1 Determinants of Manufacturing Cost

Our detailed cost data are based on 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 own commercial transactions (see section 3.2). We use this data set to estimate the relationship between cost and its many determinants.

We specify the cost of manufacturing product j in fab k (of firm f) at time t as

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

where $\mathbb{1}\{gen_k = g\}$, $\mathbb{1}\{age_{kt} = a\}$, odf_k, $cf_{f(k)t}$, and $\mathbb{1}\{capa_{kt} = c\}$ are indicators for generation-g fab, age-a fab, the one-drop-fill (ODF) method of putting liquid crystal between glass sheets,[37] the in-house manufacturing of CFs,[38] and the capacity utilization-level bin c, respectively. The dummy variables $\tilde{\delta}_t$, $\tilde{\delta}_{f(k)}$, and $\tilde{\delta}_j$ are fixed effects for time periods, firms, and products, respectively. The error term η_{jkt} captures all other factors and measurement error. The coefficients θ^g, θ^a, θ^{odf}, θ^{cf}, and θ^c represent the effects of the five main factors.

The most important parameters for our analysis are θ^g, θ^a, and θ^{odf} because they are directly related to the conscious decisions of firms (i.e., fab investments). By contrast, we do not interpret θ^{cf} and θ^c as process innovation.[39] 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.

Table 3 reports the results in an increasing order of flexibility. Column 1 uses a linear specification for all regressors. Column 2 adds the quadratic terms of three fab-level variables (gen_k, age_{kt}, and $capa_{kt}$) and time. Column 3 uses time dummies $\tilde{\delta}_t$. Column 4 is the most flexible specification (equation 2), which we use in all of our subsequent analyses.

[37] This method improves 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 was commercialized in 5G fabs. See Akabane (2014) for technical details.

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

[39] θ^{cf} reflects the internalization of an upstream industry's rent, not any physical improvement. Capacity

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.

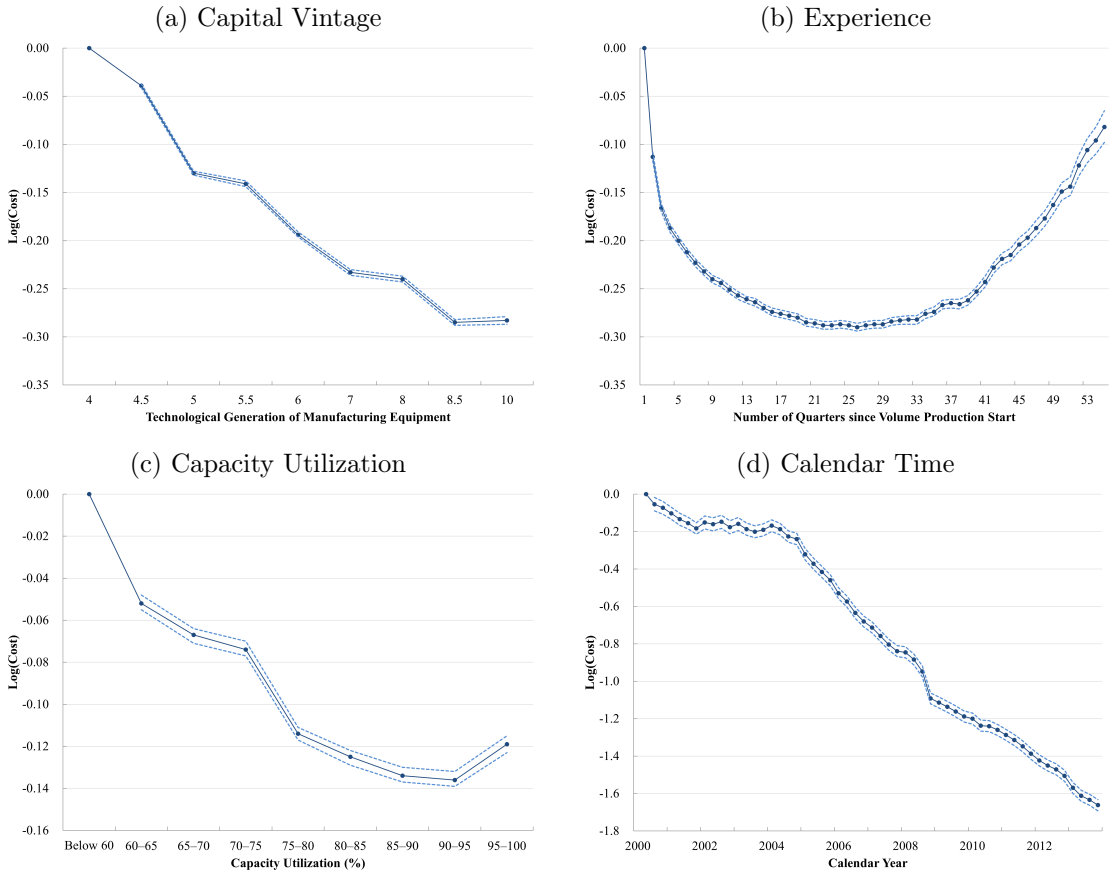
The linear model in column 1 helps us develop an intuitive understanding of costs. The coefficients on the fab-level characteristics in section A of Table 3 suggest: (i) the average vintage-capital effect is 4.5%, (ii) an extra quarter of operation reduces cost by 0.3%, (iii) the ODF method reduces cost by 10.2%, (iv) in-house CFs reduce cost by 2.2%, and (v) changing the capacity utilization from 0% to 100% reduces cost by 21.3%. Section B (firm-level characteristics) shows that the "tier-1," Korean, and Taiwanese firms have approximately 10%–30% cost advantages over "tier-2" Japanese firms (reference category).[40] Section C

utilization is not a technological choice.

[40]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

(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 layout ("edge" or "direct"). Finally, the time-trend estimate in section D suggests that the input cost decreases by 3% per quarter. Despite its simplicity, the linear model achieves the adjusted R^2 of 0.963 because we control for everything that goes into the engineering cost model.

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.

Figure 5 visualizes our preferred estimates based on column 4. Panel (a) shows that 5G, 6G, and 8.5G led to larger cost reductions than other vintages. Panel (b) shows that more

key suppliers.

than half of learning-by-doing occurs within the first two quarters of volume production. Yield improvement continues until around quarter 25 (end of year six), and then goes into reverse as physical depreciation (e.g., wear and tear) starts to kick in.[41] Each of these effects can reduce cost by nearly 30%. Hence, both vintage capital and learning-by-doing are quantitatively important and comparable in magnitude.

Panel (c) shows the effect of capacity utilization. The 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.[42] However, operating below 75% (and then below 60%) results in increased costs of 4%–5%. The reason is the lumpiness of the rotating labor schedule, in which four groups of workers take turns to perform three 8-hour shifts per day (the fourth shift is a break).

Finally, panel (d) shows the fixed effects of calendar time, which reflect the secular decreasing trend in the cost of materials and components. Relatively little improvement occurred until 2004, but subsequent advances led to an industry-wide cost reduction by more than an order of magnitude (note the logarithmic scale on the vertical axis).

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 $\theta^g = 0$.[43] Second, we turn off learning by doing by setting $\theta^a = 0$. Based on these counterfactual costs histories, we recompute equilibrium prices, sales, and welfare outcomes in each t.

Table 4 reports the results, which are similar across panels A–C. The aggregate numbers in panel D show that the absence of (i) the vintage capital effects would have reduced SW by 10.5%. Eliminating (ii) learning-by-doing would have had a greater impact of 30.5% because (i) affects only the newer fabs, whereas (ii) affects all the fabs in the data. The total absence of process innovation in (iii) would have led to a welfare loss of 38.9%.

[41] 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).

[42] The mean and standard deviation of capacity utilization in our data are 83% and 10%, respectively. The median is 85%.

[43] We also set $\theta^{odf} = 0$ because the ODF process was typically adopted with 5G fabs.

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 effects	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)
(iii) Neither	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 effects	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)
(iii) Neither	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 effects	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)
(iii) Neither	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 effects	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)
(iii) Neither	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.

5.3 Welfare Accounting by the Technological Generation of Fabs

Sections 5.1–5.2 organized the welfare results by the type of innovation. However, in reality, multiple types of innovation arrived together as a bundle in each generations of fabs. We reorganize our results by the technological generation of fabs in this subsection.

Exactly what subcategories of product and process innovations belong to such a bundle? Of the two types of product innovation, the first (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 4G–4.5G, which could produce notebook and monitor panels of all sizes but not TV panels above 40 inches.[44] Thus, no LCD-TVs above 40 inches would have existed without post-4.5G technologies.[45] Of the two channels of process innovation, vintage capital is synonymous with new-generation fabs. Accordingly, we treat new-generation fabs as a bundle of larger new products and the vintage capital effects.

We assess the welfare contribution of each technological generation as follows. First, we

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

[45]Note this definition of "larger new products" is slightly different from the one we used in section 5.1, which was not necessarily connected to the physical size limit of each fab generation. In this subsection, only TVs above 40 inches are considered "larger new products."

hypothetically eliminate all vintages beyond 4.5G, along with any larger new products and cost reductions. This counterfactual becomes the baseline for measuring the contributions of all post-4.5G technologies. Second, we add the 5G technology. The difference between this simulation and the baseline counterfactual reflects the marginal contribution of the 5G fabs. We then cumulatively add each of the 5.5G, 6G, 7G, 8G, 8.5G, and 10G technologies.

Table 5 shows the results. The newer 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.[46]

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 for a robustness check with respect to the assumption on competitive conduct.

[46] 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.

We also find 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. Recall that larger new products are the main driver of welfare growth in the nascent market for LCD-TVs, whereas the panels for notebooks and monitors had limited room for larger new products. This contrast conforms to the typical narrative of product life cycles (e.g., Klepper 1996). That is, product innovation matters relatively more in earlier stages of a new market; process innovation becomes essential for firms' survival in later stages (i.e., after the industry converges on a "dominant design" of popular products).

6 Social and Private Returns on Investment

This section compares the welfare gains from fab investments (section 5) with their costs, so that we can measure the social and private returns on technological investments. Section 6.1 calculates the aggregate ROI under the actual market structure (i.e., seven major firms and fringe). Section 6.2 does the same for hypothetical monopoly. Section 6.3 measures the individual firms' incentives to innovate under oligopoly.

6.1 High Social Returns, Low Private Returns

This subsection introduces the cost of fab investments and measures their aggregate returns. Table 6 lists the total dollar amount of investments by firm. Samsung and LG lead the industry with $28.6 billion and $27.1 billion, respectively, followed by CMO ($25.1 billion) and AUO ($19.9 billion). Their smaller rivals, CPT ($5.3 billion) and HS ($2.3 billion), lag behind, as they stopped investing 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.

Figure 6 compares the aggregate social benefits and costs. "Social benefits" are the welfare gains from all new-generation fabs (section 5.3). For clarity, we denote them by

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

where $a \equiv (a_f)_{f=1}^F$ and $\tilde{a} \equiv (\tilde{a}_f)_{f=1}^F$ represent the actual and counterfactual profiles of investment strategies ("actions") by F oligopolistic firms, respectively. Note a_f represents firm f's

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

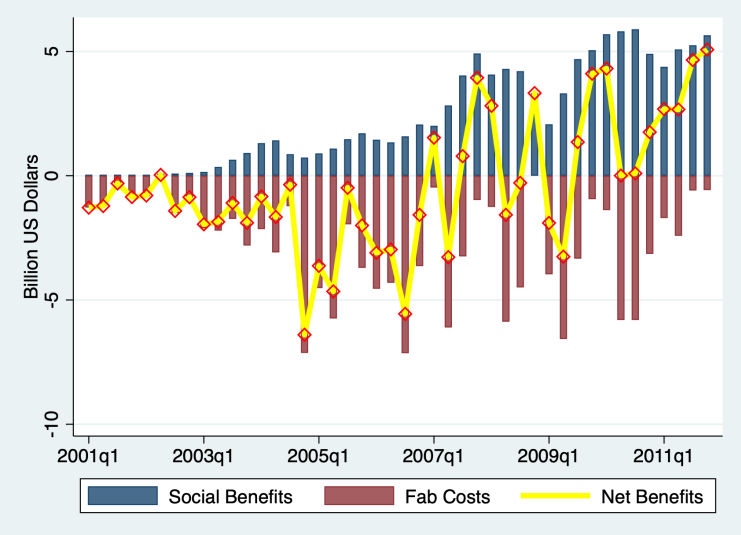
Note: All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

entire history of investments, $a_f \equiv (a_{ft})_{t=0}^{T}$, where a_{ft} is f's investment at t. The actual investment profile a includes all generations (4G–10G) of the fabs, whereas the counterfactual $\tilde{a}$ contains only the initial technology (4G–4.5G) fabs. Similarly, the "fab costs" in Figure 6 are the total investment in new-generation fabs, analogously defined as

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

Figure 6 shows that 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.

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



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

This figure 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 discount at the annual rates of 1%, 2.5%, 5%, and 10%, respectively. Regarding the post-sample period, we 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 are made (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.

Rows 1–3 report the discounted present values (DPVs) of the changes in CS, PS, and SW as of 2001:Q1, respectively, whereas row 4 reports the DPV of 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

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

and report it in row 5. We find that the net social benefit is positive even at a relatively high discount rate of 10%. Thus, investments in 5G–10G technologies were socially desirable.

Whether those 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,

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

Although $\Delta NPV(a, \tilde{a}) > 0$ at low r, it is negative at 5% and 10%. The industry-wide internal rate of return (IRR)—the break-even discount rate—is 4.05%, barely covering the lowest possible cost of capital (risk-free rates). The true return is likely to be even lower because the cost of fab is only the most tangible part of the overall costs for developing and implementing new technologies, including R&D expenditures and other economic costs. In short, the industry as a whole represented 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.

Despite low aggregate returns, some firms were much more profitable than others. Table 8 decomposes the realized returns in Table 7 in 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; they would have been better off had the industry not moved on to post-4.5G technologies. Innovations did not "lift all boats."[47]

6.2 Greater Appropriability under Monopoly

Competition reduces firms' ability to appropriate social returns, which is why most firms experienced low returns. How much could the industry have benefited from greater mar-

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

ket power? We repeat the analysis of Table 7 in a counterfactual market structure with monopoly, in three steps. First, we recompute equilibrium prices and sales in each period under the assumption that all products were sold by a monopolist (with access to all 4G–10G fabs in the data). Second, we eliminate all new (5G–10G) fabs and recompute another trajectory of prices and sales under monopoly. Third, we calculate the difference between these two scenarios.

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.

Table 9 reports the results under monopoly. Rows 1–3 show that monopoly reduces the positive impact of innovations on CS by approximately 45% compared to the actual oligopoly in Table 7, increases $DPV(\Delta PS)$ by approximately 55%, and reduces the total gain in welfare by approximately 22% at all levels of r. Consequently, ΔNSV decreases between 24.1% (at $r = 1\%$) and 53.4% (at $r = 10\%$), whereas ΔNPV improves significantly. Monopoly increases PS at the expense of CS and produces a dead weight loss, as expected.

The only "bright spot" is that monopoly increases $\Delta NPV(a, \tilde{a})$, suggesting that monopoly might be good for innovation (and hence socially desirable in the long run). However, that is not a foregone conclusion, for two reasons. First, innovation *per se* is not the ultimate social goal, but only a means of achieving it. Rows 3 and 5 of Table 9 show massive decreases in $DPV(\Delta SW)$ and ΔNSV relative to the actual oligopoly, and hence monopoly cannot be socially desirable unless some long-run gains compensate for these short-run losses. Second, the presumption of a positive impact on innovation could be wrong. This subsection compared the hypothetical monopoly with the results in section 6.1 and showed that ΔNPV is greater under monopoly. However, ΔNPV in Table 7 is not the right benchmark for studying the incentive to innovate, for reasons we explain in the next subsection.

6.3 Competitive Pressure under Oligopoly

The preceding analyses compared outcomes *with* and *without* the industry-wide investments in new-generation fabs. The no-investment counterfactual is equivalent to an industry-wide

ban on new technologies. In reality, no single firm had the ability to impose such a ban. Hence, even though section 6.1 presented valid measures of aggregate ROI, they fail to capture individual firms' strategic incentives. This subsection addresses this issue.

We investigate whether each firm could have made more profits by unilaterally deviating from the actual investment profile (denoted by $a = 1$) and not investing in any new fabs. Let $\check{a}(f) \equiv (\check{a}_{f'})_{f'=1}^{F}$ denote such a counterfactual profile of investments, where $\check{a}_f = 0$ (by which we mean that f does not invest in any t) and $\check{a}_{f'} = 1$ for all $f' \neq f$ (i.e., all other firms invest as in the data). Then the difference between firm f's NPVs under a and $\check{a}(f)$,

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

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.

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 incentives of the weakest firms (CPT, HS, and Others) are still nonpositive at any r, but the magnitude of losses is much smaller than in Table 8. The rewards and threats from business stealing seem to provide

sufficient incentives for more firms to keep investing.[48] Thus, even though the industry as a whole did not make much return, no-investment was not necessarily an attractive alternative for individual firms.

To measure the overall impact of competition on innovation, let us define the sum of individual incentives to innovate (SII) as

$$SII \equiv \sum_f \Delta NPV_f(a, \check{a}(f)). \tag{8}$$

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, suggesting that the positive incentive effect of business stealing (competitive pressure) can offset the negative incentive effect of lower appropriability under oligopoly. We study the effects of market structure on SII more comprehensively in section 7.

7 Market Structure and the Incentive to Innovate

This section investigates the relationship between competition and innovation more systematically. Section 6 compared the actual oligopoly (i.e., seven major firms and Others) and hypothetical monopoly; we now consider an entire spectrum of concentration between these polar cases by simulating all possible mergers and the resulting market structures. Section 7.1 studies the impact of seven-to-six mergers. Section 7.2 considers all subsequent stages of industry consolidation. Section 7.3 investigates the extent to which the effects of mergers could be predicted by commonly used statistics such as ΔHHI.

7.1 Seven-to-Six Mergers among Major Firms

This subsection measures the effects of seven-to-six mergers on static welfare and the incentive to innovate. Table 11 lists all of the 21 possible seven-to-six mergers (excluding those that involve Others) in the descending order of magnitude of $\Delta DPV(SW)$ at $r = 5\%$.[49] The

[48] 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.

[49] Note all mergers reduce $\Delta DPV(SW)$ by construction because we do not model any efficiency gains in the short run or any (positive or negative) feedback from ΔSII in the long run, which would require an explicitly dynamic model. Hence, $\Delta DPV(SW)$ and ΔSII should be interpreted independently as measures

top five mergers involve Samsung, LG, CMO, and AUO (i.e., the four largest firms by the amount of investments) and lead to significant reductions in SW. 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.

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 $r = 5\%$. In each row, we label the merging firm with a larger dollar amount of fab investment as "acquirer" and the other firm as "target" for the sake of illustration. Switching these labels will not affect our simulation results.

In contrast, the impact of mergers on the incentive to innovate is 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 the incentive effect is not closely correlated with that of the welfare effect. Another interesting finding is that seven of the 21 mergers (9, 11, 12, 14, 15, 19, and 21) reduce SII, which makes them unambiguously bad from social perspectives. Interestingly, 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 those at the top of Table 11.

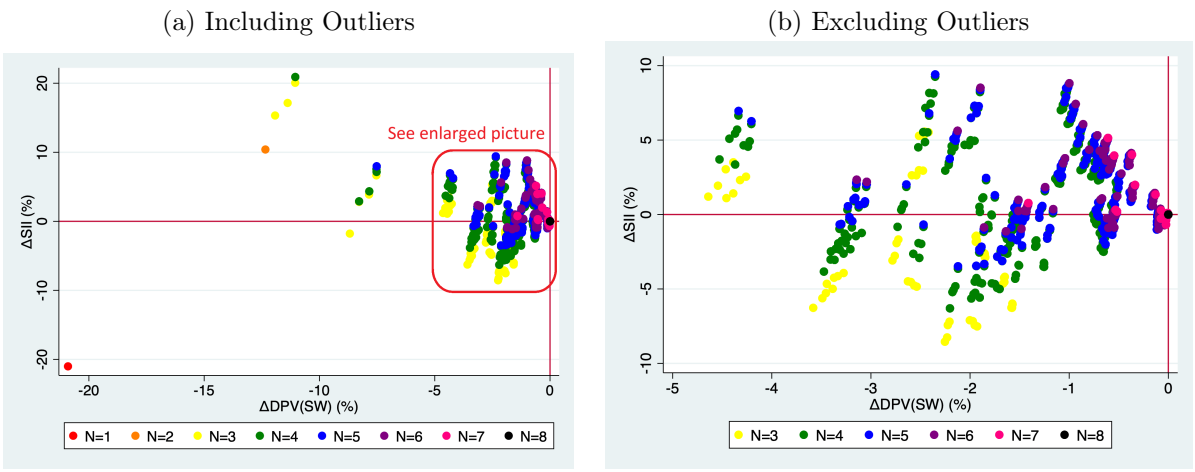
of the static welfare effect and the dynamic incentive effect, respectively, both of which must be considered for the truly dynamic long-term welfare effect of a merger.

In summary, a merger's impact on the incentive to innovate is quite heterogeneous—ΔSII could be either positive or negative. Hence, antitrust scrutiny of the innovation incentive effect should be at least as case-specific as that of the conventional welfare analysis (and probably more so).

7.2 All Other Mergers and Market Structures

This subsection extends our merger simulations to include all possible combinations of firms. We simulate all 140 possible market structures with five firms (i.e., there are 140 possible combinations of the seven original firms into five merged entities). Likewise, there are 350 four-, 301 three-, and 63 two-firm configurations, as well as a quasi-monopoly situation ("quasi" because we keep Others independent). Finally, we also simulate a perfect monopoly in which all seven major firms and Others are consolidated.[50]

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



Note: Each dot represents a specific configuration of firms and is color-coded by the number of active firms (including Others). Both the 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 baseline (actual) market structure with seven firms and Others. Panel (b) is an enlarged picture of the crowded part of Panel (a). See Appendix A.7 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 that arises from specific combinations of firms), with its impact on static welfare on the horizontal axis and its innovation-incentive effect on the vertical axis. The reference point $(0, 0)$ is the original market structure with

[50]This setting is identical to the hypothetical monopoly in section 6.2.

the seven major firms and Others, shown as a black dot (and labeled $N = 8$ in the legend to acknowledge the presence of Others as an independent firm). The effects of all other configurations are expressed as changes from this initial state.

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

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

Number of	Possible	Welfare effect, $\Delta DPV(SW)$ (%)				Incentive effect, ΔSII (%)					
firms	config.	Mean	Stdev	Min	Max	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 the 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 actual market structure with seven firms and Others. The bottom row (No Others) is a perfect monopoly that consolidates Others as well.

Similar but more nuanced patterns emerge as we visually inspect the blue dots ($N = 5$), green dots ($N = 4$), yellow dots ($N = 3$), and orange dot ($N = 2$). Several outliers in the top center part of Figure 7 (a) could create the impression that industry consolidation would tend to encourage innovation, but that is a misinterpretation. Table 12 shows that both the mean and median of ΔSII decrease between $N = 5$ ("4 + Others") and $N = 3$ ("2 + Others"). Meanwhile, the fraction of market structures with $\Delta SII < 0$ (in the right column) more than doubles from 0.30 to 0.65. Thus, the vast majority of mergers result in steady shifts toward the south-west in the diagram, that is, reductions in both static welfare and innovation incentives.

The orange dot (only one major firm and Others) is an exception to this negative tendency but it would seem a risky target for public policy.[51] The red dot ($N = 1$) in the lower left corner of Figure 7 (a) represents perfect monopoly. Its outcomes are strictly worse than under any other market structure, with $\Delta DPV(SW) = -20.9\%$ and $\Delta SII = -21.0\%$. Even though greater market power helps the monopoly appropriate more returns, the total

[51] In Appendix A.7, we examine each of the outliers and find all of them to be "unrealistic" cases.

lack of business-stealing incentives makes it a lazy innovator.

7.3 How Do Mergers Affect Innovation Incentives?

This subsection further investigates policy implications for merger control by studying the outcomes at the level of mergers (rather than market structures, as in section 7.2). Table 13 examines the changes in $DPV(SW)$ and SII immediately before and after each of the 4,803 possible mergers. Both the mean and median of ΔSII are positive in the 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 heavily influenced by positive outliers—becomes negative (-0.4%) in four-to-three mergers. The positive mean and median of two-to-one mergers reverse this negative tendency but are overshadowed by the large negative impact of the creation of a perfect monopoly in the penultimate row.

Table 13: Summary of All Possible Mergers and Their Effects

Merger	Possible	Welfare effect, $\Delta DPV(SW)$ (%)				Incentive effect, ΔSII (%)					
from/to	mergers	Mean	Stdev	Min	Max	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
Total	4,803	−1.15	1.9	−10.9	−0.0	−0.1	−0.34	4.1	−28.4	25.3	0.64

Note: Both the 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 penultimate row (No Others) is a merger to perfect monopoly that consolidates Others.

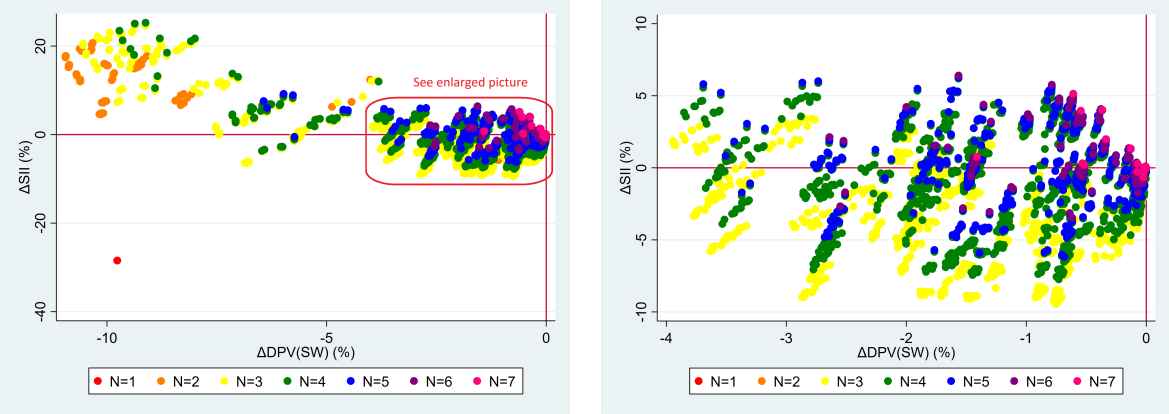
The scatter plots in Figure 8 illustrate the underlying patterns. Panels (a) and (c) visualize the full sample of 4,803 mergers with color schemes based on the post-merger number of firms (N) and the post-merger HHI of sales volumes, respectively. These full-sample plots suggest a negative correlation between $\Delta DPV(SW)$ and ΔSII, that is, a trade-off between short-run welfare and long-run innovation.

However, a closer inspection reveals that such "trade-offs" are largely an artifact of unrealistic outliers. Panels (b) and (d) of Figure 8 focus on a subsample consisting of 4,530 mergers that are located in the densely populated region of panels (a) and (c), delineated by $\Delta DPV(SW) \in [-4\%, 0\%]$ and $\Delta SII \in [-10\%, 10\%]$. Once we exclude outliers in this manner, the correlation between $\Delta DPV(SW)$ and ΔSII becomes positive. This subsample

Figure 8: Effects of Mergers on Social Welfare and Innovation Incentives

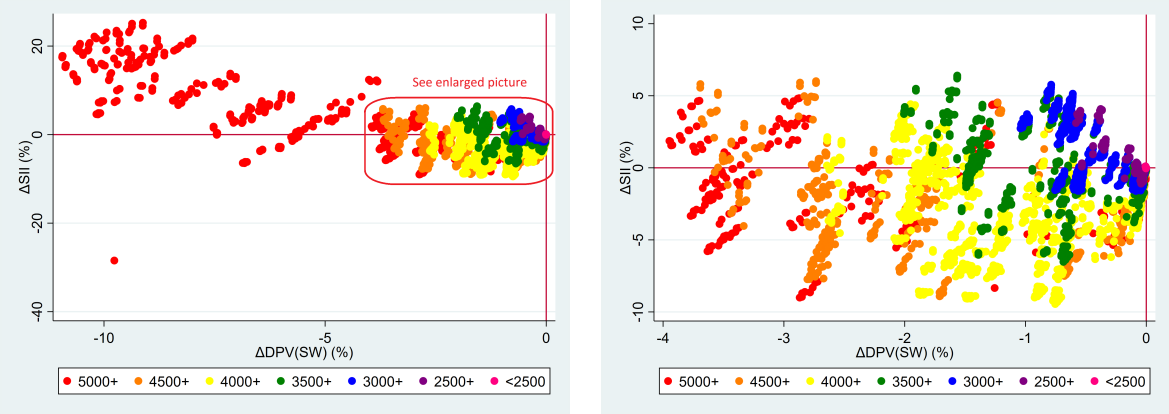
(a) Including Outliers, by Post-merger N

(b) Excluding Outliers, by Post-merger N



(c) Including Outliers, by Post-merger HHI

(d) Excluding Outliers, by Post-merger HHI



Note: Each dot represents a specific merger and is color-coded by the number of post-merger firms including Others in (a) and (b), and by the post-merger HHI in (c) and (d). Both the 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. Panels (b) and (d) are enlarged pictures of the crowded part of Panels (a) and (c), respectively.

not only contains 94% of all possible mergers but also covers the entire spectrum of "realistic" mergers that could reasonably be approved by antitrust authorities. More specifically, panel (d) includes all the yellow, green, blue, purple, and pink dots, which correspond to the post-merger HHI below 4,500. The upper screening threshold for post-merger HHI in the 2010 Horizontal Merger Guidelines (HMG) is 2,500. According to Nocke and Whinston (2022), even this threshold level is likely to be "too lax, unless one expects efficiency gains of 5 percent or greater" (p. 1915).[52] In other words, none of the upper left data points in

[52]In terms of the change in HHI (ΔHHI), our plots include almost all mergers with ΔHHI $< 1{,}000$. The upper screening threshold for ΔHHI in the 2010 HMG is 200. Nocke and Whinston (2022) show that this threshold is too lax as well.

panels (a) and (c) represents an acceptable case.

Table 14 confirms these data patterns with regressions, where the LHS variable is ΔSII. Panel A uses the full sample and shows that ΔSII is positively correlated with HHI, ΔHHI, IHHI, ΔIHHI, and UPP in columns (1)–(5), respectively, and that it is negatively correlated with $\Delta DPV(SW)$ in column (6). In contrast, panel B excludes outliers and shows that ΔSII is negatively correlated with the same measures of concentration and market power and that it is positively correlated with $\Delta DPV(SW)$. Thus, there is no trade-off between $\Delta DPV(SW)$ and ΔSII as far as the vast majority of mergers (with more acceptable characteristics than outliers) are concerned.

Another important finding from Table 14 is the difficulty in predicting the incentive effect of mergers. The predictive power of the first five regressors is low when they are used individually (the highest R^2 is 0.172 in panel B, column 1). Column 7 uses all of them together, including $\Delta DPV(SW)$, and achieves the adjusted R^2 of 0.534 in Panel B, which is respectable but far from perfect.[53]

The lack of predictability becomes clearer when we compare these results with similar regressions in Table 19 (in Appendix A.7), in which the LHS variable is $\Delta DPV(SW)$ instead of ΔSII. The same set of regressors perform really well in terms of fit—ΔHHI alone achieves the R^2 of 0.901 (panel B, column 2). Almost all of the coefficient estimates are negative and readily interpretable: greater concentration and/or market power reduces welfare.[54] Thus, the innovation-incentive effect of mergers is significantly more complicated and difficult to predict than their static-welfare effect.

In summary, three messages emerge from the merger simulations in section 7. One is that the much-debated positive incentive effect of mergers is possible, but only in limited forms—positive outcomes are far from being guaranteed because both the direction and magnitude of the incentive effect are highly merger-specific. Another is that its direction becomes predominantly negative once the number of major firms reaches five. The third finding is that the effect on innovation incentive is substantially more difficult to predict

[53] We refrain from interpreting the coefficient estimates in detail because many of the RHS variables contain similar information, creating collinearity issues.

[54] The only two exceptions arise in the all-regressor specification of column 6 (panels A and B). They could be the manifestation of collinearity issues. Note that the predictive performances are impressive but not surprising if one is familiar with the recent literature on merger control. The superiority of ΔHHI to HHI confirms the main message of Nocke and Whinston (2022) that ΔHHI (rather than HHI) is closely related to the static welfare impact of mergers. Likewise, column 5 of Table 19 demonstrates similarly good performance of UPP, thus empirically validating the simulation results of Miller, Remer, Ryan, and Sheu (2017).

Table 14: Predictors of the Effect of Mergers on Innovation Incentives

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Including Outliers							
Post-merger HHI	0.083						−0.144
	(0.007)						(0.015)
Change in HHI		0.168					−1.216
		(0.010)					(0.023)
Post-merger IHHI			0.072				−0.034
			(0.004)				(0.010)
Change in IHHI				0.150			−0.226
				(0.006)			(0.015)
UPP					0.408		1.504
					(0.016)		(0.036)
$\Delta DPV(SW)$						−1.183	−3.612
						(0.026)	(0.040)
Constant	−3.331	−1.150	−3.060	−1.651	−2.058	−1.463	5.498
	(0.265)	(0.087)	(0.175)	(0.083)	(0.095)	(0.058)	(0.257)
Number of observations	4,803	4,803	4,803	4,803	4,803	4,803	4,803
R^2	0.032	0.051	0.062	0.116	0.119	0.300	0.727
Adjusted R^2	0.031	0.051	0.062	0.115	0.119	0.300	0.726
B. Excluding Outliers							
Post-merger HHI	−0.169						−0.160
	(0.006)						(0.014)
Change in HHI		−0.135					−1.173
		(0.009)					(0.025)
Post-merger IHHI			−0.098				−0.015
			(0.004)				(0.010)
Change in IHHI				−0.055			−0.271
				(0.006)			(0.015)
UPP					−0.031		1.409
					(0.014)		(0.035)
$\Delta DPV(SW)$						0.303	−4.087
						(0.047)	(0.119)
Constant	5.696	0.058	3.121	−0.200	−0.551	−0.458	5.621
	(0.212)	(0.063)	(0.148)	(0.065)	(0.074)	(0.054)	(0.246)
Number of obs.	4,530	4,530	4,530	4,530	4,530	4,530	4,530
R^2	0.172	0.049	0.136	0.020	0.001	0.009	0.534
Adjusted R^2	0.172	0.049	0.136	0.020	0.001	0.009	0.534

Note: The dependent variable is $\Delta DPV(SW)$ in percentage change from the pre-merger market structure. All results are based on OLS. Standard errors are in parentheses. The HHI, ΔHHI, IHHI, and ΔIHHI are expressed in the range between 0 and 100 (instead of the more conventional 0–10,000 scale) to ensure the decimal alignment of coefficient estimates. See the main text for the definition of the outliers.

than the effect on prices and static welfare. Together, these results highlight the difficulty of justifying mergers based on a prediction of positive innovation effects.

8 Sensitivity Analysis

We evaluated the sensitivity of our findings with respect to three categories of modeling choices and parameters. Section 8.1 considers the implications of the durability of the prod-

uct. Section 8.2 examines the well-known tendency of the logit-style demand model to exaggerate the welfare gains from product variety. Section 8.3 studies the competition-innovation relationship under alternative parameter values.

8.1 Product Durability

The literature on durable goods suggests that product durability could fundamentally alter the economics of demand and supply in at least three ways: (i) both buyers and sellers will behave differently if they are forward-looking; (ii) the composition of buyers may change over time if they are forward-looking and heterogeneous; and (iii) previously purchased goods become part of the outside goods.

(i) Forward-looking Behaviors. If consumers and firms are forward-looking and patient, their attitude toward durable goods will change the nature of demand and supply. On the demand side, forward-looking consumers who expect lower prices in the future would want to wait until prices are sufficiently low. On the supply side, forward-looking firms that face these consumers would want to engage in intertemporal price discrimination.

Curiously, Conlon's (2012) investigation into the durable-good aspect of LCD-TVs in 2006–2009 shows that these economic forces play relatively minor roles. On the demand side, the equilibrium price paths remain mostly unchanged regardless of whether the model assumes myopic or forward-looking consumers. On the supply side, he finds that "static pricing does not appear to be bad approximation" (p. 20) of the actual pricing patterns. Hence, theoretical predictions about forward-looking behaviors may not be particularly relevant in our empirical context.

(ii) Changing Demand over Time. One implication of forward-looking consumers is that demand parameters may change over time. If high-value consumers buy the product early and do not make repeat purchases, only low-value consumers will remain on the market in later periods. As a result, the composition of buyers will change over time, making demand more price sensitive. To test this prediction, we estimate the demand parameters by subsample period and report the results in Tables 20 and 21 in Appendix A.8.1(a). Contrary to the prediction of an increase in price sensitivity, $|\alpha|$ decreases over time for notebooks and monitors and only increases marginally for TVs.

Whether these patterns affect our main results is a separate issue. Figure 10 in Appendix

A.8.1(a) shows that the implied monopoly and Bertrand prices are similar to their baseline counterparts in Figure 3. Hence, the time-variation in demand is unlikely to change our subsequent results about welfare gains, ROI, and competition.

Finally, another empirical study of durable goods by Gowrisankaran and Rysman (2012) shows that if high-value consumers leave the market early, conventional methods could overestimate welfare gains by approximately 26.6% in their final sample period. Our demand estimates in Tables 20 and 21 do not support this assumption (see above), but we can emulate their scenario by deflating our welfare estimates in the later sub-sample period by 26.6%. Table 22 in Appendix A.8.1(b) shows that although the levels of welfare gains are mechanically reduced, their relative changes remain mostly unchanged.

(iii) Previously Purchased Goods as the Outside Goods. Recall that we estimated the value of outside goods, γ_t, in each t and find upward time trends (Appendix A.4.1). Yet another implication of product durability is that any previously purchased products could play the role of outside goods because consumers who already own them can continue to use them in all subsequent periods. This observation suggests that at least some of the upward trends in $\hat{\gamma}_t$ could be due to the durability of the product. Hence, we may assess the sensitivity of our results to the durability of the product by changing γ_t to some $\tilde{\gamma}_t < \hat{\gamma}_t$.

Table 23 in Appendix A.8.3(c) shows how the DPVs of ΔCS, ΔPS, and ΔSW change as γ_t decreases. By construction, all welfare measures increase under lower γ_t because they are defined relative to γ_t.[55] We also find that they scale more or less proportionally, which means the ratios between them remain mostly unchanged. Consequently, our main findings in sections 6 and 7—most of which are about such ratios and comparisons—are unlikely to change.

8.2 Welfare Gains from Variety

All discrete choice models of demand with individual taste for products (i.e., ε_{ijt} in equation 1) share a common property that an addition of any product will mechanically increase CS regardless of its characteristics. In this sense, our estimates of the gains from new products in section 5.1 can be interpreted as an "upper bound" that incorporates the gains from both better products (the "quality effect") and more products (the "variety effect").

[55] This property is common across all discrete-choice models of demand.

We assess the magnitude of this issue by computing a "lower bound" that eliminates the variety effect.[56] Table 24 in Appendix A.8.2 reports additional counterfactual results in which we keep the number (or composition) of products constant across simulations. We find that a large fraction of the estimated gains is derived from the quality effect: (i) 25.1% points of the 35.0% gains from larger new products, (ii) 25.3% points of the 34.4% gains from other new products, and (iii) 62.4% points of the 70.6% gains from all new products. Based on these lower bounds, we compute a variety-neutral version of the SW gain from new-generation fabs in Table 25, which is 20.8% and broadly similar to the baseline result (23.6% in Table 5). The variety-neutral version of the subsequent ROI analysis shows the same general patterns (Table 26).

We have also considered other approaches to address the issue of overestimation, including the adjustment proposed by Ackerberg and Rysman (2005), as well as the estimation of the pure characteristics model proposed by Berry and Pakes (2007). However, we have chosen not to pursue them in our main analysis, for reasons we explain in Appendix A.8.2.

8.3 Relationship between Competition and Innovation

The relationship between competition and innovation is complex and is 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. We first show the robustness of our findings to small, plausible changes in parameter values and then explore the consequences of extremely large changes.

(i) Robustness to Small Changes in Parameter Values Let us examine 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.[57] We perturb α and β by their respective standard errors in Table 1; we set $r \in \{4\%, 6\%\}$ instead of 5%. Table 28 in Appendix A.8.3 shows broadly similar results to the baseline ones in Table 13 (section 7.3). Mergers' static-welfare effects barely change. 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

[56] Similar methods have been used in the recent IO literature, including Dafny, Ho, and Varela (2013), Ciliberto, Moschini, and Perry (2019), and Grieco, Murry, and Yurukoglu (2024).

[57] We also show robustness with respect to the sunk cost of fab investments, FC, in part (ii).

count Others as another firm).[58] Thus, the estimated competition-innovation relationship in section 7 is robust to plausible changes in parameter values (e.g., due to statistical errors).

(ii) Conditions for Qualitatively Different Results We now experiment with much larger changes to determine the conditions under which qualitatively different results emerge. First, we multiply α and β by 1.5 and 0.5, respectively, which are changes of the order of magnitude larger than the ones above. Second, we try $r \in \{2.5\%, 10\%\}$. Third, we multiply the sunk cost of the fabs, FC, by 1.5 and 0.5. Tables 29 and 30 in Appendix A.8.3 show that only two of the eight results exhibit qualitatively different patterns. Specifically, drastically low price sensitivity ($\alpha = 0.5 \times \hat{\alpha}$) makes mergers more pro-innovation, whereas drastically low 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 cost reductions. Mergers increase market power, further strengthening these higher expected returns. The same mechanism works in reverse under lower β: Lower quality sensitivity leads to 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 would 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 extremely 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

Four main findings emerge from this study. First, both product and process innovations led to massive welfare improvements in the LCD industry, the relative contributions of which vary across market segments. Second, the sunk cost of investment was so high that the actual (realized) returns were low for most firms. Third, some mergers among the seven

[58] 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 28 in Appendix A.8.3.

major firms could have increased their collective incentive to innovate. However, both the direction and magnitude of these effects are highly merger-specific, and the majority of mergers are unambiguously harmful when the number of major firms is less than or equal to five. Fourth, this competition-innovation relationship is robust to almost any variation in key parameters; for the incentive effect of mergers to become clearly positive, the price sensitivity of demand must be extremely low.

The unique strength of this study lies 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 additional structures. The results suggest that 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 concurrent competitive environment. Another is that it cannot allow the 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 with endogenous collusion and innovation in a companion paper (Igami, Qiu, and Sugaya 2023) to address these issues.

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Online Appendix

The section numbers of the Appendix reflect those of the corresponding main-text sections. These numbers have gaps by design because not all sections have supplemental material.

A.4 Demand Estimation Appendix

This Appendix section supplements section 4 (Demand Estimation).

A.4.1 Unobserved Quality and Outside Goods

This subsection discusses the possibility of separately identifying the unobserved product quality and the value of the outside goods. Let the utility of the outside option change over time: $u_{i0t} = \gamma_t + \varepsilon_{0it}$. 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. 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, Pakes, Berry, and Levinsohn (1993) 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 quality ξ_{jt} can change over time within the same continuing product j, its mean change is assumed to be zero.

Figure 9 plots the net appeal of the inside goods ($\tau_t - \gamma_t$) and its two components (τ_t and γ_t) based on these identification assumptions. In the notebook and monitor markets, net appeal follows a downward trend, suggesting that the inside products 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 is due to the increasing attractiveness of the latter. Meanwhile, the former exhibits either negligible changes (in notebooks) or a slightly decreasing trend (in monitors). The results

are qualitatively different in the TV market. The net appeal of inside goods ($\tau_t - \gamma_t$) does not follow any clear trend but fluctuates in a vaguely cyclical pattern. Its decomposition suggests that the mean unobserved quality of inside goods decreased in the first few years and never recovered afterward.

Figure 9: Mean Values of Inside and Outside Goods

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



Note: See equation (9) for the underlying decomposition of the unobserved quality term.

We do not further pursue this line of investigation because some of these patterns (at the level of $\hat{\tau}_t$ and $\hat{\gamma}_t$) are not particularly intuitive, casting doubts on the validity of the identification assumption (10) in the current high-tech context. Specifically, the decreasing trends in $\hat{\tau}_t$ are difficult to reconcile with the fact that the physical quality of LCD panels improved over time in many dimensions, including the range of possible brightness, sharpness, response speed, viewing angle, and other determinants of picture quality.[59] We revisit the upward trends of $\hat{\gamma}_t$ in section 8.3 (and Appendix A.8.3).

A.4.2 Paired t Tests for Price Comparison

We systematically investigate the conduct of firms. The task is much simpler in our data context (i.e., with cost data) than in a more typical environment (i.e., without cost data).[60] The reason is that we can directly compare the actual price p_t with the three theoretical benchmarks ($p_t^{mo}, p_t^{bn}, p_t^{sp}$) that are implied by (the cost data and) the three conduct assumptions, respectively.

Table 15 shows the summary statistics of the four prices and of the difference between p_t

[59]These product characteristics are not systematically recorded in our dataset, but are known to have improved during the sample period.

[60]For the latter envinronment, new testing methods have been proposed by Duarte, Magnolfi, Sølvsten, and Sullivan (2024) and by Backus, Conlon, and Sinkinson (2021).

Table 15: Summary Statistics for the Paired t Tests

Variable	Observation	Mean	Standard error	Standard deviation	95% confidence interval	
A. Earlier subsample (2001:Q1–2004:Q3)						
Actual price, p_t	15	397.57	11.53	44.67	372.84	422.31
Monopoly price, p_t^{mo}	15	368.57	14.21	55.04	338.09	399.05
Bertrand-Nash price, p_t^{bn}	15	292.04	10.51	40.72	269.49	314.59
Social-planner price, p_t^{sp}	15	254.08	9.02	34.95	234.72	273.43
Difference 1, $p_t - p_t^{mo}$	15	29.00	12.58	48.72	2.02	55.98
Difference 2, $p_t - p_t^{bn}$	15	105.53	10.98	42.54	81.97	129.09
Difference 3, $p_t - p_t^{sp}$	15	143.49	10.40	40.26	121.20	165.79
B. Later subsample (2004:Q4–2011:Q4)						
Actual price, p_t	29	248.71	14.96	80.57	218.06	279.35
Monopoly price, p_t^{mo}	29	351.04	11.41	61.44	327.67	374.41
Bertrand-Nash price, p_t^{bn}	29	250.84	11.26	60.64	227.77	273.90
Social-planner price, p_t^{sp}	29	205.86	10.38	55.88	184.60	227.12
Difference 1, $p_t - p_t^{mo}$	29	−102.33	5.15	27.75	−112.89	−91.78
Difference 2, $p_t - p_t^{bn}$	29	−2.13	4.96	26.73	−12.30	8.04
Difference 3, $p_t - p_t^{sp}$	29	42.85	5.57	30.00	31.44	54.26

Note: "Standard error" is the standard error of the (sub)sample mean, given by $sd/\sqrt{obs}$, where sd is the (sub)sample standard deviation and obs is the number of observations.

and each of $(p_t^{mo}, p_t^{bn}, p_t^{sp})$.[61] We split the sample period into the first 15 quarters (2001:Q1–2004:Q3) and the 29 remaining quarters (2004:Q4–2011:Q4) because the benchmark price closest to the data switches from p_t^{mo} to p_t^{bn} between 2004:Q3 and 2004:Q4.

Table 16 reports the results of the paired t tests. Each row examines the difference between p_t and one of the three benchmarks, and tests the null hypotheses H_0 of zero difference against three alternative hypotheses H_a that the mean of the difference is (i) less than zero, (ii) not equal to zero, and (iii) greater than zero. In panel A, the p value of the first H_0 of Difference 1 is 0.9815, which means that the test rejects the possibility of $p_t < p_t^{mo}$ in 2001:Q1–2004:Q3 with probability 0.9815. Meanwhile, the second H_a ($p_t \neq p_t^{mo}$) is rejected with probability 0.0370, which means that H_0 ($p_t = p_T^{mo}$) can be rejected at the 5% but cannot be rejected at the 1% significance level. Taken together, the three rows of panel A show that the actual price is more consistent with monopoly pricing than the other two in the earlier sub-sample. Panel B of Table 16 clearly favors the assumption of Bertrand-Nash pricing in the later sub-sample. Specifically, we cannot reject the null that $p_t = p_t^{bn}$, whereas we are more than 99% confident that $p_t \neq p_t^{mo}$ and $p_t \neq p_t^{sp}$.

[61] We focus on the average price for all products p_t, instead of product-specific ones p_{jt}, for two reasons. First, the LCD cartel operated on an industry-wide scale rather than at the product level. Second, product-specific prices could vary wildly for idiosyncratic reasons and tend to reject any null hypothesis of zero mean difference, defeating the purpose of price comparisons.

Table 16: Paired t Tests of Price Comparison

Variable	t statistic	Degree of freedom	p value of H_0: mean(diff) = 0		
			H_a: mean(diff) < 0	H_a: mean(diff) $\neq 0$	H_a: mean(diff) > 0
A. Earlier subsample (2001:Q1–2004:Q3)					
Difference 1, $p_t - p_t^{mo}$	2.3053	14	0.9815	0.0370	0.0185
Difference 2, $p_t - p_t^{bn}$	9.6076	14	1.0000	0.0000	0.0000
Difference 3, $p_t - p_t^{sp}$	13.8040	14	1.0000	0.0000	0.0000
B. Later subsample (2004:Q4–2011:Q4)					
Difference 1, $p_t - p_t^{mo}$	−19.8556	28	0.0000	0.0000	1.0000
Difference 2, $p_t - p_t^{bn}$	−0.4294	28	0.3355	0.6709	0.6645
Difference 3, $p_t - p_t^{sp}$	7.6922	28	1.0000	0.0000	0.0000

A.5 Details of the Welfare Gains from Innovation

This Appendix section supplements section 5 (Welfare Gains from Innovation) and reports the main welfare results in section 5.3 under an alternative conduct assumption of Bertrand competition throughout the sample period. Table 17 corresponds to Table 5, which underpins our analyses of ROI and competition in sections 6 and 7. 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). However, the percentage-change results are only mildly affected—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 remain almost unchanged.[62]

A.7 Merger Simulation Appendix

This Appendix section supplements section 7 (Market Structure).

Outliers. Table 18 lists the outliers in Figure 7 (i.e., mergers with $\Delta DPV(SW) < -5\%$) in ascending order of $\Delta DPV(SW)$. The column labeled "market structure configuration" shows the exact ownership structure by grouping the merged firms within brackets. The full-monopoly case in the top row is a true outlier with massively negative outcomes, as we have already discussed in section 7.2.

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

[62] Because the market size of LCD-TVs was small in the first few years of the sample period, the change of conduct assumptions in 2001:Q1–2004:Q3 hardly matters.

Table 17: 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.

returns), but falls short of totally eliminating the competitive fringe. Whether fringe firms in Others could exert much competitive pressure in reality is questionable because these firms lack the physical capacity to drastically increase production in the short run.[63]

Cases 3–6 have the largest positive incentive effects above 15%. They 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 merge with other, stronger firms. Meanwhile, their existence as independent competitors preserves the room for business stealing and helps motivate the dominant player to invest.[64]

[63]The BLP model abstracts from such capacity constraints, which is why the independence of Others matters so much in these simulations.

[64]As in Case 2, whether CPT and HS in reality could put such competitive pressure on the coalition of

Table 18: 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.

Cases 7–16 leave Sharp out of the mega-merger as well and show similar patterns, albeit in smaller magnitude. Note that all of the 16 outliers (except cases 1–2) involve consolidation of the top four firms while leaving out weaker firms as independent competitors. 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 theoretical curiosities than relevant policy targets.

Additional Table. Table 19 shows that the static-welfare outcomes of mergers are highly predictable based on the HHI and other related statistics.

A.8 Details of the Sensitivity Analysis

This Appendix section supplements section 8 (Sensitivity Analysis).

A.8.1 Product Durability

This subsection investigates the implications of the durability of the product. Part (a) reports the demand estimates by sub-sample period. Part (b) emulates the "exit of high-value buyers" that has been highlighted in the literature. These two parts supplement section 8.1(ii) in

the stronger firms is questionable due to capacity constraints. Nevertheless, the finding that the incentive to innovate hinges on a balance between strong appropriability and business-stealing opportunities is general.

Table 19: Predictors of the Effect of Mergers on Social Welfare

Specification	(1)	(2)	(3)	(4)	(5)	(6)
A. Including Outliers						
Post-merger HHI	−0.169					−0.019
	(0.002)					(0.006)
Change in HHI		−0.297				−0.088
		(0.003)				(0.008)
Post-merger IHHI			−0.108			−0.026
			(0.001)			(0.004)
Change in IHHI				−0.182		−0.098
				(0.001)		(0.005)
UPP					−0.466	0.027
					(0.004)	(0.013)
Constant	5.461	0.707	3.326	0.729	1.085	2.090
	(0.077)	(0.021)	(0.049)	(0.019)	(0.025)	(0.088)
Number of observations	4,803	4,803	4,803	4,803	4,803	4,803
R^2	0.616	0.743	0.664	0.792	0.722	0.833
Adjusted R^2	0.616	0.743	0.664	0.792	0.722	0.832
B. Excluding Outliers						
Post-merger HHI	−0.083					−0.017
	(0.001)					(0.002)
Change in HHI		−0.184				−0.094
		(0.001)				(0.003)
Post-merger IHHI			−0.055			0.006
			(0.001)			(0.001)
Change in IHHI				−0.113		−0.041
				(0.001)		(0.002)
UPP					−0.282	−0.039
					(0.002)	(0.004)
Constant	2.395	0.257	1.369	0.254	0.465	0.730
	(0.056)	(0.007)	(0.038)	(0.008)	(0.009)	(0.029)
Number of obs.	4,530	4,530	4,530	4,530	4,530	4,530
R^2	0.416	0.901	0.421	0.850	0.862	0.928
Adjusted R^2	0.416	0.901	0.421	0.850	0.862	0.928

Note: The dependent variable is $\Delta DPV(SW)$ in percentage change from the pre-merger market structure. All results are based on OLS. Standard errors are in parentheses. The HHI, ΔHHI, IHHI, and ΔIHHI are expressed in the range between 0 and 100 (instead of the more conventional 0–10,000 scale) to ensure the decimal alignment of coefficient estimates. See the main text for the definition of the outliers.

the main text. Part (c) simulates changes in the value of the outside goods, supplementing section 8.1(iii).

(a) Demand Estimates by Subsample Period. We reestimate the demand parameters by subsample period, first half (2001:Q1–2006:Q2) and second half (2006:Q3–2011:Q4), and report the results in Tables 20 and 21. Several interesting patterns emerge.

First, the price sensitivity, $|\alpha|$, visibly decreased over time in notebooks and monitors, which we interpret as follows. In mature markets for these IT products, prices became sufficiently low in later years, so that further price cuts would not stimulate as much new purchases as before. In the new market for LCD-TVs, in contrast, $|\alpha|$ increased slightly with

Table 20: Demand Estimates by Subsample (1), 2001:Q1–2006:Q2

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−574.4	60.9	−113.2	8.2	−24.3	3.9
Size nests (ρ)	0.931	0.058	0.911	0.018	0.743	0.044
Size = 12" (β^{12})	2.116	0.144	–	–	–	–
Size = 13" (β^{13})	1.283	0.153	–	–	–	–
Size = 14" (β^{14})	4.083	0.186	–	–	2.056	0.170
Size = 15" (β^{15})	4.973	0.248	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	4.297	0.192	–	–	–	–
Size = 16" (β^{16})	2.802	0.362	4.981	0.077	2.705	0.171
Size = 17" (β^{17})	4.400	0.301	–	–		–
Size = 18" (β^{18})	2.598	0.578	5.956	0.101	2.158	0.203
Size = 20" (β^{20})	–	–	6.223	0.138	3.512	0.238
Size = 22" (β^{22})	–	–	5.163	0.259	2.397	0.268
Size = 24" (β^{24})	–	–	5.658	0.290	2.516	0.245
Size = 26" (β^{26})	–	–	–	–	3.869	0.278
Size = 27" (β^{27})	–	–	5.799	0.468	–	–
Size = 28" (β^{28})	–	–	–	–	2.803	0.318
Size = 30" (β^{30})	–	–	–	–	4.080	0.386
Size = 32" (β^{32})	–	–	–	–	4.782	0.334
Size = 40" (β^{40})	–	–	–	–	4.775	0.436
Size = 45" (β^{45})	–	–	–	–	4.426	0.497
Size = 50" (β^{50})	–	–	–	–	3.679	0.547
Size = 55" (β^{55})	–	–	–	–	3.015	0.754
Size = 60" (β^{60})	–	–	–	–	2.939	0.716
Size $\geq$ 65" (β^{65})	–	–	–	–	3.617	0.762
Resolution (β^{r})	3.437	0.369	3.042	0.282	0.002	0.136
LED (β^{b})	–	–	–	–	–	–
Firm = Samsung	0.208	0.069	0.021	0.084	0.168	0.085
Firm = LG	−0.032	0.062	0.262	0.077	0.115	0.084
Firm = CMO	0.067	0.078	−0.230	0.081	0.234	0.114
Firm = AUO	–	–	–	–		–
Firm = Sharp	0.061	0.068	−0.035	0.079	0.133	0.081
Firm = CPT	−0.088	0.091	0.036	0.073	−0.293	0.098
Firm = HS	−0.106	0.114	0.018	0.075	−0.558	0.120
Firm = Others	−0.004	0.060	−0.084	0.069	−0.242	0.079
Constant	−12.053	0.842	−19.113	1.189	−10.976	0.664
Time dummies	Yes		Yes		Yes	
Own elasticity	−74.81		−26.15		−3.90	
1st-stage R^2: price	0.901		0.900		0.949	
1st-stage R^2: share	0.423		0.524		0.524	
Number of obs.	1,745		1,304		1,099	

Note: The sample period is 2001:Q1–2006:Q2. Other details are the same as in Table 1. The only exception is the reference categories of the size dummies, which vary by subsample period.

time. One plausible interpretation is that this difference reflects the heterogeneity between consumers in East Asia and elsewhere, since LCD-TVs were not marketed outside the region before 2007.

Second, the coefficients on the size bins, β^{s}, exhibit relatively small changes in notebooks and monitors. In contrast, they became considerably larger on TVs in all but two size bins (18" and 28"). The nest parameter, ρ, which represents the importance of the size bins,

Table 21: Demand Estimates by Subsample (2), 2006:Q3–2011:Q4

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−137.3	24.8	−94.4	6.8	−30.4	3.1
Size nests (ρ)	0.793	0.020	0.776	0.021	0.869	0.017
Size = 12" (β^{12})	2.084	0.094	–	–	–	–
Size = 13" (β^{13})	2.655	0.094	–	–	–	–
Size = 14" (β^{14})	3.459	0.118	–	–	–	–
Size = 15" (β^{15})	1.580	0.144	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	3.329	0.111	–	–	–	–
Size = 16" (β^{16})	4.157	0.123	–	–	2.729	0.183
Size = 17" (β^{17})	2.761	0.090	–	–	–	–
Size = 18" (β^{18})	0.150	0.143	1.415	0.057	0.757	0.187
Size = 20" (β^{20})	–	–	2.419	0.046	4.672	0.168
Size = 22" (β^{22})	–	–	1.790	0.056	4.717	0.178
Size = 24" (β^{24})	–	–	1.273	0.060	3.710	0.191
Size = 26" (β^{26})	–	–	–	–	5.004	0.173
Size = 27" (β^{27})	–	–	0.573	0.104	–	–
Size = 28" (β^{28})	–	–	–	–	2.173	0.598
Size = 30" (β^{30})	–	–	–	–	–	–
Size = 32" (β^{32})	–	–	–	–	6.808	0.181
Size = 40" (β^{40})	–	–	–	–	6.289	0.195
Size = 45" (β^{45})	–	–	–	–	5.979	0.202
Size = 50" (β^{50})	–	–	–	–	6.074	0.224
Size = 55" (β^{55})	–	–	–	–	6.021	0.263
Size = 60" (β^{60})	–	–	–	–	4.774	0.372
Size $\geq$ 65" (β^{65})	–	–	–	–	5.040	0.405
Resolution (β^{r})	0.662	0.179	1.931	0.213	0.078	0.064
LED (β^{b})	0.065	0.032	−0.183	0.039	0.260	0.034
Firm = Samsung	0.051	0.046	0.034	0.041	0.143	0.038
Firm = LG	0.057	0.046	0.121	0.038	0.035	0.027
Firm = CMO	−0.090	0.051	−0.088	0.042	0.003	0.035
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.415	0.090	−0.122	0.107	−0.083	0.035
Firm = CPT	−0.116	0.072	−0.237	0.051	−0.189	0.062
Firm = HS	−0.132	0.075	−0.214	0.060	−0.168	0.134
Firm = Others	−0.165	0.050	−0.060	0.044	−0.177	0.037
Constant	−9.880	0.718	−13.733	0.933	−10.066	0.299
Time dummies	Yes		Yes		Yes	
Own elasticity	−4.59		−5.15		−5.68	
1st-stage R^2: price	0.855		0.815		0.917	
1st-stage R^2: share	0.407		0.299		0.433	
Number of obs.	2,395		2,070		2,483	

Note: The sample period is 2006:Q3–2011:Q4. Other details are the same as in Table 1. The only exception is the reference categories of the size dummies, which vary by subsample.

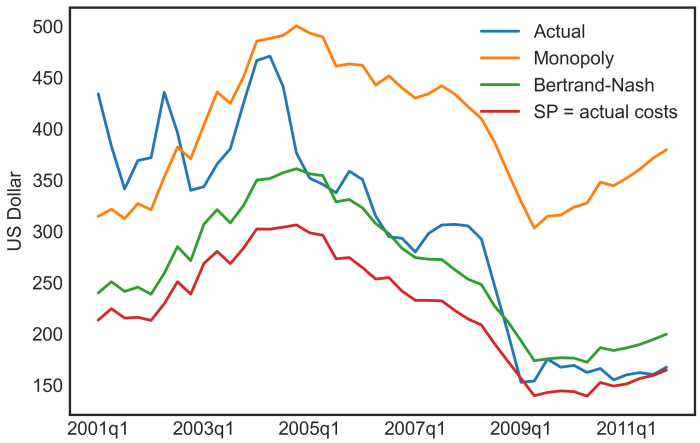
follows broadly similar patterns, as it decreased in notebooks and monitors but increased in TVs. Thus, LCD-TVs of larger sizes became more popular in later years, whereas time trends are less clear in the IT applications.

Third, the resolution coefficient, β^r, decreased over time in notebooks and monitors; it is statistically indistinguishable from zero in TVs in both subperiods. We can understand these results as a reflection of the two underlying data patterns. The first is that successful

new products did not necessarily feature a higher resolution. The second is that the split-sample version of the data on LCD-TVs lacks variation in resolution—once we condition on size, backlight type, and time period, the buyers' choice set is often reduced to a singleton. Similarly, the time trend of the LED backlight coefficient, β^b, cannot be studied because LED backlights did not exist in the first half.

Whether these time patterns affect our main results is a separate issue. Figure 10 plots the average prices in the data and the theoretical benchmarks. Compared with the baseline version in Figure 3 (section 4.2), the monopoly price implied by the split-sample estimates is slightly higher in all periods, and the Bertrand price is slightly higher in the first half but lower in the second half. Despite these minor quantitative differences, the overall patterns remain unchanged. That is, the actual price is close to the monopoly level until 2004:Q3 and then close to the Bertrand level. Thus, the implications for markups, competitive conduct, and the rest of our analyses do not change.

Figure 10: Price Comparison Based on the Demand Estimates by Subsample Period



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

(b) If High-Value Buyers Exit the Market by 2006:Q3 If consumers are forward-looking and optimally wait until prices are sufficiently low for their (heterogeneous) preferences, the composition of demand will change over time. Conlon (2012) calculates a large potential impact of the changing distribution of consumer preferences. Gowrisankaran and Rysman (2012) show that if high-value consumers exit the market early on, the welfare gains in their final sample period will be approximately 26.6% lower than what some conventional measures that ignore such changes would suggest. Our demand estimates by subsample pe-

riod (Tables 20 and 21) do not necessarily support their assumptions (i.e., we found that the price sensitivity decreased for the IT applications and increased only marginally for TVs), but we can simulate the impact of such changes anyway.

Table 22: Welfare Impact under the 26.6% Reduction in 2006:Q3–2011:Q4

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
4G–4.5G only (baseline)	261.6	(±0)	113.5	(±0)	375.2	(±0)
4G–5G only	309.1	(+18.1)	129.3	(+13.9)	438.4	(+16.8)
4G–5.5G only	311.5	(+19.0)	130.3	(+14.8)	441.8	(+17.8)
4G–6G only	319.3	(+20.0)	132.6	(+16.9)	451.9	(+20.5)
4G–8G only	322.2	(+23.1)	133.6	(+17.7)	455.8	(+21.5)
4G–10G	323.1	(+23.5)	133.9	(+18.0)	457.0	(+21.8)

Note: All welfare measures are summed across notebooks, monitors and TVs. All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

Table 22 is an alternative version of panel D of Table 5 (Welfare Impact of New Technologies, 2001–2011) in section 5.3, which summarizes how much each generation of fabs contributed to SW. The only difference from Table 5 is that we artificially reduce all welfare measures in the second sub-sample period (2006:Q3–2011:Q4) by 26.6%. This adjustment reduces the levels of CS, PS, and SW by approximately 18%. However, the welfare contributions of new technologies remain mostly unchanged in terms of percentage changes.

(c) Sensitivity to the Value of the Outside Goods One way to check the sensitivity of our results with respect to the durable good aspect of LCD panels is to change the value of the outside good, γ_t, from the estimated level. This term is directly related to the durability of the products because any previously purchased (and currently used) products play the role of the outside goods in their owners' discrete choice problem.

Appendix A.4.1 showed that $\hat{\gamma}_t$ follows an upward time trend (throughout the sample period in notebooks and monitors, and since 2004 in TVs). These positive trends are consistent with the observations that the overall quality of LCD products improved over time and that they are durable goods, which implies that the appeal of the outside goods (previously purchased products) improved as well. Hence, we may investigate the implications of durability by studying how our results change when we alter the value of γ_t.

We operationalize this idea by recomputing the equilibrium outcomes in every period under counterfactual values of γ_t,

$$\tilde{\gamma}_t = \mu \times \hat{\gamma}_t, \tag{11}$$

where $\mu \in [0, 1]$ is the multiplier to rescale γ_t (e.g., $\mu = 1$ corresponds to the estimated

model).[65] For example, $\mu \in \{0.67, 0.5\}$ dampens the time trend in $\hat{\gamma}_t$ by a third and a half, respectively. These values would represent plausible simulations of eliminating durability if (the quality improvements of) previously purchased goods account for a third and a half of the improvements in the outside goods, respectively.[66] By contrast, $\mu \approx 0$ represents extreme cases, which we simulate only for the sake of completeness.

In Table 23, columns represent different values of $\mu \in \{1, 0.67, 0.5, 0.4, 0.2, 0\}$, whereas rows list the welfare gains from all fab investments in terms of DPV of ΔCS, ΔPS, and ΔSW at $r = 5\%$. Panel A corresponds to the baseline ROI results under the actual market structure in section 6.1 (Table 7). The most obvious finding is that all kinds of welfare gains are larger at $\mu < 1$ for a mechanical reason—the welfare gains are defined relative to γ_t in any discrete-choice demand model. Another, perhaps more interesting pattern is that, as μ decreases from 1 to 0, $DPV(\Delta CS)$ increases at a faster rate than $DPV(\Delta PS)$, which actually decreases between $\mu = 0.4$ and $\mu = 0$ if we include Others. The reasons are that two of the weakest firms (CPT and Others) are made worse off by the industry-wide investments in new fabs (i.e., their individual $DPV(\Delta PS_f)$s are negative in Table 8) and that the relative loss at Others grows disproportionately fast as μ decreases. Because we are not particularly interested in the incentives at these fringe firms, we focus on $DPV(\Delta PS)$ and $DPV(\Delta SW)$ excluding Others, which behave more predictably and monotonically increase as $\mu \to 0$.

Table 23: Sensitivity of Welfare Gains to the Value of Outside Goods

Multiplier of outside values, μ	1 (baseline)	0.67	0.5	0.4	0.2	0
A. Oligopoly (actual)						
$DPV(\Delta CS)$	250.2	334.6	438.1	512.8	667.4	799.2
$DPV(\Delta PS)$ including Others	74.5	85.5	93.0	94.5	89.6	78.5
$DPV(\Delta SW)$ including Others	324.7	420.1	531.1	607.3	757.0	877.7
$DPV(\Delta PS)$ excluding Others	81.4	105.9	126.6	137.5	152.1	157.0
$DPV(\Delta SW)$ excluding Others	331.6	440.4	564.7	650.3	819.5	956.2
B. Monopoly (hypothetical)						
$DPV(\Delta CS)$	136.8	174.0	216.2	244.9	301.3	347.6
$DPV(\Delta PS)$	115.3	148.0	188.4	217.9	282.1	344.2
$DPV(\Delta SW)$	252.1	322.0	404.6	462.8	583.4	691.8
C. Monopoly/oligopoly ratio, $B \div A$						
$DPV(\Delta SW)$ including Others	0.776	0.766	0.762	0.762	0.771	0.788
$DPV(\Delta SW)$ excluding Others	0.760	0.731	0.716	0.712	0.712	0.723

Note: All DPVs are in billion US dollars as of 2001:Q1 under $r = 5\%$.

Panel B corresponds to the hypothetical-monopoly results in section 6.2 (Table 9). All

[65] Values of μ outside this range is mathematically possible, but we are primarily interested in hypothetically *reducing* the durability of the products, which is why we focus on this range.

[66] Improvements of non-LCD displays, such as those based on the cathode-ray tube (CRT) and plasma technologies, would account for the rest.

three measures monotonically decrease. In contrast to panel A, the rate of increase of $DPV(\Delta PS)$ is approximately three times between $\mu = 1$ and $\mu = 0$, and is slightly faster than that of $DPV(\Delta CS)$ (approximately 2.5 times). Despite these differences in detail, the overall pattern across panels A and B is simple: most of the welfare-gain measures scale proportionally in a predictable manner.

Panel C compares the total welfare gains, $DPV(\Delta SW)$, between panels A and B by calculating their ratios. For example, $DPV(\Delta SW)$ under monopoly is approximately three-quarters of that under the actual market structure (0.776 including Others and 0.760 excluding Others). These ratios exhibit relatively small changes as $\mu \to 0$. Their limited variability suggests that our subsequent results about the incentive to innovate and market structure are unlikely to be overturned even if we alter our assumptions on the durability of goods.

A.8.2 Separately Measuring the Welfare Gains from Quality and Variety

We decompose the welfare gains from product innovation by separately measuring the contributions of improved quality (the "quality effect") and increased variety (the "variety effect"). For each of the three categories of product innovation (larger new products, other new products, and all new products), Table 24 compares three counterfactual simulations that change only the composition of products, only the number of products, and both of them, respectively.

First, the change-composition counterfactual keeps the number of products constant (i.e., the same as in the data) but removes the larger new products from the buyers' choice set by replacing them with a random sample of the initial products.[67] This simulation separately identifies the quality effect, which accounts for (i) 25.1% points of the 35.0% total gains from larger new products, (ii) 25.3% points of the 34.4% total gains from other new products, and (iii) 62.4% points of the 70.6% total gains from all new products. Hence, most of the total gains can be attributed to the quality effect.

Second, the change-number counterfactual reduces the number of products as in our original counterfactuals, but keeps the composition of products similar to the data. More specifically, panels (i), (ii), and (iii) of Table 24 reuse the counterfactual histories of the reduced number of products in simulations (i), (ii), and (iii) in Table 2 in section 5.1.2, respectively. Because the actual choice set in each $t >$ 2001:Q1 contains more products than in these counterfactual paths, we randomly resample a subset of these actual products and

[67] We randomly resample them 100 times in each period, and report their mean SW.

Table 24: Separating the Quality Effect and the Variety Effect of Product Innovations

Setting	Number of products	Composition of products	Social welfare	
			$	(% change from baseline)
Baseline	Actual	Actual	557.1	(±0)
(i) Without larger new products				
Change composition	Actual	Without larger new products	417.5	(−25.1)
Change number	CF (i)	Actual	492.6	(−11.6)
Change both	CF (i)	Without larger new products	362.1	(−35.0)
(ii) Without other new products				
Change composition	Actual	Without other new products	416.1	(−25.3)
Change number	CF (ii)	Actual	436.6	(−21.6)
Change both	CF (ii)	Without other new products	365.6	(−34.4)
(iii) Without any new products				
Change composition	Actual	Without any new products	209.4	(−62.4)
Change number	CF (iii)	Actual	270.6	(−51.4)
Change both	CF (iii)	Without any new products	163.6	(−70.6)

Note: CF (i), CF (ii), and CF (iii) in the "number of products" column correspond to the counterfactual settings (i), (ii), and (i) + (ii) in Table 2, respectively. All dollar values are in billion US dollars and summed over 2001:Q1–2011:Q4 without discounting.

report the mean SW across 100 resampled histories. These simulations identify the variety effect, which accounts for (i) 11.6%, (ii) 21.6%, and (iii) 51.4%, respectively.

Third, the change-both counterfactual changes both the number and composition of products, which is the same design as the original counterfactuals in section 5.1 and incorporates both the quality effect and the variety effect. These results show that both the quality effect and the variety effect are quantitatively important. In terms of relative magnitude, the quality effect is larger than the variety effect and represents more than half of the total effect in the three panels of Table 24.

Table 25 is the variety-neutral version of Table 5 in section 5.3. Recall that each generation of fabs embodies a bundle of larger new products and the part of lower production costs that can be attributed to the vintage-capital effect. We recompute the counterfactual welfare levels with 4G–4.5G only, 4G–5G only, and so on, hypothetically eliminating the larger new products and the vintage capital effects that belong to the specific generations of fabs, which is the same procedure as in Table 5. The only difference between Tables 5 and 25 is that, when we "eliminate the larger new products" in the latter, we use the change-composition procedure of Table 25, which keeps the number of products the same as in the actual path.

The results for notebooks and monitors are omitted because they are identical to panels A and B of Table 5. All sizes of products in these categories could be produced by the

Table 25: Variety-Neutral Welfare Impact of New Technologies, 2001–2011

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
			(Omitted: same as in Table 5)			
B. Monitor						
			(Omitted: same as in Table 5)			
C. TV						
4G–4.5G only (baseline)	138.1	(±0)	40.1	(±0)	178.1	(±0)
4G–5G only	166.1	(+20.3)	51.3	(+28.1)	217.4	(+22.1)
4G–5.5G only	166.4	(+20.6)	52.0	(+29.8)	218.4	(+22.6)
4G–6G only	182.6	(+32.2)	53.5	(+33.5)	236.1	(+32.5)
4G–8G only	185.2	(+34.2)	54.4	(+35.8)	239.7	(+34.5)
4G–10G	186.0	(+34.7)	54.7	(+36.5)	240.7	(+35.1)
D. All applications						
4G–4.5G only (baseline)	327.8	(±0)	133.4	(±0)	461.2	(±0)
4G–5G only	376.5	(+14.9)	151.1	(+13.3)	527.6	(+14.4)
4G–5.5G only	377.5	(+15.2)	152.1	(+14.0)	529.6	(+14.8)
4G–6G only	396.1	(+20.8)	154.2	(+15.6)	550.2	(+19.3)
4G–8G only	400.0	(+22.0)	155.5	(+16.6)	555.5	(+20.5)
4G–10G	401.2	(+22.4)	156.0	(+16.9)	557.1	(+20.8)

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

4G–4.5G fabs.[68] Meanwhile, the results for TVs and the total of all applications show some differences. The baseline levels of CS, PS, and SW are slightly higher in the variety-neutral version because we ignore the potential loss of the variety effect. These higher baselines mechanically translate into lower percentage changes. However, the overall impacts are not materially different in aggregate numbers—the variety-neutral SW gain from all new technologies (4G–10G) is 20.8%, which is broadly similar to the 23.6% gain in Table 5. In other words, the lower and upper bounds of the welfare gains are reasonably close to each other.

Finally, Table 26 shows the ROI analysis based on these variety-neutral welfare gains. The DPVs of ΔCS, ΔPS, and ΔSW are somewhat smaller than the corresponding baseline results in Tables 7 and 9 (in sections 6.1 and 6.2, respectively), but overall patterns remain the same. Hence, we conclude that our main findings are not exceedingly sensitive to the way we treat the contributions of product variety.

[68] Not all of these sizes were actually manufactured and marketed in 2001:Q1. Consequently, the sets of products that we define as "larger new products" in sections 5.1 and 5.3 (and analogously in Tables 24 and 25) are slightly different. The former is based on the actual manufacturing decisions and sales outcomes as of 2001:Q1 (i.e., the set of "initial products"), whereas the latter is based on the physical/technological possibility.

Table 26: Variety-Neutral Returns on Fab Investments

Annual discount rate	1%	2.5%	5%	10%
A. Oligopoly (actual)				
1. Change in consumer surplus, $DPV(\Delta CS)$	1,468.1	531.0	224.5	80.2
2. Change in producer surplus, $DPV(\Delta PS)$	411.5	150.1	64.4	23.9
3. Change in social welfare $(=1+2)$, $DPV(\Delta SW)$	1,879.6	681.1	288.9	104.1
4. Fab investment cost, $DPV(\Delta FC)$	116.6	106.7	92.1	68.9
5. Change in net social value $(=3-4)$, ΔNSV	1,763.0	574.4	196.8	35.3
6. Change in net producer value $(=2-4)$, ΔNPV	294.9	43.3	−27.7	−45.0
B. Monopoly (hypothetical)				
1. Change in consumer surplus, $DPV(\Delta CS)$	783.8	284.5	121.1	44.0
2. Change in producer surplus, $DPV(\Delta PS)$	661.5	240.2	102.3	37.3
3. Change in social welfare $(=1+2)$, $DPV(\Delta SW)$	1,445.3	524.8	223.4	81.2
4. Fab investment cost, $DPV(\Delta FC)$	116.6	106.7	92.1	68.9
5. Change in net social value $(=3-4)$, ΔNSV	1,328.7	418.0	131.3	12.4
6. Change in net producer value $(=2-4)$, ΔNPV	544.9	133.5	10.2	−31.6

Note: All discounted present values (DPVs) are in billion US dollars as of 2001:Q1 unless otherwise noted. Panels A and B corresponds to Tables 7 and 9, respectively.

Alternative 1: Demand Estimates with the Ackerberg-Rysman Adjustment. To assess the extent to which additional products crowd out existing products, Ackerberg and Rysman (2005) propose the inclusion of the natural logarithm of the number of products, $ln(n_t)$, into the utility function. Note that our baseline specification already incorporates the time fixed effects, which also play the role of the market fixed effects, thereby obviating the need for $ln(n_t)$ because they absorb any systematic variation across t.[69] We revisit this point after reviewing the results.

Table 27 reports the parameter estimates. The coefficient on $ln(N_t)$ is −0.638 (notebooks), −1.489 (monitors), and 0.641 (TVs). The negative numbers in the first two applications suggest the crowding-out effect does exist, but the positive coefficient in TVs suggests otherwise. Given that TVs became the largest category by dollar value during the sample period, the direction of bias in the aggregate results is ambiguous.

Other parameter estimates are less intuitive than in the baseline version (Table 1). First, the price coefficient is much smaller in magnitude. Second, the resolution coefficient is smaller in monitors, and negative in notebooks and TVs. Third, the LED coefficient is smaller as well. Based on these estimates, Figure 11 shows that the implied monopoly and Bertrand prices become much higher than in Figure 3—the actual price is below the Bertrand level in all periods since 2004:Q4, which is difficult to rationalize.

What is the source of these counterintuitive results? As we briefly mentioned above, the term $ln(n_t)$ is "redundant" in our setting. Our baseline specification already includes the

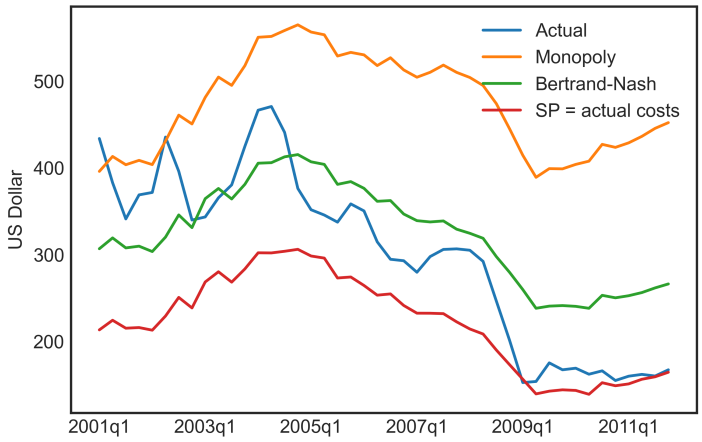
[69] We thank Dan Ackerberg and Marc Rysman for a useful discussion on this issue.

Table 27: Demand Estimates with the Ackerberg-Rysman Adjustment

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−41.21	3.30	−59.66	2.03	−26.24	1.13
Size nests (ρ)	0.560	0.027	0.601	0.018	0.676	0.025
Resolution (β^r)	−0.678	0.140	0.671	0.183	−0.155	0.072
LED (β^b)	0.105	0.043	−0.053	0.054	0.001	0.035
$ln(n_t)$	−0.638	0.091	−1.489	0.109	0.641	0.064
Time dummies	No		No		No	
Own elasticity	−1.45		−2.71		−2.70	
1st-stage R^2: price	0.879		0.885		0.910	
1st-stage R^2: share	0.368		0.366		0.436	
Number of obs.	4,140		3,374		3,582	

Note: Aside from the inclusion of the number-of-products term, $ln(n_t)$, and the exclusion of the time/market fixed effects, other details are the same as in Table 1. For brevity, the coefficient estimates for the size dummies and firm dummies are suppressed.

Figure 11: Price Comparison Based on the Ackerberg-Rysman Demand Estimates



time fixed effects, which control for any systematic variation across time. Table 27 is based on an alternative specification in which we replace the time fixed effects with $ln(n_t)$. Hence, any differences in the estimates stem from the lack of control for other systematic changes (e.g., in the value of the outside goods and the mean unobserved quality of the inside goods).

Alternative 2: Pure Characteristics Demand Model. Yet another approach to address the overestimation of the gains from variety is to use an entirely different class of demand models: the pure characteristics demand model (PCDM). By dropping the individual taste for each good ε_{ijt}, the PCDM eliminates the root cause of the problem. Despite this obvious appeal, we have not chosen to pursue this approach for the following reasons.[70]

[70]We thank Steve Berry and Minjae Song for advice on this matter. We are aware of more promising results in Cuesta and Tebaldi (2024), in which the authors exploit micro-data and a method of simulated

First, the PCDM is known to produce an implausibly high price elasticity. A numerical example by Berry and Pakes (2007, Table 6) features own-price elasticity in the range between -11 and -100, which is an order of magnitude greater than what is deemed plausible in most of the IO literature. An empirical application to personal computers by Song (2015, Table 4) shows the own-price-elasticity estimate of $-3,368$. The cause of these extraordinary numbers is that the room for horizontal product differentiation is extremely limited in the PCDM. Eliminating ε_{ijt} is akin to imposing a vertical-differentiation structure; the PCDM often predicts strictly zero sales when products have high prices and low qualities because all buyers strictly prefer other products.

Second, as a consequence of imposing close substitution patterns between products, the PCDM tends to predict extremely low markups. For example, Song (2015, Table 5) reports that PCDM predicts average markups in the range of 0.0018%–0.0037%, which is practically zero (i.e., perfect competition). In contrast, three different specifications of his logit-style models predict 1.252%–1.517%, 0.514%–0.610%, and 1.275%–1.544%, respectively. Our data show visibly positive markups in almost every period (Figure 3).

Third, the estimation algorithms for the PCDM are known to be slow and/or unreliable. Berry and Pakes (2007) proposed three methods to compute the unobserved product characteristics, which is a critical step: (i) the BLP contraction mapping, (ii) the element-by-element inverse, and (iii) a homotopy method. They report that no single method works well in all situations because (i) is inaccurate in some realistic settings, (ii) is not guaranteed to converge, and (iii) is slow. Song's (2006) computational note reports that Algorithm (i) alone is insufficient in virtually all cases. The only exceptions are those with only five or fewer products, but our data include hundreds of products in each category.

These problems with PCDM are more than just "technical" problems. The goal of this research is to estimate not only the welfare gains from new products but also the gains from other innovations, as well as the relationship between market structure and the incentive to innovate. Obtaining reasonable demand elasticities and markup implications is crucial for these purposes. Our main results on competition and innovation heavily rely on the availability of fast, reliable computational tools, such as Conlon and Gortmaker's (2020) PyBLP. For these reasons, we chose the BLP model over the PCDM.

maximum likelihood. The authors thank Pietro Tebaldi for kindly sharing their preliminary findings.

A.8.3 Competition-Innovation Relationship

This subsection reports the sensitivity results on the competition-innovation relationship.

Robustness to Small Changes. Table 28 reports detailed statistics of the six sensitivity analyses with respect to small perturbations in parameter values. The static welfare effect shows only minor quantitative changes. The innovation incentive effect exhibits larger changes, but the general tendency (e.g., in terms of median outcomes and fraction of cases with $\Delta SII < 0$) is remarkably similar to the baseline result in Table 13 in section 7.2.

Larger Changes in Demand-Side Parameters. Table 29 reports the four sensitivity analyses with respect to greater changes in demand parameters α and β. Panel (a) shows that extremely high price sensitivity makes most mergers anti-innovative. The reason is that a more concentrated market structure will not translate into much higher markups when buyers are highly price sensitive. In contrast, panel (b) shows that an extremely low price sensitivity tends to make $\Delta DPV(SW)$ more positive. The policy implication of this finding is that an innovation-based justification of mergers deserves attention only when demand is unusually price-insensitive.

Panel (c) of Table 29 shows that extremely high quality sensitivity does not change the baseline pattern. Meanwhile, panel (d) shows that extremely low quality sensitivity makes the incentive effect of mergers mostly negative (albeit with a small magnitude). Our interpretation is that when the buyers' WTP for product innovation is low, the lack of competition simply makes firms slack off.

Larger Changes in Supply-Side Parameters. Table 30 summarizes the sensitivity to large changes with respect to the two parameters on the supply side that govern the cost of LCD production: r (the cost of capital to finance investments) and FC (the initial cost of investments). Panel (a) shows that ΔSII is mostly negative under $r = 10\%$. That is, most mergers are clearly harmful when the cost of capital is high and/or the promise of future benefits is uncertain. In contrast, panel (b) shows that the incentive effect is less negative under $r = 2.5\%$. However, the majority of four-to-three and three-to-two mergers, as well as $N = 1$, are still unambiguously bad.

Finally, panels (c) and (d) of Table 30 show that FC does not affect the fraction of mergers with $\Delta SII < 0$ at all.

Table 28: 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.

Table 29: 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: See the note to Table 13 for definitions and explanations.

Table 30: Sensitivity (3)—Larger Changes in Supply-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) *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: See the note to Table 13 for definitions and explanations.