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

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Abstract

We study welfare gains from innovations in the global markets for liquid crystal display (LCD) panels. We show direct evidence on both product and process innovations by using detailed data on sales, costs, and investments. We then estimate a structural model of demand and supply to quantify their contributions. Results suggest social return on technological investment was positive, but private gains for most firms were negligible due to competition. We further investigate how competition affects firms' incentives to innovate in a series of counterfactual simulations with hypothetical mergers.

Keywords: competition and innovation, market structure, mergers, product innovation, process innovation, new products, vintage capital, learning by doing

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1 Introduction

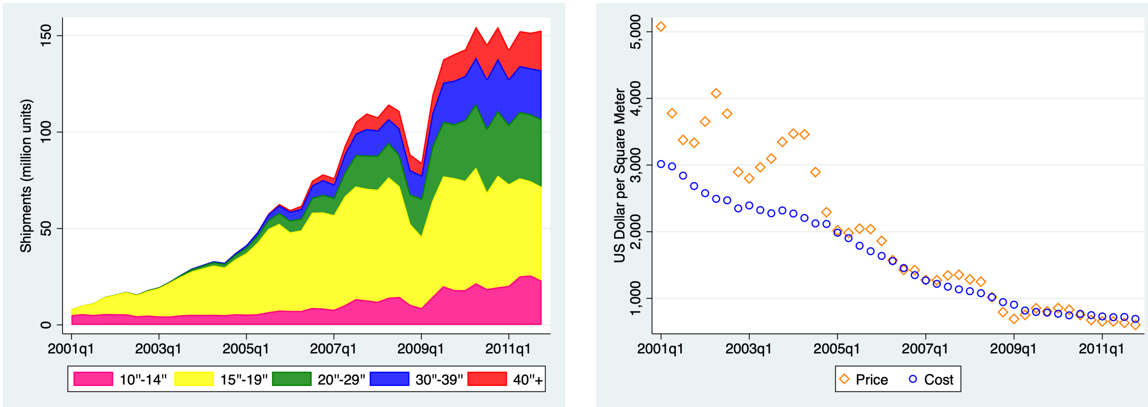
Precise measurement of innovations and their welfare impact is a fundamental problem in economics (e.g., Griliches 1957). Without quantifying them, we cannot empirically assess the extent to which our standard of living has improved, or critically evaluate numerous public policies aimed at fostering innovations. The large literature on new-product introduction ("product innovation") and productivity growth ("process innovation") has identified multiple channels of innovation (c.f., Bresnahan and Gordon [1997]). After reviewing existing studies on their determinants, however, Syverson (2011) concludes that "the relative quantitative importance of each ... is still unclear" (page 258).

This paper quantifies the welfare effects of product and process innovations in the global liquid crystal display (LCD) panel industry from 2001 to 2011. This empirical context is suitable for studying various types of innovation—larger and better new products became increasingly common, and the average manufacturing cost (per square meter of surface area) decreased by 77% from \$3,015 to \$692 (Figure 1). The LCD industry resembles other high-tech hardware industries in basic features, including fierce competition among a handful of firms, global supply chains that are centered around East Asia, and the critical role of investment in new-generation fabrication plants ("fabs"). Semiconductor devices, hard disk drives, personal computers (PCs), and many other electronics industries share these characteristics. Moreover, detailed data are available on not only product prices and sales quantities but also manufacturing costs and investment records, at all fabs of all major firms. Hence, LCD panels are both convenient and instructive for welfare analysis of innovations in broader contexts.

This comprehensive dataset facilitates the identification of gains from innovations in four important ways. First, manufacturing costs are immediately useful as an instrumental variable (IV) for identifying a demand model, which is an essential step in measuring buyers' surplus (BS). Second, they allow us to observe markups and calculate producers' surplus (PS) without making assumptions on firms' competitive conduct. Third, by regressing manufacturing cost on observed characteristics of fab investments, we can summarize cost-reducing effects of various technical changes, such as new generations of fab equipment ("vintage capital"), elapsed time since the start of volume production at each fab ("learning by doing"), and the use of specific production methods. Fourth, because the fixed costs of fab investments are also known, we can conduct a cost-benefit analysis for the entire industry, evaluating social and private returns on technological investments on a global scale.

Figure 1: Product and Process Innovations in the LCD Industry

(a) Unit Shipment by Size (b) Average Price and Cost



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

Our analysis proceeds in four stages, which we outline below with a preview of the findings. The first is the construction and description of a comprehensive dataset on the global LCD industry. Cost data are a particularly unique element, and we constructed this database as follows. We obtained a detailed engineering model of manufacturing cost that has been used as a reliable reference by both buyers and sellers in the wholesale markets for LCD panels. Experienced analysts at the data vendor have built and maintained this model by reverse-engineering the detailed cost breakdown of all possible fab-product combinations. With advice from their lead analyst, we were able to extract relevant information from the fab-investment records and use it as an input to the cost model. Its output is a collection of cost estimates for all product-fab-firm combinations in all calendar quarters. Our descriptive analysis employs this and two other databases (on sales and investments) to provide direct evidence on product and process innovations, such as rapid turnover of products, notable improvements in their characteristics, and the details of cost reductions driven by technical changes. We also show evidence that these wholesale price reductions were passed on to final goods markets.

The second stage of our analysis is the estimation of a structural model of the spot market. On the demand side, we use a random-coefficient nested-logit model for differentiated products, where we incorporate heterogeneous price-sensitivity among buyers based on the geographical distribution of end-users. The estimated demand system translates the changes in available products and their prices into the changes in compensating variation, a standard measure of demand-side surplus. We found an improvement in BS of $25 billion between 2001:Q1 and 2011:Q4, which translates into a more than 99.9% reduction in prices if converted to a cost-of-living index.[1] This result suggests that even though the decrease in average price per square meter is large (88.1%), such a direct measure still underestimates the true extent of welfare gains from innovations.

Our specification of the supply side builds on the demand estimates and exploits the availability of the cost data as follows. Based on the combination of demand estimates and cost data, we compute equilibrium prices under hypothetical monopoly and Bertrand competition, respectively. We then statistically test which of these prices is closer to the price in the data. Our tests favored monopoly pricing in the first 15 quarters and Bertrand competition for the rest of our sample period, respectively, which is broadly consistent with the existence of an infamous price-fixing cartel between 2001:Q4 and 2006:Q1. Accordingly, all of our counterfactual simulations in the subsequent analyses commonly assume monopoly pricing and Bertrand competition in these subsample periods, respectively.

In the third stage of our analysis, we conduct three sets of counterfactual simulations to measure the welfare impact of each type of innovation. Product innovation is the focus of the first set of counterfactuals, in which we hypothetically eliminate (i) larger new products, (ii) other new products, and (iii) both of them, respectively. In each t of each scenario, we recompute equilibrium prices, sales, BS, and PS. Similarly, the second set of counterfactuals measures the impact of process innovation by hypothetically removing the productivity contributions of (iv) vintage capital, (v) learning by doing, and (vi) both of them, respectively. In the third set of counterfactuals, we reclassify innovations according to the technological generation of fab equipment, each of which embodies a bundle of (i) specific larger new products that require it and (iv) a specific level of cost reduction associated with its vintage. The rationale for this reclassification is that these specific innovations are physically rooted in new-generation fabs and amenable to benefit-cost calculations.

Results suggest product and process innovations contributed up to $432 billion (71%) and $212 billion (35%) to the total surplus (TS) during our sample period, respectively.[2] We found substantial heterogeneity across markets (applications): product innovation was more important in the nascent market for LCD TVs, whereas process innovation was the main driver of welfare gains in the more mature markets for notebook PCs and desktop monitors. Hence, the relative importance of product and process innovations depends on

[1] The cost-of-living index falls exponentially with per-capita surplus. The introduction of new products from a high reservation utility base can easily drive the index close to zero.

[2] The two percentages are not meant to add to 100% because they come from separate counterfactuals.

the phase of the product life cycle. After the reclassification of innovations by technological generation, we find advanced fabs (5G–10G) contributed \$113 billion to TS relative to the initially available generations of fabs (4G–4.5G). The discounted present value (DPV) of social benefits from 5G–10G investments is positive even at a relatively high annual discount rate of 10%. However, the DPV of net producer benefits is negative at any discount rate above 3.18%, suggesting that the industry as a whole would have been better off without these technologies. Nevertheless, the realized returns on investment were reasonably high at two of the seven major firms. Hence, there were both winners and losers from the industry-wide shift to new technologies.

In the fourth and final stage of our analysis, we leverage our accounting framework in the above to further investigate the relationship between market structure and the return on technological investment. Specifically, we hypothetically reduce the number of major firms (held constant throughout the sample period) from seven to six, five, four, three, two, and one, simulating all of the 4,803 sequential pairwise combinations. We find that the majority of these mergers lead to decreases in the DPVs of both TS and the industry-wide sum of private gains from investments. Thus, absent merger-specific efficiency gains (which we do not assume), justifying mergers on the grounds of positive innovation effects would seem difficult.

We have organized the rest of the paper as follows. The remainder of this section reviews the related literature and clarifies our contributions. Section 2 explains our conceptual framework. Section 3 provides background information on the industry, technology, and data. Section 4 documents descriptive evidence. Section 5 presents our demand model and reports estimation results, along with their implications for welfare and supply-side conduct. Section 6 quantifies the gains from innovations. Section 7 investigates the relationship between market structure and firms' incentives to innovate. Section 8 concludes. The Online Appendix contains supplementary materials for sections 4–7.

Related Literature. Previous works studying product innovation, including Trajtenberg (1989), Hausman (1996), Petrin (2002), Ciliberto, Moschini, and Perry (2019), and Grieco, Murry, and Yurukoglu (2024), have primarily relied on discrete-choice demand models and sales data. Without data on costs and investments, however, these studies must rely on assumptions about firms' conduct to identify marginal costs and cannot compute returns on investment. We complement this literature by using engineering cost data, the value of which has been reappreciated by Genesove and Mullin (1998), Asker, Collard-Wexler, and de Loecker (2018), and Agarwal et al. (2019).

Existing studies on process innovation have either estimated total-factor productivity from census-style data (c.f., Syverson 2011) or focused on detailed administrative data on a single product (Benkard 2000), single plant (Levitt, List, and Syverson 2013), or single division of a firm (Sinclair, Klepper, and Cohen 2000). The combination of demand estimation and industry-wide cost data allows us to assess the quantitative importance of both product and process innovations on a global scale.

The literature on the rate of return on technological investments has mostly relied on R&D and patent data (Hall, Mairesse, and Mohnen [2010], Aghion et al. [2005]), but they suffer from various measurement issues (Lerner and Seru 2022). We exploit the availability of direct measures of innovation and the institutional context in which fabs (i.e., capital expenditure) are the single most important vehicle of technological investments, which provides a clear lower bound on the economic costs of innovation.

This paper also adds to the growing literature on innovative industries in empirical IO: Benkard (2004), Goettler and Gordon (2011), Conlon (2012), Igami (2017), Björkegren (2019), Yang (2020), Igami and Uetake (2020), Mohapatra and Zhang (2024), Qiu (2023), Dix and Lensman (2025). Whereas they use dynamic structural models, we leverage the granularity of our data—which cannot be fully accommodated in dynamic oligopoly models due to computational limitations—by keeping our framework as simple as possible.

2 Conceptual Framework

This section explains our approach to quantifying the benefits and costs of innovations, clarifying our accounting framework before introducing data and econometrics.

Setting. For each of N oligopolistic firms (indexed by f), we observe its product portfolio $\mathcal{J}_{f,t}$ and production technology $\mathcal{C}_{f,t}$ at two different points in time; before ($t = 0$) and after ($t = 1$) innovations. We also know the demand system, the firms' variable-profit functions, their competitive conduct, and the fixed cost FC_f of investment in their respective innovations.

We use the following "two-period model" as an accounting framework. We put the word "model" in quotation marks because we do not intend to solve it for any equilibrium of the overall (unspecified) investment game, focusing instead on the measurement of realized returns in the data. We discuss this modeling choice at the end of this section.

At $t = 0$, each firm is endowed with an initial set $\mathcal{J}_{f,0}$ of differentiated products and an initial production technology (a set of cost functions $\mathcal{C}_{f,0} = \{C_{j,0}\}_{j \in \mathcal{J}_{f,0}}$, where j is an index for products). Each firm can pay FC_f to improve their products and processes from $(\mathcal{J}_{f,0}, \mathcal{C}_{f,0})$ to $(\mathcal{J}_{f,1}, \mathcal{C}_{f,1})$. Because we are interested in comparing the outcomes *with* and *without* all/only innovations, we restrict our attention to only two actions, $a_f \in \{0, 1\}$, where $a_f = 0$ means not investing in any improvements, and $a_f = 1$ is investing in all of the actual innovations in the data.

In each period, the firms observe the profile of all products and technologies, $\mathcal{J}_t = \bigsqcup_{f=1}^{N} \mathcal{J}_{f,t}$ and $\mathcal{C}_t = \bigsqcup_{f=1}^{N} \mathcal{C}_{f,t}$, and participate in spot-market competition (the set of all products is a disjoint union of all firms' products because we regard firm identity as a product characteristic). If their competitive conduct is Bertrand competition, firms independently set prices $p_{f,t} = (p_{j,t})_{j \in \mathcal{J}_{f,t}}$ to maximize their respective profits, $\pi_{f,t} = \sum_{j \in \mathcal{J}_{f,t}} \pi_{j,t}$; otherwise, they charge some other prices (to be specified in section 5.3). The profit from each product is $\pi_{j,t} = (p_{j,t} - c_{j,t}) \times q_{j,t}$, where $c_{j,t}$ is the cost of producing j given technology $\mathcal{C}_{f,t}$ and $q_{j,t} = D_j(p_t; \mathcal{J}_t)$ is the quantity demanded of product j, which is a function of the prices of all available products, $p_t = (p_{j,t})_{j \in \mathcal{J}_t}$, and their characteristics (to be specified in section 5.1).

Firm-Level Gains. Let $\mathcal{J}_{-f,t}$ and $\mathcal{C}_{-f,t}$ denote all non-f firms' products and technologies, respectively. Given all rivals' innovations ($a_{f'} = 1$ for all $f' \neq f$), firm f's gain from innovation ($a_f = 1$) is

$$
\begin{aligned}
\Delta \pi_f &= \pi_{f,1}(a_f = 1, a_{-f} = 1) - \pi_{f,1}(a_f = 0, a_{-f} = 1) - FC_f \\
&= \pi_f(\mathcal{J}_{f,1}, \mathcal{C}_{f,1} | \mathcal{J}_{-f,1}, \mathcal{C}_{-f,1}) - \pi_f(\mathcal{J}_{f,0}, \mathcal{C}_{f,0} | \mathcal{J}_{-f,1}, \mathcal{C}_{-f,1}) - FC_f,
\end{aligned} \tag{1}
$$

where $a_{-f} = 1$ means $a_{f'} = 1$ for all $f' \neq f$. The first equation defines firm f's gain relative to its unilateral deviation ($a_f = 0$) from the observed action. The second equation makes the dependence of $\pi_{f,t}$ on $(\mathcal{J}_t, \mathcal{C}_t)$ explicit.

Industry-Wide Gains. We consider two measures of industry-wide gains. One sums the firm-level gains across firms,

$$SII = \sum_{f=1}^{N} \Delta\pi_f, \tag{2}$$

which we refer to as the sum of individual incentives (SII). The other compares producer surplus (PS), $PS_t = \sum_{f=1}^{N} \pi_f(\mathcal{J}_t, \mathcal{C}_t)$, with and without innovations net of fixed costs:

$$ICI = \Delta PS - \sum_{f=1}^{N} FC_f = (PS_1 - PS_0) - \sum_{f=1}^{N} FC_f = PS(\mathcal{J}_1, \mathcal{C}_1) - PS(\mathcal{J}_0, \mathcal{C}_0) - \sum_{f=1}^{N} FC_f. \tag{3}$$

It measures the extent to which the industry as a whole benefited from all investments. Hence, we call it the industry's collective incentive (ICI).

Total/Social Gains. We measure total (social) gains from innovations as follows. The demand system, production technology, and the mode of competition co-determine the prices, sales quantities, and buyer surplus (BS) in spot-market equilibrium as functions of $(\mathcal{J}_t, \mathcal{C}_t)$. Hence, the impact of all innovations on BS is

$$\Delta BS = BS_1 - BS_0 = BS(\mathcal{J}_1, \mathcal{C}_1) - BS(\mathcal{J}_0, \mathcal{C}_0), \tag{4}$$

and the social gain in total surplus (TS) is

$$\Delta TS = \Delta PS + \Delta BS. \tag{5}$$

Product and Process Innovations. So far, we have treated all kinds of innovations as a bundle, but we can isolate the contributions of specific innovations as well. For example, the impact of product innovation is identified by the comparison of outcomes under $(\mathcal{J}_1, \mathcal{C}_1)$ and $(\mathcal{J}_0, \mathcal{C}_1)$. Likewise, the impact of process innovation can be measured by comparing outcomes under $(\mathcal{J}_1, \mathcal{C}_1)$ and $(\mathcal{J}_1, \mathcal{C}_0)$. We explain further details of innovations in section 3.2.

Effects of Mergers. So far, we have assumed the profile of N firms and their product ownership structure, O, is fixed.[3] In section 7, we alter them to simulate the effects of

[3]Ownership structure O is the partitioning of all products across firms. We introduce this notation for expositional convenience, even though it is slightly redundant (we have already defined $\mathcal{J}_{f,t}$ for each firm).

mergers. Consider a hypothetical merger between firms f and f'' to create the merged entity f' at the beginning of $t = 0$. The number of firms decreases from N to $N - 1$. Product ownership changes from O to O', where O' encapsulates two changes: (i) $\mathcal{J}_{f,t} = \mathcal{J}_{f'',t} = \varnothing$ for all t, and (ii) $\mathcal{J}_{f',t} = \mathcal{J}_{f,t} \bigsqcup \mathcal{J}_{f'',t}$ for all t. In words, (i) the product portfolios of the merging parties become empty, and (ii) the merged entity inherits all of their products in all time periods. Correspondingly, we assume the merged entity inherits all of their fabs and cost functions: $\mathcal{C}_{f',t} = \mathcal{C}_{f,t} \bigsqcup \mathcal{C}_{f'',t}$ for all t. Its profit is $\pi_{f',t} = \sum_{j \in \mathcal{J}_{f',t}} \pi_{j,t}$. The combined cost of innovation is $FC_{f'} = FC_f + FC_{f''}$. In short, we model a merger as a combination of two product portfolios, their associated cost functions, two sets of innovations, and their fixed costs. We do not assume any additional changes in marginal costs or fixed costs.

The effect of ownership change $O \rightarrow O'$ on the merging firms' gains is

$$\Delta^2 \pi_{f'}(O', O) = \Delta \pi_{f'}(O') - \left(\Delta \pi_f(O) + \Delta \pi_{f''}(O)\right), \tag{6}$$

where the symbol Δ^2 refers to a "change of change" (i.e., how the merger changes $\Delta\pi_f$s, which are themselves the changes in π_fs due to the firms' own innovations). The effect on non-merging firm f''' is simply

$$\Delta^2 \pi_{f'''}(O', O) = \Delta \pi_{f'''}(O') - \Delta \pi_{f'''}(O). \tag{7}$$

Hence, the effect of the merger on all firms' incentives to innovate (SII) is

$$\Delta SII(O', O) = \sum_{f=1}^{N-1} \Delta \pi_f(O') - \sum_{f=1}^{N} \Delta \pi_f(O) = \sum_{f=1}^{N-1} \Delta^2 \pi_f(O', O). \tag{8}$$

Static or Dynamic Framework? Despite its simplicity, this static framework is suitable for our task. Dynamic oligopoly models might appear to offer an attractive alternative, but their main appeal is the ability to simulate *counterfactual* histories of investments. The goal of this paper is to quantify the *realized* returns on actual investments in the data, with as much detail about various types of innovations as possible.[4] Our accounting framework is sufficient for these purposes and can accommodate the rich details in our data.

[4]The combinatorial nature of fab investments (e.g., a firm can potentially invest in multiple fabs of different technological generations in each period) makes the set of possible strategies in a dynamic model extremely large. For computational feasibility, such a model would have to forgo the details of products and fabs in the data.

3 Institutional Background and Data

This section provides background information on the LCD industry and data.

3.1 Industry Background

Main Players and Key Events. Several Japanese firms, such as Sharp, Seiko, and Hitachi, pioneered the development and commercialization of LCD technology since the 1970s, 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, the latter soon became self-sufficient and marginalized the Japanese firms by 2001, the first year of our main dataset.

The dot-com bust in 2001 dampened the demand for many IT products, including notebook PCs and desktop monitors, the two main applications of LCD panels 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 firms. The "crystal cartel" had monthly price-targeting meetings from October 2001 to February 2006, when Samsung and LG applied for corporate leniency programs at the US Department of Justice and the European Commission. Meanwhile, LCD TVs became mainstream household products since the mid to late 2000s.

Most of the Japanese firms exited these (large-area display) markets by the end of the 2000s.[5] The only exception was Sharp, which continued to invest in new-generation fabs. 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. Our analysis will focus on the seven major firms (two Korean, four Taiwanese, and one Japanese) and treat the rest as a competitive fringe.

Supply Chains. LCD panels contain many different components and materials, including sheet glass, color filters, polarizer films, backlights, and liquid crystal. Their suppliers were mostly Japanese firms in the materials, fine chemicals, and electronic device industries. The suppliers of fab equipment were engineering firms from Japan as well.

[5] 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.

The buyers of LCD panels included many final assemblers of notebook PCs, desktop monitors, and TVs around the world, as well as their intermediaries and contract manufacturers, which were typically based in Taiwan or mainland China. The top brand-name buyers in the 2000s were the following: notebooks (HP, Dell, Acer, Lenovo, and Apple), monitors (Dell, HP, Acer), and TVs (Samsung, LG, Sony, Sharp, and Panasonic). Within each segment, the largest firm's market share was 18%–20%, and the five-firm concentration ratio (CR5) was 40%–60%. The Herfindahl-Hirschman index (HHI) was below 1,000.

Most global brands did not buy panels directly but through contract manufacturers—original design/equipment manufacturers (ODMs/OEMs)—which assembled electronics on their behalf, buying components and integrating them into final products.[6] No systematic data exist on ODMs/OEMs or their interactions with panel makers; exactly how the bargaining played out between panel makers, ODMs/OEMs, and brands is unclear.[7]

Despite the prevalence of contract manufacturing, some firms chose to vertically integrate. Samsung and LG manufactured their own TVs, and virtually all Japanese firms were part of conglomerates. Curiously, most of them maintained supply relationships with multiple external parties and did not engage in exclusive dealing with in-house partners. Both Samsung Display and LG Display operated as independent subsidiaries of their respective parent conglomerates.

Trade Costs. The costs of transportation and tariffs were relatively low for LCD panels. IT products and their components generally have high value-to-weight ratios. The supply chains of LCD panels and their final goods were spatially concentrated in East Asia. Moreover, Japan, Korea, Taiwan, the United States, and the European Union (EU) were among the early signatories of the Information Technology Agreement (ITA) at the World Trade Organization (WTO), which had eliminated tariffs on most IT hardware—including LCD panels, PCs, and monitors—by January 1, 2000. China joined the ITA in 2003 as well.

Trade costs played a greater role in the final-good markets, in which products needed to be shipped to other regions. The average transport and insurance costs between East Asia

[6] Taiwanese ODMs manufactured over 90% of the world's notebook PCs in the 2000s; key players were Quanta, Compal, Wistron, Inventec, Pegatron, and Foxconn. For monitors, notable ODMs were TPV, Innolux, Foxconn, Wistron, Qisda, Compal, Lite-On, and Proview. For LCD TVs, TPV, AmTRAN, Quanta, Proview, Vestel, Wistron, Jabil, Foxconn, Changhong, and Skyworth had a significant presence.

[7] Contractual details, such as duration and volume discounts, are also unclear. Long-term contracts, spot-market transactions, and procurement auctions were known to coexist. However, given the rapid decline of LCD prices, any quantity pre-commitment at fixed prices beyond 1–3 months would seem unsustainable unless contractual prices were allowed to change based on spot prices.

(as origins) and the OECD countries (as destinations) were 4%–6% of the value of goods in the 2000s.[8] Additionally, LCD TVs were subject to some import tariffs in many countries (e.g., 3.9% in the United States) because the ITA did not cover consumer electronics.

Government Support. The types of government support varied across countries. In Japan, some of the government-supported R&D consortia covered displays, and certain regional governments facilitated land acquisitions to attract fab investments. The governments of Korea and Taiwan also provided indirect support, such as R&D funding, infrastructure improvements (e.g., roads, power, and water), and tax breaks. However, we found no evidence on direct subsidies for fab equipment or manufacturing costs in these countries. More aggressive direct subsidies became more prominent in China in the 2010s. Some reports allege that government subsidies covered 50%–70% of investment costs for display manufacturers.[9] These subsidies and the rise of Chinese firms in the 2010s are outside the scope of this paper (our main dataset ends in 2011).

3.2 Production Technology

Fabrication Plants and Equipment. The production technology is capital-intensive—firms have to spend billions of dollars to purchase fab equipment. The machines were developed, manufactured, and sold by several engineering firms in Japan. It also required knowledge and experience, as production engineers had to tune each machine to improve "yield," the fraction of products without defects. Once these physical requirements were satisfied, the costs of basic inputs such as labor and electricity were critical for the firm's competitiveness, as the exit of (relatively high-cost) Japanese firms illustrated.

Hundreds of physically differentiated products appear in our data, but all of them could in principle be produced at a single fab, as long as their basic physical requirements are met (i.e., fab equipment must be capable of handling input sheet glass at least as large as the output panel size. Thus, the technological generation of a fab is defined by the size of the input glass. The most advanced fabs in 2001:Q1 used fourth-generation (4G) equipment or its variant (4.5G), which processed 730mm×920mm input glass and produced up to 40-inch panels. The frontier technology gradually shifted to 10G (2,850mm×3,250mm) by 2011:Q4.

[8] The International Transport and Insurance Costs of Merchandise Trade (ITIC) database of the OECD.
[9] See, for example, this article by Reuters (link)

Product and Process Innovations. We define and categorize innovations in LCD production by following Schumpeter's (1934) classical definition of economic innovation as a "new combination of productive means" (page 66), regardless of whether it relies on new scientific discoveries or patented inventions. We have chosen this economic—rather than scientific or legal—definition for its direct relevance to welfare analysis, as well as its capability to quantify and compare various types of innovations in dollar values.

Under this umbrella definition, we focus on two categories: (i) "the introduction of a new good or of a new quality of a good," which we refer to as product innovation, and (ii) "the introduction of a new method of production," which we refer to as process innovation. Empirically, we categorize all goods that were not available in 2001:Q1 (our initial sample period) as new goods. Similarly, we categorize any changes to the LCD production process that systematically improved productivity (relative to a brand new fab in 2001:Q1) as process innovations, including the use of new-generation fab equipment ("vintage capital") and the yield improvement through experimentation ("learning by doing").

An important feature of LCD innovations is that an investment in new-generation fabs can deliver (a subset of) both product and process innovations. New products with larger panels required larger input glass sheets, which only more advanced fab equipment could handle. A 42-inch TV could not be manufactured at a 4G fab, for example. More advanced fabs also enjoyed lower manufacturing costs per product, because the fixed cost of processing a larger input glass did not increase as much as the surface area of output panels. That is, slicing a single sheet of large input glass into many output panels is cheaper than producing them from many smaller sheets. For these reasons, our analyses from section 6.3 onward treat each new generation of fab technology as a bundle of (A) larger new products and (B) cost reductions for all products due to vintage-capital effects.

3.3 Data

Our main data 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, costs, and investments.

Database 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.[10] 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, $1,280 \times 800$ 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.

Database 2: Manufacturing Costs. The second database contains the average unit cost of manufacturing each product at each fab on a quarterly frequency between 2000:Q2 and 2016:Q4. We constructed this database from the engineering cost model (and the list of all fabs and their technological specifications) from *Display Search*. Their cost model is designed to replicate the cost of any product at any fab in each period. As inputs, the user specifies the characteristics of the product, fab, and firm.[11] The cost model calculates the amount of materials, components, intermediate inputs, and hours worked that are needed to make the product, based on the specific equipment of the fab and the fab-generation-specific patterns of yield improvements over time.[12] These input requirements are combined with data on input prices to calculate item-by-item expenditures.[13] The output of the cost model is a collection of spreadsheets, each of which corresponds to a specific pair of a fab and a product, with average unit cost in each period and its breakdown across rows, and time periods across columns. These cost estimates at the level of product-fab-firm-quarter are merged with Database 1 by finding the lowest-cost fab within each product-firm-quarter and matching it with the product-firm-quarter observation in the sales data. Thus, our cost data rely on the precision of their engineering model and its underlying data.

[10] Transaction-level prices and quantities are not available, which precludes the analysis of buyer-specific discounts or other contractual details.

[11] The user specifies the following characteristics: (1) the calendar year-quarter in which the fab started mass production, (2) the size of the input glass that its equipment can handle (i.e., the fab's technological generation), (3) the application, size, resolution, and backlight of the output LCD panel, (4) the firm's "tier" $\in \{1, 2, 3\}$, which captures its level of technological sophistication as well as bargaining power in input procurement, (5) whether the fab uses the one-drop-fill (ODF) method of combining glass sheets with liquid crystal, (6) whether color filters are manufactured in-house or purchased from external suppliers, (7) the number of work shifts, (8) capacity utilization, and (9) the share of selling, general, and administrative (SG&A) expenses in overall costs. The method of depreciation accounting can also be specified, but we did not include depreciation as part of variable costs.

[12] The staff analysts visit all fabs every year, check capacity utilization and yield improvements, and aggregate their estimates at the level of fab generations.

[13] The prices of all key materials and components for LCD panels are recorded, including sheet glass, sputtering targets, liquid crystal, color filters, polarizer films, backlights, printed circuit boards, and driver integrated circuits (see Appendix A.2 for details). The database also includes wage rates as well as the costs of water, electricity, and other intermediate inputs in Japan, Korea, Taiwan, and mainland China.

Database 3: Investment in New Fabs. The list of fabs that we mentioned above contains a comprehensive record of all major firms' investments in new fabs at a monthly frequency between December 1994 and July 2024. For each of the 572 fabs, we observe (a) the technological generation of its manufacturing equipment, (b) production capacity[14], and (c) the timing of investment. *Display Search* also collected (d) the typical dollar cost of fab equipment and building for each generation. Based on (a), (b), and (d), we calculated the cost of each fab investment. The timing record (c) includes time stamps of monthly frequency at 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. We recognize the cost of fab investment when it starts volume production (mass production ramp).[15]

4 Descriptive Evidence

This section describes key data patterns. Sections 4.1 and 4.2 present descriptive evidence on product innovations, as well as basic facts about outputs and market structure. Sections 4.3 and 4.4 do the same for process innovations, exploiting our detailed cost data. Section 4.5 shows the producers' revenues, profits, and cash flow (net of fab investments). Section 4.6 summarizes additional findings about the demand side of the market.

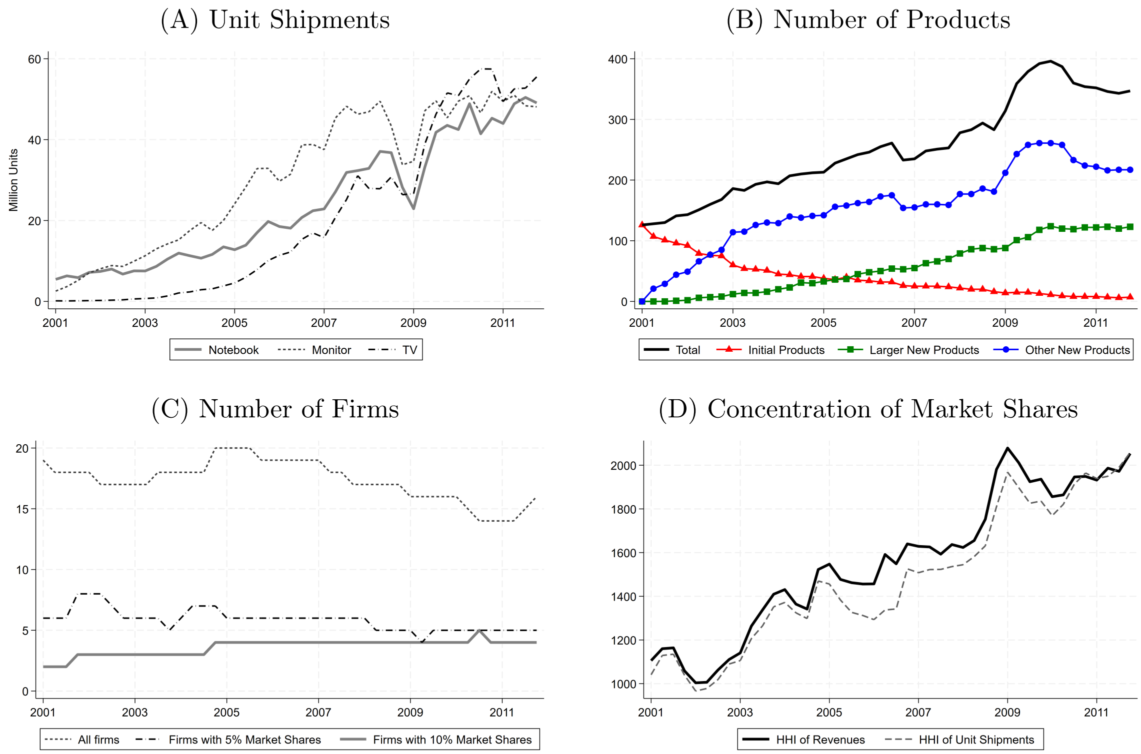
4.1 Outputs, Number of Products, and Market Structure

Figure 2 summarizes outputs, the number of products, and market structure. Panel A shows that notebook PC was the main application in 2001 in terms of shipment volume, but desktop monitors surpassed notebooks in 2002 as LCD monitors started replacing cathode ray tube (CRT) monitors. LCD TVs became popular first in East Asia around 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. Given the relative novelty of LCD panels, most of the purchases of LCD monitors and LCD TVs were replacing their CRT counterparts, not previously purchased LCD products (see section 4.6).

[14] Production capacity is measured in the increment of 30,000 input glass sheets per calendar quarter.

[15] An alternative is to use accrual-based depreciation accounting, spread the cost of capital expenditure across 4–6 years, and recognize it as part of the unit cost of manufacturing. However, accounting rules vary across countries and would add ambiguity to the measure of manufacturing cost.

Figure 2: Outputs, Number of Products, and Market Structure



Note: See the main text for definitions and other details.

Panel B reports the steady increase in the number of products, which we split into three categories: initial products, larger new products, and other new products. The "initial products" are those available in 2001:Q1, the largest of which were 15.7-inch notebooks, 24-inch monitors, and 28-inch TVs. We classify any larger products as "larger new products." Meanwhile, "other new products" represent other new combinations of size, resolution, and backlight type.[16]

Panel C shows that the total number of firms (dotted line) fluctuated between 14 and 20, with a peak around 2005. Many of them were Japanese electronics firms that became marginalized by lower-cost rivals from Korea and Taiwan. The dashed and solid lines count only firms with market shares above 5% and 10%, respectively, typically between 4 and 6.

Panel D captures the gradual increase of market-share concentration measured by the HHIs based on revenues and unit shipments, respectively. The initial increase in 2001–2005 reflects the decline and exit of fringe firms; the rapid increase in 2008–2009 was driven by the growing dominance of Samsung and LG, which expanded market shares during and

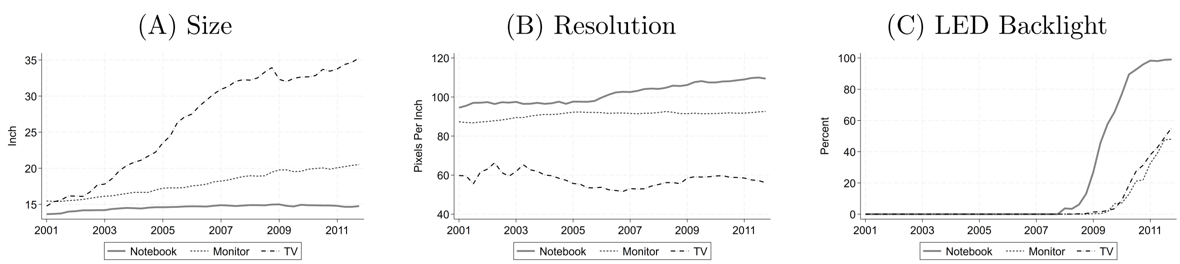
[16]The number of available products roughly tripled from 2001 to 2011, with rapid turnovers.

after the Great Recession at the expense of weaker rivals in Taiwan. With the HHIs in the range of 1,000–2,000, the LCD industry in 2001–2011 was moderately concentrated—more concentrated than any of the three downstream markets (see section 2.1).

4.2 Product Characteristics

Figure 3 provides further details of product innovations by plotting average product characteristics over time. Panel A shows that the average size of LCD TVs grew from 15 to 35 inches, while the average monitor size grew from 15 to 21 inches. The change for notebooks was less dramatic (from 13.6 to 14.8 inches).

Figure 3: Product Characteristics



Note: Panel A and B display shipment-volume-weighted average characteristics by application. Panel C plots the percentage of panels with LED backlights (instead of CCFL backlights) in the total shipments.

Panel B shows that the improvements in notebook panels occurred mostly in terms of picture quality: the average resolution increased from 95 to 109 pixels per inch (PPI). The average monitor resolution grew more modestly from 87 to 93 PPI. TVs recorded a slight decrease from 60 to 56 PPI because a larger panel size mechanically reduces PPI unless the number of pixels increases at the same rate.[17]

Panel C plots the percentage of LCD panels with LED backlights. Notebooks were the first to switch to LED backlights from cold cathode fluorescent lamps (CCFL) ones, because LEDs' lower power consumption was essential for mobile devices. TVs were slower, but 55% of them used LED backlights in 2011:Q4. The LED adoption rate among monitors was 48% in 2011:Q4.

In summary, LCD panels for all applications exhibited improvements in some or all observed characteristics. Whether and how much of these product innovations contributed

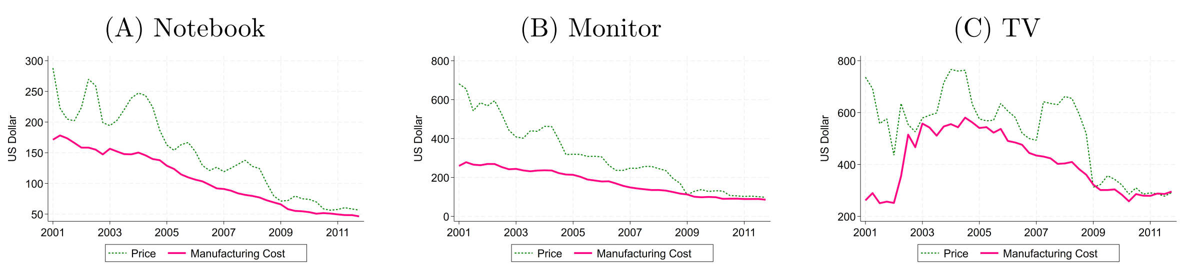
[17]For example, a 15-inch panel with 1,024×768 pixels (a typical configuration in 2001:Q1) contains 85 pixels per square inch, whereas a 42-inch panel with 1,920×1,080 pixels (typical in 2011:Q4) has only 52 PPI — despite containing more than twice as many pixels overall — because its surface area is much larger.

to economic surplus is the question that we seek to answer in sections 5 and 6.

4.3 Prices and Manufacturing Costs

Figure 4 displays average unit prices and manufacturing costs by application. Between 2001 and 2011, average prices dropped by \$232 (80%) for notebooks, \$584 (86%) for monitors, and \$445 (60%) for TVs. The fact that prices fell while the HHIs increased (Figure 2, Panel D) and product qualities improved (Figure 3) might appear counterintuitive, but the speed of cost reduction explains most of these price reductions. The average manufacturing costs dropped by \$125 (73%) for notebooks and \$174 (67%) for monitors. In the case of TVs, the average cost increased in the first two years, during which the volume production of much larger panels (30 inches and above) started and pushed up costs. Between 2003 and 2011, the average prices and costs of TVs fell by \$288 (50%) and \$262 (47%), respectively. Thus, both prices and costs exhibit secular downward trends over most of the 11 years. However, in the shorter run, prices moved cyclically while costs did not. The cyclical nature of IT demand explains this pattern—see Matthews (2005) for a detailed account of "crystal cycles," in which small shifts in demand can lead to larger swings in prices.

Figure 4: Prices and Manufacturing Costs



Note: Prices and manufacturing costs are averaged across all available products in each calendar quarter.

In terms of markups, the price-cost margin for notebooks and monitors shrank over time because of three historical developments. First, the crystal cartel engaged in price-fixing until February 2006 (see section 2.1). Second, the Great Recession reduced demand in 2008:Q4–2009:Q2, with some lingering effects. Third, none of the major firms exited the industry; some of them kept building new fabs despite the recession, adding excess capacity and putting downward pressure on prices.

The evolution of markups was more complicated in the TV market. The initial shift to larger sizes in 2002–2003 temporarily squeezed markups, but in 2004, the first boom in demand (in East Asia) increased prices and markups. Another price upswing in 2007 also coincides with the boom in North America and Western Europe.

Overall, neither product nor process innovation seems to have improved markups in the long run, even though newer products and processes did tend to command higher markups in the short run (see Appendix A.1 for a comparison of markups across technological generations). Most of the cost reductions were passed on to the wholesale prices, which in turn were passed on to retail prices (see section 4.6).

4.4 Determinants of Manufacturing Costs

What drove these rapid cost reductions? We need a parsimonious cost function to simulate the absence of process innovations in section 6. We quantify the relationships between cost and its determinants by running regressions of the following form: the cost of manufacturing product j in fab k (of firm f) in year-quarter t is

$$\ln c_{jkt} = \underbrace{\sum_{g} \theta^{g} \mathbb{1}\{gen_k = g\} + \sum_{a} \theta^{a} \mathbb{1}\{age_{kt} = a\} + \theta^{odf} odf_k}_{\text{process innovations}} + \theta^{cf} cf_{kt} + \sum_{l} \theta^{l} \mathbb{1}\{capa_{kt} = l\} + \underbrace{\tilde{\delta}_t + \tilde{\delta}_{f(k)} + \tilde{\delta}_j}_{\text{time, firm, \& product dummies}} + \eta_{jkt}, \quad (9)$$

where $\mathbb{1}\{gen_k = g\}$, $\mathbb{1}\{age_{kt} = a\}$, odf_k, cf_{kt}, and $\mathbb{1}\{capa_{kt} = l\}$ are indicators for generation-g fab, age-a fab, the ODF method,[18] in-house manufacturing of color filters, and capacity utilization (bin l in a discretized grid with 5% intervals), respectively. The dummy variables $\tilde{\delta}_t$, $\tilde{\delta}_{f(k)}$, and $\tilde{\delta}_j$ are fixed effects for time, firms, and products, respectively. The error term η_{jkt} reflects measurement errors. The coefficients θ^g, θ^a, θ^{odf}, θ^{cf}, and θ^l represent the effects of the first five factors, of which θ^g, θ^a, and θ^{odf} are the changes in physical productivity that directly relate to the firm's fab-investment decisions.[19] These parameters will be manipulated to simulate costs in the absence of process innovations. (e.g., by setting $\theta^g = 0$) in section 6.2.

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

[19]By contrast, θ^{cf} merely reflects the internalization of the rent of an upstream industry, not a physical improvement, and θ^l is a scale economy within a given process. The time fixed effects $\tilde{\delta}_t$ reflect changes in the costs of materials and components, some of which can be attributed to the upstream firms' innovations. Other fixed effects do not vary over time.

Table 1 reports the estimates. Column 1 uses a linear specification for all variables, whereas column 2 uses a full set of dummies as shown in (9). Both specifications achieve extremely high fit with the adjusted R^2 of 0.971 and 0.99, respectively. Recall that we generated our cost data from *Display Search*'s engineering cost model. Hence, we can control for literally all factors that go into this model. Our regressions are effectively reverse-engineering their engineering model with relatively simple parameterization.

Table 1: Determinants of Manufacturing Cost

Specification	(1)		(2)	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.
A. Fab specs				
Tech. gen.	-0.045	(0.000)	–	(–)
Fab age	-0.003	(0.000)	–	(–)
ODF method (θ^{odf})	-0.102	(0.001)	-0.005	(0.001)
In-house CF (θ^{cf})	-0.025	(0.001)	0.003	(0.001)
Capa. util.	-0.178	(0.003)	–	(–)
B. Firm specs				
Tier-1	-0.192	(0.003)	-0.081	(0.002)
Korea	-0.101	(0.001)	–	(–)
Taiwan	-0.280	(0.003)	–	(–)
C. Product specs				
Surface area	0.926	(0.001)	–	(–)
Monitor	-0.106	(0.001)	–	(–)
TV	0.091	(0.002)	–	(–)
LED (edge)	0.111	(0.001)	–	(–)
LED (direct)	-0.063	(0.001)	–	(–)
D. Time and others				
Time	-0.034	(0.000)	–	(–)
Constant	14.292	(0.012)	5.354	(0.015)
Tech. gen. dummy (θ^g)	No		Yes	
Fab age dummy (θ^a)	No		Yes	
Capa. util. dummy (θ^c)	No		Yes	
Firm dummy ($\tilde{\delta}_{f(k)}$)	No		Yes	
Product dummy ($\tilde{\delta}_j$)	No		Yes	
Time dummy ($\tilde{\delta}_t$)	No		Yes	
Number of obs.	340,471		340,471	
R^2	0.971		0.990	
Adjusted R^2	0.971		0.990	

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 are meant to summarize the engineering cost model underlying the data. See Figure 5 for most of the coefficient estimates for column 2.

Linear Estimates. The linear estimates in column 1 of Table 1 portrays basic patterns. The coefficients on the fab-level characteristics (section A) suggest: (i) each new generation of fab equipment reduces cost by $|e^{-0.045} - 1| \times 100 = 4.4\%$ (the same formula is used to translate all other coefficient estimates into percentage changes in the following); (ii) an extra calendar quarter of operation reduces cost by 0.3%; (iii) the ODF method reduces cost by 9.7%; (iv) the in-house manufacturing of color filters reduces cost by 2.5%; and (v) increasing capacity utilization from 0% to 100% reduces cost by 16.3%.

Section B shows the effects of firm-level characteristics. Tier-1 firms, Korean firms, and Taiwanese firms enjoy significant cost advantages relative to tier-2 Japanese firms (omitted category). Tier-1 designation reflects both technological sophistication and bargaining power in input procurement, and is given to several firms in Japan, as well as Samsung and LG, but not Taiwanese or Chinese firms. Hence, the cost gap between these Korean firms and tier-2 Japanese firms is $|e^{-0.192-0.101} - 1| \times 100 = 25.4\%$, whereas Taiwanese firms' advantage is slightly smaller at $|e^{-0.280} - 1| \times 100 = 24.4\%$.

Section C reports the effects of product characteristics. The surface area of a display is measured in the natural logarithm of m^2; hence, the coefficient estimate of 0.926 means that a 1% increase in panel size leads to only a 0.93% increase in cost. Monitors are 10.1% cheaper than notebooks (omitted category), whereas TVs are 9% costlier. Relative to CCFL (omitted category), LED backlights can be either costlier or cheaper depending on their layout ("edge" or "direct").

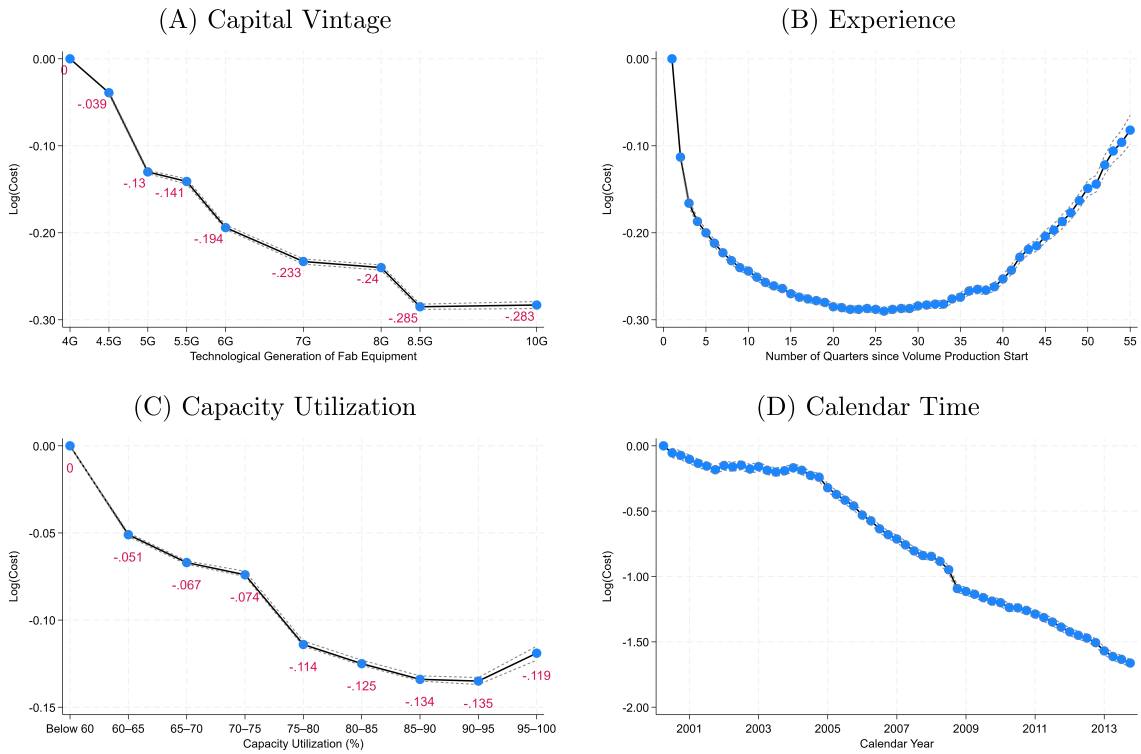
In section D, the time trend reduces costs by $|e^{-0.034} - 1| \times 100 = 3.3\%$ per quarter, or $|e^{-0.034\times 43} - 1| \times 100 = 76.8\%$ over the entire sample period. As we control for all user-specified inputs into the engineering cost model, the only remaining variation across time is the steady decrease of input prices, which we scrutinize in Appendix A.2.

Nonlinear Estimates. Column 2 of Table 1 uses a full set of dummies, the estimates of which we visualize in Figure 5. Panel A reports the cost by generation. Productivity effects are heterogeneous across vintages. For example, the differences between 4G and 4.5G, 5G and 5.5G, and 7G and 8G are relatively small, whereas 5G fabs can produce a given panel at $|e^{-0.13} - 1| \times 100 = 12.2\%$ lower cost than 4G fabs. The most advanced (8.5G–10G) fabs are 24.8% more efficient than 4G fabs.

Panel B shows the age effect by quarter. The learning curve is steep in the first few quarters of volume production (e.g., the cost is 15.3% lower in quarter 3 than in quarter 1). Yield improvement continues until quarter 26 (year seven), at which point the cost is 25.2% lower than in quarter 1. Subsequently, physical depreciation (wear and tear) dominates the positive impact of learning by doing.[20]

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

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 1. 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.

Panel C shows how specific levels of capacity utilization affect productivity. For example, 60%–75% utilization conveys 5%–7% cost advantage over the baseline rate of below 60% (omitted category). The benefit is even larger (11%–13%) if a fab operates in the 75%–100% utilization range.[21] Most of the fabs operated above 75% in our data—the mean, median, and standard deviation of capacity utilization are 83%, 85%, and 10%, respectively—but never reached 100%.

Panel D shows the time fixed effects. Relatively small changes occurred between 2000 and 2004, but the subsequent improvements were substantial. Overall, cost decreased by

fabs gain experience). The upward-sloping part is intriguing but unlikely to affect the overall competitive landscape because a six-year-old fab is officially obsolete (i.e., fully depreciated in terms of financial accounting) and because most of the major firms kept adding newer-vintage fabs every 1–2 years—their firm-level competitiveness depended on the latest fabs, not older ones.

[21] These discrete jumps arise from the lumpiness of worker-rotation schedules. Machines run for 24 hours a day. Meanwhile, four groups of workers take turns to perform three 8-hour shifts per day (daytime, night, and midnight shifts). The fourth shift is a break.

approximately $|e^{-1.284} - 1| \times 100 = 72.3\%$ between 2001:Q1 and 2011:Q4.

Summary. These findings clarify the major productivity effects of both vintage capital (new generations of fabs that embody new technologies) and learning by doing (better use of physical assets via yield engineering). Each of these process improvements contributed to the reduction of manufacturing costs by approximately 25%–29%. By contrast, scale economy in terms of capacity utilization played only a minor role because most of the fabs operated above 75% of capacity, and unit cost varied by at most 2% within that range.

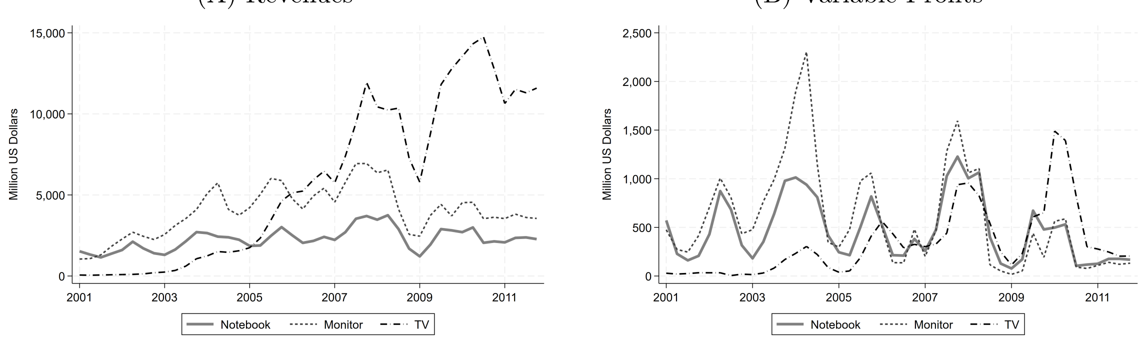
Appendix A.2 presents concrete examples of cost reductions at 4.5G, 5G, and 7G fabs of Samsung, as well as their detailed breakdown for a 17-inch monitor panel. We also report the prices of key materials and components.

4.5 Revenues, Variable Profits, and Cash Flow

Figure 6 compares industry-wide revenues (panel A) and variable profits (panel B) by application. Revenue growth for notebooks and monitors was slow before the recession and stagnant thereafter, whereas TVs recorded faster growth and became the largest application by 2006. However, revenue growth did not necessarily translate into profit growth because price-cost margins shrank (see section 4.3). Aside from the steady rise of TVs, cyclical ups and downs dominate the time series of profits. These patterns suggest that much of the gains from innovations were passed on to the downstream industries, which in turn seemed to transmit most of the benefits to final users (see section 4.8).

Figure 6: Revenues and Variable Profits

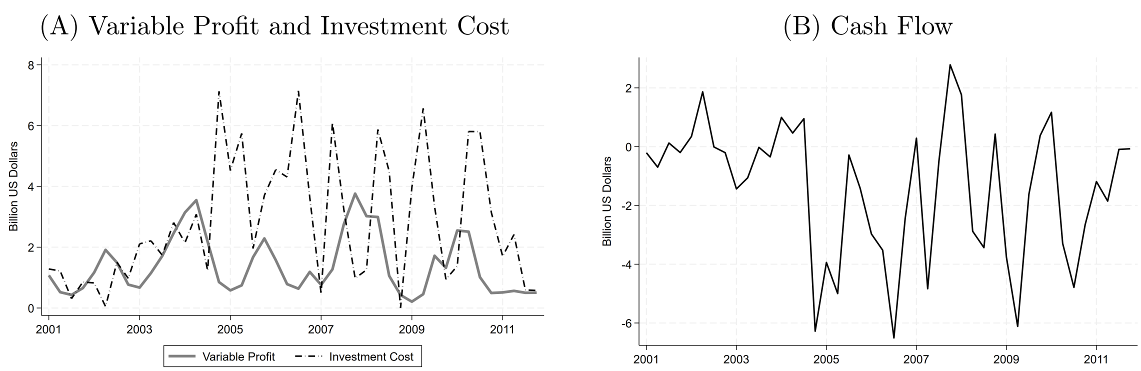
(A) Revenues (B) Variable Profits



Note: For each product, revenue equals total unit shipment times average unit price, and variable profit equals total unit shipment times price-cost margin (i.e., average unit price minus average unit cost).

Figure 7 summarizes the net profitability of the LCD business. Panel A compares the total costs of fab investments (see Appendix A.3 for details) with the total variable profits from all applications (i.e., the sum of profits shown in Panel B of Figure 6). These profits and costs were roughly proportional to each other between 2001:Q1 and 2004:Q3. The situation changed in 2004:Q4–2005:Q2, when many new fabs of 5G–7G technologies started production. The industry-wide investment cost more than doubled during this period, and the intensified investment race continued even after the Great Recession. Panel B plots net cash flow, which we define as the difference between total variable profits and investment costs.[22] The industry-wide cash flow was typically between −\$1 billion and −\$6 billion per quarter. It was negative in 23 out of the 29 quarters since 2004:Q4.

Figure 7: Variable Profit, Investment Cost, and Cash Flow



Note: In Panel A, variable profit is the sum of variable profits in Figure 6 (Panel B) across all applications. Investment cost is the sum of costs for buildings and equipment for all fabs in Figure 12 and recognized in the month of mass-production start at each fab. In Panel B, cash flow is the difference between the variable profit and investment cost in Panel A.

Overall, the LCD industry did not seem to offer lucrative investment opportunities during our sample period. The mostly negative cash flow implies a massively negative return on investment for some producers. Section 6 presents a more formal analysis of their returns on investments, based on the demand and supply model that we estimate in section 5.

4.6 Other Descriptive Evidence

We summarize additional descriptive evidence that relates to the demand side.

[22]For simplicity, we assume that the cash payments for both revenues and manufacturing costs were settled in the same quarters as sales were recorded, and that the capital expenditures were paid in cash at the time of mass production start.

Pass-Through of Wholesale Prices to Retail Prices. Appendix A.4 investigates the extent to which the price reductions in LCD panels benefited the final users of LCD products. Results suggest an almost complete pass-through.

First-Time versus Replacement Purchases. Appendix A.5 examines the relative importance of first-time and replacement purchases of LCD TVs.[23] We find that first-time buyers account for the vast majority of purchases during our sample period.

5 Demand Estimation and Its Implications

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 5.1). Based on the estimates, we calculate the changes in BS between 2001:Q1 and 2011:Q4, as well as the implications for the price index (section 5.2). We also assess the firms' competitive/collusive conduct implied by the combination of the demand estimates and the data on prices and costs (section 5.3).

5.1 Model and Estimates

The demand for large-area LCD panels is derived from the final-good demand for notebooks, monitors, and TVs, which we treat as separate markets. Their supply chains involve many intermediaries, including contract manufacturers, brand names, and wholesale/retail traders (see section 3.1). We abstract from these details and use a random-coefficient nested-logit model as a flexible functional form to capture the overall demand-side response to product prices and qualities. Hence, we have to be careful about the interpretation of the "utility" function, which we discuss at the end of this subsection.

Model. We define the size M_t of each application market to be the current total population of the countries that belong to the Organization for Economic Co-operation and Development (OECD), a club of relatively high-income countries.[24] Our results are not sensitive to M_t (see Appendix B.4) because we include a full set of time dummies in the following. Meanwhile,

[23]We do not study this issue for notebooks and monitors, because the repurchasing cycle of PCs is known to be driven by semiconductors and software, not LCD panels.

[24]We use data from the World Bank on the population and income levels of the OECD member countries for which complete time series are available. These variables exhibit secular growth trends over time.

the distributions of average income and geographical locations across countries generate heterogeneity among buyers.

For exposition, let us tentatively ignore the complexity of the supply chains and assume each buyer is an individual end-user of the final good. Buyer i's utility from product j—defined by characteristics (i)–(v) in section 3.3—in year-quarter t is

$$u_{ijt} = \alpha_{it} p_{jt} + \sum_{s} \beta^{s} \mathbb{1}\{size_j = s\} + \beta^{r} \ln ppi_j + \beta^{b} led_j + \gamma_{f(j)} + \tau_t + \xi_{jt} + \zeta_{ist} + (1-\rho)\varepsilon_{ijt}, \quad (10)$$

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, $\gamma_{f(j)}$ and τ_t are firm and time effects, respectively, ξ_{jt} represents unobserved product quality, and ζ_{ist} and ε_{ijt} are buyer-specific preference shocks. 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 also Gumbel. We normalize the value of the outside good ($j = 0$) as $u_{i0t} = \varepsilon_{i0t}$.[25] 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 $\alpha_{it} = \frac{\alpha}{y_{it}} \times (1 + CFM_{it})$, where α is the baseline price coefficient, y_{it} is the income level of i drawn from the OECD income distribution at t, and CFM_{it} is the transport cost from East Asia to i's location.[26]

Three considerations have led to this specification. First, we try to incorporate the contributions of lower prices and larger sizes with as much flexibility as possible, because these are the primary channels through which process and product innovations improve BS, respectively.[27] Second, we include all observed characteristics (and a full set of firm and time

[25] Previously purchased LCD panels did not play a major role during our sample period. See section 4.6.

[26] We use the CIF-FOB margin in the ITIC database from the OECD as a measure of transport and insurance cost, $CFM_{it} = (CIF_{it} - FOB_{it})/CIF_{it}$, where CIF_{it} is the value of imports including "cost, insurance, and freight," and FOB_{it} is the "free on board" value that does not include any of these costs. See section 3.1 for other trade costs, including tariffs.

[27] The specification of α_i extends Berry, Levinsohn, and Pakes (1999). Its combination with the size-bin nests is similar to Brenkers and Verboven (2006). We have also experimented with various specifications to include an additional random coefficient on the size dimension, including one on $size_j$ as a continuous variable, as well as random slopes on the size-bin dummies. However, these specifications led to highly counter-intuitive estimates of both α and β^{s}_{i} that implied implausibly low price-elasticity and degenerate heterogeneity in the taste for size. One possibility is that the lack of buyer-level microdata precludes their identification. Another possibility is that the nearest sizes are not necessarily the closest substitutes in the current setting because the immediate buyers of LCD panels are downstream manufacturers with production plans that are not flexible across sizes in the short run. Finally, Grigolon and Verboven (2014) show that adding random coefficients and nests on multiple product characteristics could lead to imprecise

dummies) to capture the contributions of product qualities, as well as any other systematic factors. Third, we have chosen not to include time dummies in u_{i0t} because they do not seem to be separately identified from τ_t in our context (see Appendix B.1).

Instrumental Variables. We address the endogeneity concern (that prices p_{jt} and within-nest market shares might be correlated with unobserved quality ξ_{jt}) by using three types of instrumental variables (IVs): (i) the unit cost of production c_{jt}, (ii) a dummy variable indicating the firm's participation in the cartel in 2001:Q4–2006:Q1, and (iii) the measures of product differentiation proposed by Gandhi and Houde (2025).[28] We use the BLP estimation algorithm in Conlon and Gortmaker's (2020) *PyBLP* Python implementation.

The use of the differentiation IVs warrants further discussions in the context of product innovations. If the firms could perfectly predict ξ_{jt} of potential new products and immediately start selling them in the same period, the extent of product differentiation would be correlated with ξ_{jt}. In our empirical setting, however, larger new products require new-generation fabs, the preparation of which takes at least 24 months of planning and implementation. Accurate predictions of ξ_{jt} eight quarters in advance would seem unrealistic. Hence, we assume that the firms do not know the realization of future ξ_{jt} at the time of investment decisions, following much of the literature on the estimation of static demand models.

Estimates. Table 2 reports the parameter estimates. All price coefficients are negative, but their magnitude varies from notebook (more negative) to TV (less negative). The median own-price elasticities are -6.26 (notebook), -6.10 (monitor), and -8.81 (TV), which suggest that lower prices significantly increase utility. The values of the nest parameter are 0.795 (notebook), 0.761 (monitor), and 0.889 (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 30" and above (TV), are particularly popular. The coefficients on the two other physical characteristics (β^r and β^b) are also mostly positive, as expected. Thus, ample room exists for both process and product innovations to improve BS.

The estimates of $\gamma_{f(j)}$ suggest different firms excel in different applications. AUO (reference category) is the top firm in notebooks, followed by Samsung, CPT, and LG. LG is the strongest firm in monitors, followed by Samsung and AUO. The ranking changes again in the

or unreasonable estimates when they are highly correlated with each other.

[28] We use the default differentiation IVs generated by *PyBLP*: for every continuous characteristic, sums of absolute and squared differences (and their interactions), split by within-firm versus rival products.

Table 2: Demand Estimates

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−109.083	14.601	−93.788	4.305	−35.098	2.176
Size nests (ρ)	0.795	0.026	0.761	0.026	0.889	0.027
Size = 12" (β^{12})	1.928	0.062	–	–	–	–
Size = 13" (β^{13})	2.083	0.074	–	–	–	–
Size = 14" (β^{14})	3.356	0.083	–	–	2.104	0.181
Size = 15" (β^{15})	3.069	0.094	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	3.004	0.089	–	–	–	–
Size = 16" (β^{16})	3.417	0.112	4.330	0.089	2.968	0.160
Size = 17" (β^{17})	2.515	0.084	–	–	–	–
Size = 18" (β^{18})	−0.009	0.132	5.320	0.109	2.119	0.180
Size = 20" (β^{20})	–	–	6.027	0.135	4.490	0.183
Size = 22" (β^{22})	–	–	5.434	0.139	3.789	0.197
Size = 24" (β^{24})	–	–	5.165	0.137	3.402	0.185
Size = 26" (β^{26})	–	–	–	–	4.903	0.199
Size = 27" (β^{27})	–	–	4.305	0.158	–	–
Size = 28" (β^{28})	–	–	–	–	3.511	0.269
Size = 30" (β^{30})	–	–	–	–	4.853	0.256
Size = 32" (β^{32})	–	–	–	–	6.653	0.214
Size = 40" (β^{40})	–	–	–	–	6.403	0.232
Size = 45" (β^{45})	–	–	–	–	6.122	0.237
Size = 50" (β^{50})	–	–	–	–	6.168	0.253
Size = 55" (β^{55})	–	–	–	–	6.216	0.286
Size = 60" (β^{60})	–	–	–	–	4.886	0.351
Size $\geq$ 65" (β^{65})	–	–	–	–	5.762	0.384
Resolution (β^r)	1.064	0.138	1.713	0.160	0.240	0.059
LED (β^b)	0.129	0.035	−0.106	0.047	0.364	0.034
Firm = Samsung	−0.038	0.046	0.015	0.043	0.105	0.039
Firm = LG	−0.082	0.048	0.117	0.038	0.062	0.034
Firm = CMO	−0.130	0.053	−0.176	0.044	−0.052	0.041
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.393	0.073	−0.213	0.073	−0.045	0.036
Firm = CPT	−0.046	0.062	−0.146	0.051	−0.092	0.064
Firm = HS	−0.167	0.072	−0.111	0.057	−0.462	0.103
Firm = Others	−0.234	0.045	−0.156	0.053	−0.158	0.045
Constant	−9.983	0.494	−13.890	0.665	−11.300	0.355
Time dummies	Yes		Yes		Yes	
Own elasticity	−6.26		−6.10		−8.81	
1st-stage R^2: price	0.946		0.898		0.921	
1st-stage R^2: share	0.325		0.273		0.329	
337 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.

TV market, where Samsung is the leader, followed by LG, AUO, and Sharp. Although the relative strengths of these firms are broadly consistent with their background (e.g., Taiwan is the global hub of notebook production), the magnitude of these effects is much smaller than that of most other observed characteristics, such as price, size, and resolution.

Interpretations. Before proceeding to the welfare analysis, let us revisit the issue of interpretation. Given that the immediate buyers of LCD panels are mostly contract manufacturers and other intermediaries, we consider three interpretations, of which two are literal and one is functional. The first interpretation is to literally take (10) as the end-user's utility, which is reminiscent of the healthcare literature (e.g., the decision-maker for drug choice is often modeled as a combination of an individual patient and a physician). As extreme as it might first appear, our finding of almost complete pass-through (section 4.6) suggests that the difference between wholesale and retail prices was mostly constant. Such a constant gap will not bias α, the price coefficient.[29] The second interpretation is to take (10) as a reduced-form of the downstream firms' expected profit from production lot i, which targets end-user i (with income y_{it} and location with transport cost τ_{it}). This interpretation shares the spirit of Ciliberto, Moschini, and Perry (2019), where i represents a piece of agricultural land owned by a farm. The third (and our preferred) interpretation is to focus on the demand system as a whole, and to think of the details of the discrete choice and its underlying utility simply as part of a flexible functional form. This stance is close to Berry and Haile (2021) when they say that "deriving demand from a specification of utilities" is "a matter of convenience rather than necessity" but "can have significant practical advantages" because "such an approach can represent a demand system for many goods (...) with a relatively small number of parameters" (page 13). Regardless of the interpretations, we acknowledge our data limitations (i.e., the details of the downstream supply chains are not recorded), which preclude the separate identification of consumer surplus and downstream firms' profits. Hence, we use the term "buyer surplus" (BS) instead of "consumer surplus" when we describe demand-side benefits.

[29] An additive retail margin m enters utility as $\alpha_{it}m$. Because this term is constant across products, its time-average component is absorbed by the time dummies, while its individual-specific component is absorbed by the unobserved taste shock. Thus, the wholesale-retail gap does not bias the price coefficient.

5.2 Changes in Buyer Surplus

We use the estimated demand system to measure changes in BS. The expected surplus for buyer i from choice set $\mathcal{J}_t$ supplied by the industry with cost profile $\mathcal{C}_t$ is

$$E(BS_{it}) = \frac{1}{\alpha_i} E\left[\max_{s\in\mathcal{J}_t}\{u_{ist}(\mathcal{C}_t)\}\right] = \frac{1}{\alpha_i}\ln\left(\sum_{s\in\mathcal{J}_t}\exp\left(\delta_{ist}(\mathcal{C}_t)\right)\right), \tag{11}$$

where

$$\delta_{ist}(\mathcal{C}_t) = (1-\rho)\ln\left(\sum_{j\in\mathcal{J}_{st}}\exp\left(\frac{\delta_{ijt}(\mathcal{C}_t)}{1-\rho}\right)\right) \tag{12}$$

is the inclusive value for all products in size-nest s, $\mathcal{J}_{st}$, and $\delta_{ijt}(\mathcal{C}_t) \equiv u_{ijt}(\mathcal{C}_t) - \varepsilon^*_{ijt}$ is the mean utility (recall ε^*_{ijt} is the composite gumbel shock). We write $u_{ijt}(\mathcal{C}_t)$ to clarify the dependence of u_{ijt} on $\mathcal{C}_t$ because it affects p_{jt}, a component of u_{ijt}. The change in all buyers' expected surplus is

$$\Delta E(BS) = \sum_i \frac{1}{\alpha_i}\left[\ln\left(\sum_{s\in\mathcal{J}_1}\exp\left(\delta_{is1}(\mathcal{C}_1)\right)\right) - \ln\left(\sum_{s\in\mathcal{J}_0}\exp\left(\delta_{is0}(\mathcal{C}_0)\right)\right)\right], \tag{13}$$

which is the empirical counterpart to (4) under our demand specification.

Table 3 reports the changes in (13) between 2001:Q1 and 2011:Q4. The total change across all applications is $25,027 million, of which TVs account for 66%, followed by monitors (20%) and notebooks (14%). This ranking is consistent with the fact that TVs recorded the largest revenue growth, followed by monitors and notebooks (section 4.5).

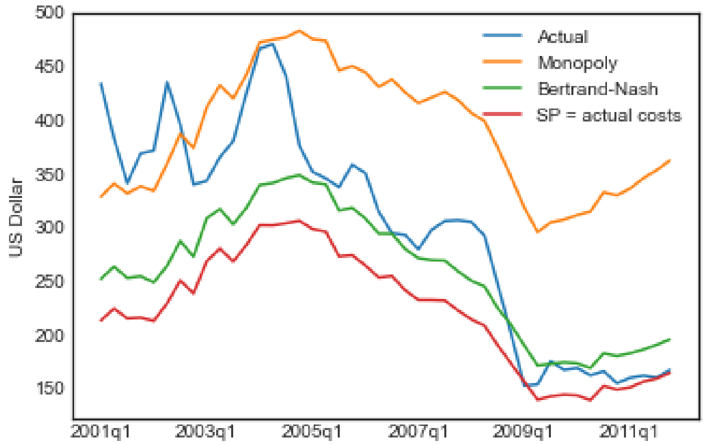
Table 3: Changes in Buyer Surplus

	2001:Q1	2011:Q4	Change	Contribution
Notebook PC	573	4,140	3,567	14%
Desktop monitor	347	5,222	4,875	20%
TV	36	16,621	16,585	66%
All applications	956	25,983	25,027	100%

Note: All dollar values are in million US dollars per calendar quarter.

Expressed in terms of the cost-of-living (price) index $\frac{\Delta E(BS)}{\Delta E(BS)+\bar{p}_1}$ (equation 1.19 in Trajtenberg (1989), where $\bar{p}_1$ is the average post-innovation price), this increase in BS is equivalent to a 99.99999838% reduction in prices, which is reminiscent of Trajtenberg's finding for computerized tomography (CT) scanners. Appendix B.2 shows that other, more conventional price indices grossly underestimate its significance.

Figure 8: 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.

5.3 Implications for Suppliers' Conduct

These changes in BS illustrate the magnitude of overall economic impact, but a finer decomposition of the gains from innovations requires a systematic comparison of carefully designed counterfactual simulations. For example, the calculation of surpluses in the absence of new-generation fabs needs an equilibrium model of demand and supply under imperfect competition, so that we can recompute the prices of available products in each t that would have prevailed under the less attractive profiles of products ($\tilde{\mathcal{J}}_t$) and costs ($\tilde{\mathcal{C}}_t$). Since we have already estimated the demand model and the cost functions, the only missing piece is the specification of the mode of competition between major LCD suppliers in each t.

We empirically 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 8 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 2001:Q4–2006:Q1.[30] 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}.

[30]Even though the antitrust investigation and litigation determined 2001:Q4 as the official beginning of the crystal cartel (see section 3.1), an expert report by Bernheim (2011) suggests the possibility that some price-fixing attempts date back to earlier periods. Likewise, the effectiveness of the cartel appears to decline before its formal end.

The main takeaway is that the monopoly and Bertrand conduct are reasonable approximations to the data in 2001:Q1–2004:Q3 and 2004:Q4–2011:Q4, respectively. Because this split of the sample period captures actual pricing behavior more closely than the legal timeline, we use these supply-side assumptions in our subsequent analyses. As a robustness check, we also compute some of the key results under a simpler assumption (Bertrand-Nash throughout the sample period) in Appendix C.2. A paired t test in Appendix B.3 fails to reject $H_0 : p_t = p_t^{mo}$ (with a p value of 0.71) in the former, and fails to reject $H_0 : p_t = p_t^{bn}$ (with a p value of 0.11) in the latter.

6 Welfare Gains from Innovations

We now apply the two-period framework of section 2 to our data quarter-by-quarter, using the demand-and-supply model from section 5 to flesh out the details. We measure the welfare gains from innovations by hypothetically eliminating them in counterfactual simulations and calculating the discounted sum of these quarterly differences. Sections 6.1 and 6.2 focus on product and process innovations, respectively, whereas section 6.3 reclassifies innovations by the technological generation of fabs, which facilitates the benefit-cost analysis of fab investments in section 6.4.

6.1 Product Innovation

This subsection measures the welfare impact of product innovations. Recall from section 4.1 that our data allow us to distinguish between two types of product innovation: larger and other new products. Any panels larger than the largest available in 2001:Q1 are "larger new products," whereas "other new products" embody new combinations of size, resolution, and backlight type that are simply different from the initial ones.

As in Petrin (2002) and others, we measure the gains from new products by comparing the welfare outcomes (BS, PS, and TS) in each t between two equilibria. One is the baseline equilibrium with all available products in the data at t, $\mathcal{J}_t^*$; the other is a counterfactual equilibrium in which only its subset $\tilde{\mathcal{J}}_t \subset \mathcal{J}_t^*$ is available.[31] We use the actual cost profile in the data, $\mathcal{C}_t^*$, in both cases.

Table 4 reports the baseline and three counterfactual outcomes: (i) without larger new products, (ii) without other new products, and (iii) without any new products. Results are

[31] $\tilde{\mathcal{J}}_t$ and $\mathcal{J}_t^*$ correspond to $\mathcal{J}_0$ and $\mathcal{J}_1$ in section 2, respectively.

heterogeneous across markets. Panels A and B show that, in the relatively mature markets of IT applications (notebooks and monitors), the impact of (ii) is much larger than that of (i), because most of the popular sizes in these categories had already been introduced by 2001:Q1. In contrast, larger new products were much more important than other new products in the nascent TV market (Panel C)—eliminating TVs larger than 28 inches would have reduced TS by $\$280.2 - \$68.0 = \$212.2$ billion (75.7%). Thus, the relative importance of different types of product innovations depends on product life cycles. Panel D shows the overall welfare impact on all applications. The contributions of larger new products (37.4%) and other new products (31.8%) are broadly similar, with the total effect of $\$605.2 - \$173.3 = \$431.9$ billion (71.4%). Note the individual percentage changes do not sum to the total because each of them is computed from a separate counterfactual experiment.

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

Welfare measure	Buyer surplus		Producer surplus		Total surplus	
Counterfactual simulation	\$	(% change)	\$	(% change)	\$	(% change)
A. Notebook						
Baseline	94.8	(±0)	27.4	(±0)	122.2	(±0)
(i) Without larger new products	87.0	(−8.2)	25.5	(−7.0)	112.5	(−7.9)
(ii) Without other new products	57.9	(−38.9)	21.6	(−21.1)	79.5	(−34.9)
(iii) Without any new products	41.6	(−56.1)	17.3	(−36.6)	58.9	(−51.8)
B. Monitor						
Baseline	149.2	(±0)	53.7	(±0)	202.8	(±0)
(i) Without larger new products	145.7	(−2.3)	52.5	(−2.2)	198.2	(−2.3)
(ii) Without other new products	65.6	(−56.0)	35.2	(−34.5)	100.8	(−50.3)
(iii) Without any new products	62.0	(−58.5)	33.9	(−36.9)	95.8	(−52.8)
C. TV						
Baseline	242.9	(±0)	37.3	(±0)	280.2	(±0)
(i) Without larger new products	59.5	(−75.5)	8.5	(−77.1)	68.0	(−75.7)
(ii) Without other new products	196.3	(−19.2)	36.3	(−2.7)	232.7	(−17.0)
(iii) Without any new products	11.0	(−95.5)	7.6	(−79.8)	18.5	(−93.4)
D. All applications						
Baseline	486.8	(±0)	118.4	(±0)	605.2	(±0)
(i) Without larger new products	292.2	(−40.0)	86.5	(−27.0)	378.7	(−37.4)
(ii) Without other new products	319.8	(−34.3)	93.1	(−21.4)	412.9	(−31.8)
(iii) Without any new products	114.5	(−76.5)	58.8	(−50.4)	173.3	(−71.4)

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

Sensitivity to Variety Effect. These estimates account for both improvements in observed product quality and the increasing number of products. Appendix C.1 shows that the overall TS gain remains large (63.6%) even if we ignore the latter.

6.2 Process Innovation

This subsection measures gains from process innovations by simulating counterfactual costs, $\tilde{\mathcal{C}}_t \neq \mathcal{C}_t^*$, based on the marginal-cost function (9) in section 4.4.[32] We use the same (actual) product set $\mathcal{J}_t^*$ across all simulations to isolate the impact of cost-reducing innovations.

We consider three counterfactuals. First, the productivity premium of new-generation equipment (vintage capital), as represented by parameters $\hat{\theta}^g \leq 0$, where $g \in \{4, 4.5, 5, 5.5, 6, 7, 8, 8.5, 10\}$ is the fab's technological generation, can be suppressed by setting $\tilde{\theta}^g = 0$ for all g. We also set $\tilde{\theta}^{odf} = 0$ to mute the effect of the ODF method because it was mostly adopted as part of 5G fabs. We then recompute the no-vintage-effect equilibrium in each t under this counterfactual cost profile, $\tilde{\mathcal{C}}_t^{(i)}$. Second, the effects of yield improvement through experimentation (learning by doing) are captured by $\hat{\theta}^a \leq 0$, where $a = 1, 2, \ldots$ is the age of the fab measured in calendar quarters. Setting $\tilde{\theta}^a = 0$ for all a nullifies this mechanism. We use the resulting cost profile, $\tilde{\mathcal{C}}_t^{(ii)}$, to recompute the no-learning equilibrium in each t. Third, we remove all process innovations by setting $\tilde{\theta}^g = \tilde{\theta}^{odf} = \tilde{\theta}^a = 0$ for all g and a, and using the associated cost profile, $\tilde{\mathcal{C}}_t^{(iii)}$, in recomputing the no-process-innovation equilibrium in each t.

Table 5 reports similar results across markets (panels A–C). Even though both the price-elasticity of demand and the exact number of competing products and firms are different across applications, the underlying changes in costs do not vary much. Hence, the overall welfare effects are broadly comparable in percentages. The industry-wide totals in panel D show that vintage capital, learning by doing, and their combination were responsible for 13.6%, 23.3%, and 35.1% of TS, respectively. In dollar value, the total gain from process innovations was \$605.2 − \$392.8 = \$212.4 billion.

6.3 Technological Generations of Fabs

Sections 6.1–6.2 organized welfare gains by the conceptual type of innovation. In reality, a mix of them was embodied by each generation of fabs and arrived as a bundle. Because investments in fabs were the most important innovation-relevant decision of the LCD firms, this subsection reclassifies the gains based on their technological generation.

We now consider each generation of technology as a bundle of products and cost functions, $\mathcal{T}^g \equiv (\mathcal{J}^g, \mathcal{C}^g)$. Not all innovations are amenable to this reclassification, however. Of the two types of product innovation, larger new products are closely connected to new-generation

[32] $\tilde{\mathcal{C}}_t$ and $\mathcal{C}_t^*$ correspond to C_0 and C_1 in section 2, respectively.

Table 5: Welfare Impact of Process Innovation, 2001–2011

Welfare measure	Buyer surplus		Producer surplus		Total surplus	
Counterfactual simulation	\$	(% change)	\$	(% change)	\$	(% change)
A. Notebook						
Baseline	94.8	(±0)	27.4	(±0)	122.2	(±0)
(i) No vintage-capital effects	87.1	(−8.1)	25.2	(−8.0)	112.3	(−8.1)
(ii) No learning by doing	76.9	(−18.9)	21.9	(−19.9)	98.8	(−19.1)
(iii) Neither	69.6	(−26.6)	19.8	(−27.5)	89.4	(−26.8)
B. Monitor						
Baseline	149.2	(±0)	53.7	(±0)	202.8	(±0)
(i) No vintage-capital effects	129.3	(−13.3)	47.5	(−11.5)	176.8	(−12.8)
(ii) No learning by doing	110.3	(−26.1)	38.8	(−27.7)	149.1	(−26.5)
(iii) Neither	92.9	(−37.7)	33.4	(−37.7)	126.3	(−37.7)
C. TV						
Baseline	242.9	(±0)	37.3	(±0)	280.2	(±0)
(i) No vintage-capital effects	203.6	(−16.2)	30.4	(−18.5)	234.0	(−16.5)
(ii) No learning by doing	187.5	(−22.8)	28.5	(−23.7)	216.0	(−22.9)
(iii) Neither	154.2	(−36.5)	22.8	(−38.9)	177.0	(−36.8)
D. All applications						
Baseline	486.8	(±0)	118.4	(±0)	605.2	(±0)
(i) No vintage-capital effects	420.0	(−13.7)	103.1	(−12.9)	523.2	(−13.6)
(ii) No learning by doing	374.7	(−23.0)	89.3	(−24.6)	463.9	(−23.3)
(iii) Neither	316.7	(−35.0)	76.1	(−35.7)	392.8	(−35.1)

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

fabs, whereas resolution and backlights (i.e., other new products) are not. 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. Thus, no LCD TVs above 40 inches would have existed without post-4.5G technologies.[33] Of the two channels of process innovation, vintage capital is linked to fab generations, whereas learning by doing is not. Thus, we treat each technological generation as a bundle of larger new products and vintage capital effects, and simulate their absence, while keeping other channels of innovation unchanged.

We start with the initially available fab generations, 4G–4.5G. We recompute a counterfactual equilibrium in which $\mathcal{T}^{4.5} \equiv (\mathcal{J}^{4.5}, \mathcal{C}^{4.5})$ is the best available technology. That is, we eliminate all products in $\mathcal{J}_t^*$ that could not have been produced with $\mathcal{T}^{4.5}$ (i.e., any $j \notin \mathcal{J}^{4.5}$). We also constrain the cost functions in $\mathcal{C}_t^*$ to be no more cost-competitive than $\mathcal{C}^{4.5}$. The first row of each panel in Table 6 reports BS, PS, and TS under this setting ($\mathcal{T}^{4.5}$) as a baseline.

Subsequently, we simulate additional counterfactuals under $\mathcal{T}^5$, $\mathcal{T}^{5.5}$, $\mathcal{T}^6$, $\mathcal{T}^8$, and $\mathcal{T}^{10}$

[33] This definition of "larger new products" is slightly different from the one we used in section 6.1, which was purely based on (their absence from) the sales data in 2001:Q1. By contrast, only TVs above 40 inches are excluded from $\mathcal{J}^{4.5}$ and considered "larger new products" for the analysis in this subsection.

Table 6: Welfare Impact of New-Generation Fabs, 2001–2011

Welfare measure	Buyer surplus		Producer surplus		Total surplus	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
4G–4.5G only (baseline)	88.9	(±0)	25.8	(±0)	114.7	(±0)
4G–5G only	93.3	(4.9)	27.0	(4.9)	120.3	(4.9)
4G–5.5G only	93.9	(5.6)	27.2	(5.4)	121.1	(5.6)
4G–6G only	94.4	(6.2)	27.3	(5.8)	121.7	(6.1)
4G–8G only	94.7	(6.5)	27.3	(6.1)	122.0	(6.4)
4G–10G	94.8	(6.6)	27.4	(6.2)	122.2	(6.5)
B. Monitor						
4G–4.5G only (baseline)	132.8	(±0)	48.8	(±0)	181.7	(±0)
4G–5G only	146.5	(10.3)	53.0	(8.4)	199.5	(9.8)
4G–5.5G only	146.5	(10.3)	53.0	(8.5)	199.5	(9.8)
4G–6G only	148.1	(11.5)	53.4	(9.3)	201.5	(10.9)
4G–8G only	148.9	(12.1)	53.6	(9.7)	202.5	(11.5)
4G–10G	149.2	(12.3)	53.7	(9.9)	202.8	(11.7)
C. TV						
4G–4.5G only (baseline)	172.6	(±0)	23.3	(±0)	195.8	(±0)
4G–5G only	226.1	(31.0)	33.6	(44.5)	259.7	(32.6)
4G–5.5G only	229.2	(32.8)	34.6	(48.8)	263.8	(34.7)
4G–6G only	238.7	(38.4)	36.3	(56.0)	275.0	(40.4)
4G–8G only	242.0	(40.2)	37.1	(59.4)	279.0	(42.5)
4G–10G	242.9	(40.8)	37.3	(60.5)	280.2	(43.1)
D. All applications						
4G–4.5G only (baseline)	394.3	(±0)	97.9	(±0)	492.2	(±0)
4G–5G only	465.9	(18.2)	113.6	(16.1)	579.5	(17.7)
4G–5.5G only	469.6	(19.1)	114.7	(17.2)	584.3	(18.7)
4G–6G only	481.3	(22.1)	116.9	(19.5)	598.2	(21.5)
4G–8G only	485.6	(23.1)	118.0	(20.6)	603.6	(22.6)
4G–10G	486.8	(23.5)	118.4	(21.0)	605.2	(23.0)

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 C.2 for a robustness check with respect to the assumption on competitive conduct.

(we skip $\mathcal{T}^7$ and $\mathcal{T}^{8.5}$ because their results are nearly identical to the adjacent ones). Newer vintages led to visible gains, but their marginal contributions diminished in later generations. 5G fabs had the largest impact partly because their productivity improvements over 4G–4.5G were remarkable (recall Figure 5 (A)) and partly because many popular products (45"–55" TVs) required this vintage. The most advanced technology in our data is 10G; hence, the difference between $\mathcal{T}^{4.5}$ and $\mathcal{T}^{10}$ represents the overall gains during our sample period. The bottom row of Table 6 (panel D) reports the TS gain of \$605.2 − \$492.2 = \$113 billion, a 23% increase from $\mathcal{T}^{4.5}$.

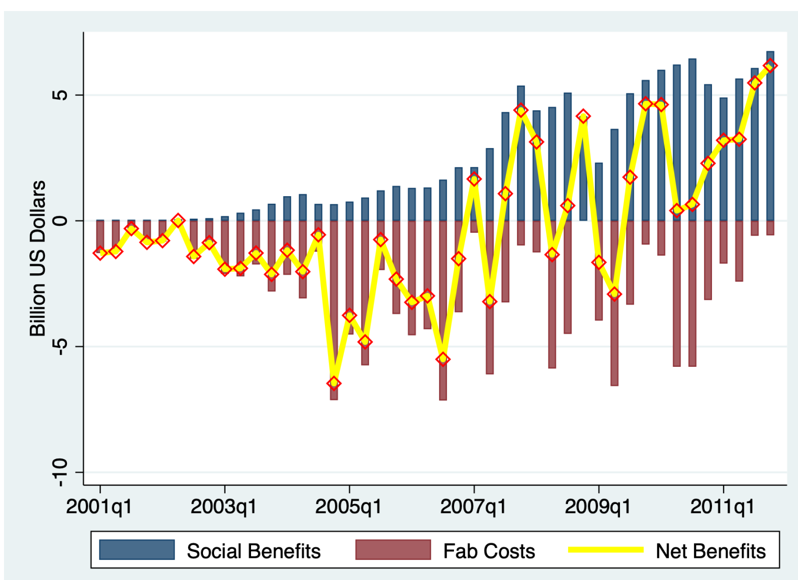
The impact of new-generation fabs is much larger for TVs (panel C) than for IT applications (panels A and B). For example, 5G fabs increased TS by 32.6% for TVs, but only by 4.9% and 9.8% for notebooks and monitors, respectively. As we saw in section 6.1, larger new products were relatively more important in the emerging market for LCD TVs, whereas the room for larger new products was limited in notebooks and monitors. This contrast echoes the typical findings about product life cycles (e.g., Klepper 1996) that product innovation matters more in earlier stages of a new market, whereas process innovation becomes essential for firms' survival in later stages.

6.4 Social and Private Returns on Investment

This subsection compares the benefits and costs of fab investments. We start with the evaluation of social returns, proceed to industry-wide PS, and conclude with the analysis of incentives at the level of individual firms.

Social Returns. Figure 9 compares the aggregate social benefits and costs. "Social benefits" displays the quarterly path of the difference in TS between $\mathcal{T}^{4.5}$ and $\mathcal{T}^{10}$ that, when summed, yields the aggregate reported in Table 6. "Fab costs" are the industry-wide total costs of fab investments (see section 4.5). The line graph for "net benefits" tracks their difference in each t, showing that costs dominated benefits until around 2007, at which point benefits started to exceed costs.

Figure 9: Social Benefits and Costs of Fab Investments (Undiscounted)



Note: "Social benefits" are the overall gains from fab investments. "Fab costs" are the industry-wide total costs of fab investments, visualized as negative numbers in the graph. "Net benefits" are their differences.

For a more complete analysis, we 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%. Regarding the post-sample period, we assume that the incremental social benefit remains constant at its 2011:Q4 level and that no new fab investments are made.

Table 7: Social and Industry Returns on Fab Investments

Annual discount rate	1%	2.5%	5%	10%
1. Change in buyer surplus	2,139.2	765.9	318.2	109.5
2. Change in producer surplus	373.4	136.2	58.5	21.7
3. Change in total surplus (= 1 + 2)	2,512.6	902.1	376.6	131.1
4. Fab investment cost	116.6	106.7	92.1	68.9
5. Net social value (= 3 − 4)	2,396.0	795.4	284.5	62.3
6. Net producer value (= 2 − 4)	256.8	29.5	−33.7	−47.2

Note: All numbers are discounted present values in billion US dollars as of 2001:Q1.

Rows 1–3 report the discounted present values (DPVs) of the changes in BS, PS, and TS as of 2001:Q1, respectively, whereas row 4 reports the DPV of fab costs (FCs). Row 5 reports net social value (NSV), defined as the DPV of ΔTS minus the DPV of FCs. This NSV is positive even at a relatively high discount rate of 10%. Thus, investments in 5G–10G technologies were socially beneficial.

Industry-wide Returns. Whether these investments made positive financial returns is a separate issue. Row 6 of Table 7 reports the industry-wide net producer value (NPV), defined as the DPV of ΔPS minus the DPV of FCs, which corresponds to the ICI in section 2 (equation 3). NPV is positive at $r = 1\%$ and 2.5% but negative at 5% and 10%. The industry-wide internal rate of return (IRR)—the break-even discount rate—is 3.18%. The true return is likely to be even lower because FCs are only part of the overall costs for developing and implementing new technologies. Our cost measure does not include R&D expenditures or other economic costs. Hence, the industry as a whole realized only a mediocre investment return ex post.

Individual Firms' Returns. Despite low aggregate returns, some firms were able to generate higher returns. Table 8 shows private gains from fab investments at the level of individual firms. The private return is positive for LG even at $r = 10\%$. Samsung's return is negative at 10% but positive at 5%. These two firms seem clear winners of the investment race. The returns for CMO, AUO, and Sharp become positive at 2.5%, but the rest of the industry (CPT, HS, and others) did not make any visible returns even at 1%.[34] These individual NPVs correspond to $\Delta\pi_f$ in equation 1.

Table 8: Private Returns Relative to Unilateral No-Investment Deviation

Annual discount rate	1%	2.5%	5%	10%
A. Change in producer surplus				
Samsung	187.8	71.6	32.9	13.7
LG	286.6	104.7	45.3	17.3
CMO	78.3	27.9	11.5	3.9
AUO	77.8	29.0	12.8	5.0
Sharp	41.9	15.5	6.8	2.5
CPT	2.0	0.9	0.5	0.3
HS	2.2	1.2	0.8	0.5
Others	0.3	0.1	0.0	0.0
B. Fab investment cost				
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. Net producer value (= $A - B$)				
Samsung	160.9	47.0	11.7	−1.9
LG	261.2	81.6	25.5	2.8
CMO	54.6	6.3	−7.0	−9.7
AUO	58.9	11.6	−2.4	−6.6
Sharp	32.6	7.1	−0.4	−2.7
CPT	−3.1	−3.9	−3.9	−3.4
HS	0.0	−0.9	−1.1	−1.0
Others	−4.9	−4.6	−4.0	−3.0
Sum of positive values	568.3	153.6	37.2	2.8
Sum of negative values	−8.0	−9.4	−18.7	−28.4
Sum of all values, SII	560.3	144.1	18.5	−25.6

Note: All numbers are discounted present values in billion US dollars as of 2001:Q1.

The last row of Table 8 sums over these individual gains to compute the "sum of individual incentives" (SII), as defined in equation 2. The SII is positive ($18.5 billion) at 5% because the large gains at Samsung and LG more than offset the smaller losses at all other firms. The contrast between this positive SII and the negative ICI (row 6 of Table 7)—at the same discount rate of 5%—highlights the role of competition in promoting investments. The negative ICI means that the industry as a whole would have been better off had the industry not moved on to the post-4.5G technologies. However, some firms (Samsung and LG) had sufficient strategic incentives to invest in newer-generation fabs. Because their private gains were larger than the losses incurred by their rivals, it would have been difficult for all firms

[34]These firms mostly stopped investments in the middle of the sample period.

to agree on an industry-wide slowdown of investments.

7 Market Structure and Innovation Incentives

This section leverages the simulation framework of section 6 to further investigate the relationship between competition and investment incentives. We alter the number of firms N and product ownership structure O to simulate the effects of mergers on TS and SII. Section 7.1 starts with the actual market structure with seven major firms and a competitive fringe, and simulates hypothetical seven-to-six mergers. Section 7.2 considers all possible mergers in the subsequent stages of industry consolidation, including the creation of a monopoly.

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. Virtually all simulated mergers reduce TS, because we do not assume any merger-specific efficiency gains or feedback from SII.[35] Hence, ΔTS and ΔSII should be interpreted independently as measures of static welfare effects and dynamic incentive effects, respectively. Note the mergers do not affect profits during the cartel period (until 2004:Q3) because all major firms are acting as a monopoly, but we report results based on the entire sample period to use the same timeline throughout the paper.

Table 9 lists 21 possible pairs that could arise from the seven major firms, in the descending order of magnitude of ΔTS at $r = 5\%$. Mergers 1–8 involve Samsung, LG, Sharp, CMO, and AUO (i.e., top five firms by fab investments) and lead to visible reductions in TS. Curiously, almost all of them increase SII. Such a merger might increase innovation incentives by allowing the consolidated firm to better internalize the profit gains from its investments, which would otherwise be competed away by a close rival. In contrast, most of Mergers 9–21 involve CPT and/or HS, the two smallest firms, with negligible but negative impacts on both ΔTS and ΔSII.

Whether the possibility of positive innovation effects could justify otherwise harmful mergers is a perennial policy question in antitrust enforcement. We find that 14 of the 21 possible combinations reduce SII. Moreover, those with positive ΔSII entail larger negative ΔTS. Thus, defending mergers on this ground would seem difficult.

[35] Capacity constraints will become less binding for the same reason (i.e., equilibrium outputs decrease after a merger).

Table 9: Seven-to-Six Mergers and Their Impacts

Rank	Acquirer	Target	Static welfare effect		Innovation incentive effect	
			ΔTS	(% change)	ΔSII	(% change)
1	Samsung	LG	−15.3	(−1.0)	3.4	(17.8)
2	LG	AUO	−5.5	(−0.4)	1.6	(8.5)
3	Samsung	CMO	−4.5	(−0.3)	−0.1	(−0.5)
4	Samsung	AUO	−4.5	(−0.3)	0.0	(0.1)
5	LG	CMO	−4.4	(−0.3)	0.6	(3.1)
6	Samsung	Sharp	−3.8	(−0.3)	2.9	(15.0)
7	CMO	AUO	−2.4	(−0.2)	0.2	(1.3)
8	LG	Sharp	−0.6	(−0.0)	0.8	(4.2)
9	Samsung	CPT	−0.3	(−0.0)	−0.1	(−0.7)
10	LG	CPT	−0.3	(−0.0)	−0.2	(−1.0)
11	Sharp	CMO	−0.3	(−0.0)	−0.1	(−0.3)
12	LG	HS	−0.2	(−0.0)	−0.1	(−0.3)
13	Sharp	AUO	−0.2	(−0.0)	−0.0	(−0.0)
14	Samsung	HS	−0.2	(−0.0)	−0.0	(−0.2)
15	AUO	CPT	−0.2	(−0.0)	−0.1	(−0.3)
16	AUO	HS	−0.1	(−0.0)	−0.0	(−0.1)
17	CMO	HS	−0.1	(−0.0)	−0.0	(−0.0)
18	CMO	CPT	−0.1	(−0.0)	−0.0	(−0.1)
19	CPT	HS	−0.0	(−0.0)	−0.0	(−0.1)
20	Sharp	CPT	−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 ΔTS. The effects are expressed as discounted present values 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," purely for the sake of exposition. Switching these labels does not affect our simulation results. The "−0.0" entries are small negative numbers that have been rounded.

7.2 All Possible Mergers in Industry Consolidation

This subsection extends the scope of analysis to all possible combinations of the seven major firms. That is, we simulate not only the 21 seven-to-six mergers but also 315 six-to-five mergers, 1,400 five-to-four mergers, and so on, including the creation of a single dominant firm that consolidates all of them. We also simulate the acquisition of competitive fringe by this dominant firm at the end of hypothetical industry consolidation.

Table 10 summarizes the changes due to the 4,803 mergers that we simulate, comparing TS and SII immediately before and after each of them. As in section 7.1, ΔTS is almost always negative (i.e., except for a few outliers among four-to-three and three-to-two mergers). The dynamic incentive effect exhibits greater heterogeneity: some mergers substantially increase SII, but the majority of them decrease it (the right-most column reports the fraction of mergers with negative ΔSII). The only exception is two-to-one mergers, 95% of which exhibit positive effects on SII, but this stage of industry consolidation is too special for any

Table 10: Summary of All Possible Mergers and Their Effects

Merger from/to	Possible mergers	Welfare effect, $\Delta DPV(SW)$ (%) Mean	Stdev	Min	Max	Incentive effect, ΔSII (%) Mean	Med	Stdev	Min	Max	Frac < 0
7 to 6	21	−0.1	0.2	−1.0	−0.0	2.1	−0.1	5.4	−1.3	18.4	0.71
		(0.01)	(0.02)	(0.10)	(0.00)	(0.52)	(0.07)	(1.63)	(0.84)	(7.07)	(0.06)
6 to 5	315	−0.2	0.3	−1.9	−0.0	2.1	−0.2	6.3	−9.5	36.8	0.68
		(0.02)	(0.03)	(0.18)	(0.00)	(0.60)	(0.11)	(1.95)	(3.05)	(13.36)	(0.05)
5 to 4	1,400	−0.3	0.6	−5.2	−0.0	1.9	−0.5	8.4	−21.3	63.2	0.68
		(0.03)	(0.04)	(0.32)	(0.00)	(0.70)	(0.20)	(2.69)	(5.86)	(25.46)	(0.04)
4 to 3	2,100	−0.7	1.1	−8.8	−0.0	2.0	−1.3	17.6	−25.6	216.0	0.66
		(0.05)	(0.05)	(0.30)	(0.00)	(1.11)	(0.41)	(5.87)	(6.82)	(90.57)	(0.03)
3 to 2	903	−1.8	2.5	−10.2	−0.0	10.0	−5.4	46.4	−28.2	225.0	0.66
		(0.10)	(0.08)	(0.30)	(0.00)	(4.41)	(1.48)	(16.47)	(7.36)	(104.32)	(0.02)
2 to 1	63	−9.2	2.2	−10.6	−0.5	139.1	147.2	57.9	−7.3	226.4	0.05
		(0.26)	(0.08)	(0.31)	(0.06)	(51.49)	(49.94)	(31.93)	(1.05)	(113.40)	(0.00)
No Others	1	−13.9	–	−13.9	−13.9	−13.1	−13.1	–	−13.1	−13.1	1.00
		(0.46)	–	(0.46)	(0.46)	(3.00)	(3.00)	–	(3.00)	(3.00)	(0.00)
Total	4,803	−0.9	1.8	−13.9	0.0	5.3	−0.9	29.2	−28.2	226.4	0.66
		(0.05)	(0.06)	(0.46)	(0.00)	(2.14)	(0.29)	(10.69)	(7.31)	(112.88)	(0.03)

Note: "No Others" is a merger to perfect monopoly that consolidates Others. All effects are computed as discounted present values in billion US dollars as of 2001:Q1 at $r = 5\%$ (reported in Table 23 in Appendix C.3) and then expressed in terms of percentage changes from the immediately preceding market structure of each merger. This table reports the mean effects across 400 parametric bootstrap samples, with standard errors in parentheses.

broader policy implications.[36] In summary, the much-debated positive incentive effect of mergers seems technically possible, but positive outcomes are far from guaranteed (absent merger-specific efficiencies).

Predicting the Effects of Mergers. Appendix C.4 examines the extent to which the effects of mergers could be predicted by commonly used statistics such as ΔHHI. We find that these statistics are useful for predicting ΔTS but not ΔSII.

8 Conclusion

Three main findings emerge from this study. First, both product and process innovations generated massive social benefits in the LCD industry, the relative contributions of which varied across market segments at different stages of product life cycles. Second, the sunk cost

[36] These 63 cases involve mergers between two super-major firms, each of which is an amalgamation of a subset of the seven original firms. Their incentive effects are mostly positive for two reasons. First, the elimination of duopolistic rivalry substantially increases markups and profits, as well as the incremental profits from investments. Second, a collection of fringe firms remains in the market, which preserves the dominant firm's incentive to invest because there is room for business-stealing. When the dominant firm absorbs these smaller competitors, the incentive effects become negative again (see the penultimate row of Table 10). Therefore, we regard the two-to-one mergers here as knife-edge cases.

of investment was so large that the realized returns were low for most firms. Nevertheless, some firms made reasonably high private gains, which suggests that an industry-wide coordination to withhold investments would have been difficult. Third, the majority of mergers would have been unambiguously harmful (absent merger-specific efficiencies), even though some of them could have increased the industry-wide incentive to innovate.

The unique strength of this study lies in our 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 explicit dynamics. 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 were present in the first half of our sample period. We are currently developing a dynamic game model with endogenous collusion and innovation in a follow-up paper to address these issues.

References

[1] Agarwal, N., I. Ashlagi, E. Azevedo, C.R. Featherstone, and Ö. Karaduman. 2019. "Market Failure in Kidney Exchange." *American Economic Review*, 109(11): 4026–4070.

[2] Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. "Competition and innovation: An inverted-U relationship." *Quarterly Journal of Economics*, 120(2): 701–728.

[3] Akabane, J.. 2014. *Higashi Asia Ekisho Panel Sangyo No Hatten: Kankoku Taiwan Kigyo No Kyuusoku Catchup To Nihon Kigyo No Taiou*. Tokyo: Keiso Shobo.

[4] Asker, J., A. Collard-Wexler, and J. de Loecker. 2019. "(Mis)Allocation, Market Power, and Global Oil Extraction." *American Economic Review*, 109(4): 1568–1615.

[5] Benkard, C.L.. 2000. "Learning and Forgetting: The Dynamics of Aircraft Production." *American Economic Review*, 90(4): 1034–1054.

[6] —. 2004. “A Dynamic Analysis of the Market for Wide-Bodied Commercial Aircraft.” *Review of Economic Studies*, 71(3): 581–611.

[7] Bernheim, B.D.. 2011. “Expert Report of B. Douglas Bernheim, PhD concerning Target Corp., et al.” In *Re: TFT-LCD (Flat Panel) Antitrust Litigation*. MDL No. 1827.

[8] Berry, S.T., and P.A. Haile. 2021. “Foundations of demand estimation,”in K. Ho, A. Hortacsu, and A. Lizzeri, eds., *Handbook of Industrial Organization*, Volume 4. Elsevier.

[9] Berry, S., J. Levinsohn, and A. Pakes. 1995. “Automobile Prices in Market Equilibrium,” *Econometrica*, 63(4): 841–890.

[10] —, —, and —. 1999. “Voluntary Export Restraints on Automobiles: Evaluating a Trade Policy,” *American Economic Review*, 89(3): 400–430.

[11] Berry, S., and A. Pakes. 2007. “The Pure Characteristics Demand Model. ” *International Economic Review*, 48(4): 1193–1225.

[12] Björkegren, D.. 2019. “The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda. ” *Review of Economic Studies*, 86(3): 1033–1060.

[13] Brenkers, R. and F. Verboven. 2006. “Liberalizing Distribution System: The European Car Market.” *Journal of the European Economic Association*, 4(1): 216–251.

[14] Ciliberto, F., G. Moschini, and E.D. Perry. 2019. “Valuing Product Innovation: Genetically Engineered Varieties in U.S. Corn and Soybeans.” *RAND Journal of Economics*, 50(3): 615–644.

[15] Conlon, C.T.. 2012. “A Dynamic Model of Prices and Margins in the LCD TV Industry.” Manuscript.

[16] —, and J. Gortmaker. 2020. “Best Practices for Differentiated Products Demand Estimation with PyBLP.” *RAND Journal of Economics*, 51(4): 1108–1161.

[17] Gandhi, A., and J.-F. Houde. 2023. “Measuring Substitution Patterns in Differentiated-Products Industries.” Manuscript revised & resubmitted to *Econometrica*.

[18] Genesove, D., and W.P. Mullin. 1998. “Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890–1914.” *RAND Journal of Economics*, 29(2): 355–377.

[19] Goettler, R.L., and B.R. Gordon. 2011. "Does AMD Spur Intel to Innovate More?" *Journal of Political Economy*, 119(6): 1141–1200.

[20] Grieco, P.L.E., C. Murry, and A. Yurukoglu. 2024. "The Evolution of Market Power in the U.S. Automobile Industry." *Quarterly Journal of Economics*, 139 (2): 1201–1253.

[21] Grigolon, L. and F. Verboven. 2014. "Nested Logit or Random Coefficients Logit? A Comparison of Alternative Discrete Choice Models of Product Differentiation." *Review of Economics and Statistics*, 96(5): 916–935.

[22] Griliches, Z.. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4): 501–522.

[23] Hall, B.H., J. Mairesse, and P. Mohnen. 2010. "Measuring the Returns to R&D." In *Handbook of the Economics of Innovation*, Vol. 2.

[24] Hausman, J.. 1996. "Valuation of New Goods under Perfect and Imperfect Competition." In *The Economics of New Goods*.

[25] Igami, M.. 2017. "Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998." *Journal of Political Economy*, 125(3): 798–847.

[26] —, and K. Uetake. 2020. "Mergers, Innovation, and Entry-Exit Dynamics: Consolidation of the Hard Disk Drive Industry, 1996–2016." *Review of Economic Studies*, 87(6): 2672–2702.

[27] Klepper, S.. 1996. "Entry, exit, growth, and innovation over the product life cycle." *American Economic Review* 86(3): 562–583.

[28] Lerner, J., and A. Seru. 2022. "The Use and Misuse of Patent Data: Issues for Finance and Beyond." *Review of Financial Studies*, 35(6): 2667–2704.

[29] Levitt, S.D., J.A. List, and C. Syverson. 2013. "Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant." *Journal of Political Economy*, 121(4): 643–681.

[30] Matthews, J.A.. 2005. "Strategy and the Crystal Cycle." *California Management Review*, 47(2): 6–32.

[31] Mohapatra, D.P., and Y. Zhang. 2024. "Rx-to-OTC Switch, Market Exclusivity, and Consumer Welfare: A Study of the US Anti-Ulcer Drug Market." *RAND Journal of Economics*, forthcoming.

[32] Nocke, V., and M.D. Whinston. 2022. "Concentration Thresholds for Horizontal Mergers." *American Economic Review*, 112(6): 1915–1948.

[33] Pakes, A., S. Berry, and J. Levinsohn. 1993. "Applications and limitations of some recent advances in empirical industrial organization: Price indexes and the analysis of environmental change." *American Economic Review P&P*, 83(2): 240–246.

[34] Petrin, A.. 2002. "Quantifying the Benefits of New Products: The Case of the Minivan." *Journal of Political Economy*, 110(4): 705–729.

[35] Qiu, J.Y.J.. 2023. "The Matthew effect, research productivity, and the dynamic allocation of NIH grants." *RAND Journal of Economics*, 54(1): 135–164.

[36] Schumpeter, J.A.. 1934. *Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Harvard University Press.

Bull's Eye?" in *The Rate and Direction of Inventive Activity Revisited*. Chicago, IL: University of Chicago Press.

[37] Sinclair, G., S. Klepper, and W. Cohen. 2000. "What's Experience Got to Do with It? Sources of Cost Reduction in a Large Specialty Chemicals Producer." *Management Science*, 46(10): 28–45.

[38] Syverson, C.. 2011. "What Determines Productivity?" *Journal of Economic Literature*, 49(2): 326–365.

[39] Trajtenberg, M.. 1989. "The Welfare Analysis of Product Innovations, with an Application to Computed Tomography Scanners." *Journal of Political Economy*, 97(2): 444–479.

[40] Yang, C.. 2020. "Vertical Structure and Innovation: A Study of the SoC and Smartphone Industries." *Rand Journal of Economics*, 51(3): 739–785.

Online Appendix

Appendix A presents additional descriptive evidence. Appendix B reports supplementary results related to demand estimation. Appendix C contains materials related to counterfactual simulations.

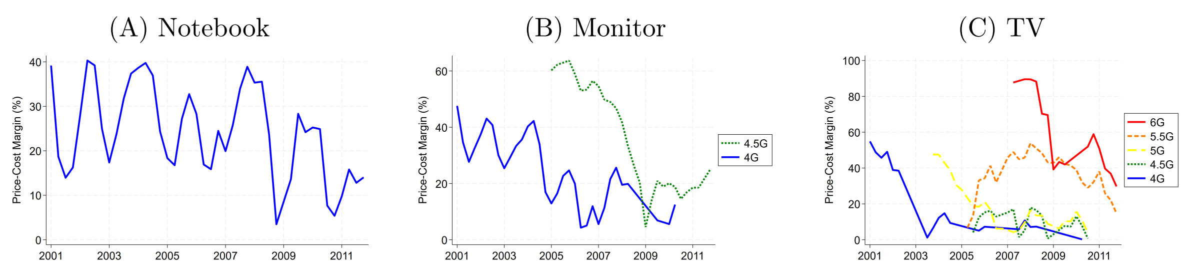
A. Supplementary Descriptive Evidence

A.1 Price-Cost Margin by Product Generation

This section compares markups between older and newer products. The goal is to investigate the short-run dynamics of profitability across generations of products. For each product, we define its generation based on the earliest generation of required fab equipment.

Figure 10 plots price-cost margins by product generation. Only a single line graph appears in Panel A because 4G technology is sufficient for notebook panels of all sizes. Its cyclical pattern mostly reflects IT demand cycles.

Figure 10: Price-Cost Margin by Product Generation



Note: Price-cost margins are averaged across products within each generation, which is defined by the earliest generation of fab equipment that can manufacture them. Panel A plots a single line graph because 4G technology is sufficient for notebook panels of all sizes.

Panel B features two line graphs for monitors. 4G products' margins look similar to notebook panels, but the overall level shifted down around 2005 and never recovered again. By contrast, 4.5G panels commanded higher margins in their first three years.

Panel C plots five generations of TV products (4G, 4.5G, 5G, 5.5G, and 6G). 4.5G and 5.5G were niche variants that were adopted by fewer firms. A comparison between 4G, 5G, and 6G shows that newer products initially achieved high margins, which then shrank and gradually converged to the lower levels typical of older products, because multiple firms started operating new-generation fabs, intensifying price competition.

A.2 Concrete Examples of Cost Reductions

Cost Breakdown. To illustrate cost reductions with concrete examples, Table 11 shows the cost breakdown of a 17-inch monitor panel at one of Samsung's 4.5G plants (Chonan L4 Phase 2), as well as total cash cost at two other fabs with 5G and 7G technologies, respectively (Chonan L5 Phase 1 and Tangjong L7-1 Phase 1). Rows 1–3 are the costs of materials and components for the three main processes (array, cell, and module), respectively. Row 4 is their sum. Row 5 includes additional costs for "wasted" materials and components due to defective outputs. Rows 6 and 7 are the costs of labor and intermediate inputs, respectively. Row 8 is the overall unit cost—excluding depreciation—at the 4.5G fab; rows 9 and 10 report the same for the 5G and 7G fabs, respectively. These examples demonstrate how each of the three cost drivers—(i) vintage capital, (ii) learning by doing, and (iii) input price decrease—worked in practice.

First, the impact of new-generation equipment is evident from the comparison of cash costs between rows 8, 9, and 10. The same 17-inch monitor could be produced in 2011:Q4 for \$64.22, \$58.04(−10%), and \$52.04(−19%) at the 4.5G, 5G, and 7G fabs, respectively.

Table 11: Manufacturing Cost Breakdown (17-inch Monitor)

Year:Quarter	2001:Q1	2004:Q1	2007:Q1	2010:Q1	2011:Q4
(A) 4.5G fab since 2001:Q1 (Samsung's Chonan L4 Phase 2)					
1. Array material	15.60	12.30	9.70	7.78	7.06
2. Cell material	29.62	51.01	26.87	19.34	18.08
3. Module component	104.46	66.45	35.83	16.01	13.12
4. Material & component total $(= 1 + 2 + 3)$	149.67	129.76	72.40	43.13	38.26
5. Yielded material & component total cost $(= 4 \div yield)$	181.22	134.77	74.12	45.00	39.96
6. Personnel cost	32.41	17.86	18.27	24.53	20.26
7. Indirect expense	16.97	12.37	8.82	4.50	4.00
8. Cash cost $(= 5 + 6 + 7)$	230.59	165.00	101.21	74.03	64.22
(B) 5G fab since 2002:Q4 (Samsung's Chonan L5 Phase 1)					
9. Cash cost	–	163.65	96.60	60.93	58.04
(C) 7G fab since 2005:Q2 (Samsung's Tangjong L7-1 Phase 1)					
10. Cash cost	–	–	96.37	57.57	52.04

Note: This table shows the breakdown of manufacturing cost in US Dollars for a 17-inch monitor (with twisted-nematic technology, 1,280×1,024 pixels, and CCFL backlight) at three different fabs of Samsung. "Array material" includes glass, sputtering target, and chemicals. "Cell material" includes color filter, polarizer film, liquid crystal, and others. "Module component" includes driver integrated circuits, backlights, and printed circuit boards. "Yielded material and component total cost" is the overall cost of material and component, including those that have to be wasted for defective output. The input price data for the color filter is missing for 2001:Q1–2003:Q4.

Second, the combined effect of learning by doing and input price decreases manifests itself in row 5, which tracks the cost of materials and components, including those wasted for defective products. Their effects are multiplicative, as learning by doing reduces defects and wastes (i.e., input volume), whereas the reduction in input prices reduces expenditures on all inputs regardless of whether they are wasted. In the example of Panel A, the combined effect was a \$181.22 − \$39.96 = \$141.26 (78%) reduction between 2001:Q1 and 2011:Q4.

Third, a further decomposition is possible. Row 4 accounts for the cost of materials and components that are used in defectless products, thereby measuring the impact of input price decreases alone. The difference between Rows 4 and 5 reflects the cost of waste. In Panel A, the pure input price effect was a \$149.67−\$38.26 = \$111.41 (74%) decrease during the sample period. The cost of defect was substantial at the beginning (\$181.22−\$149.67 = \$31.55) but became negligible in the end (\$39.96 − \$38.26 = \$1.7) thanks to learning by doing—yield improved from 0.5 to 0.93 (not reported in the table).

Input Prices. The magnitude of the input price decrease is large and deserves further investigation. Figure 11 plots the prices of materials and components for 17-inch monitors at 4.5G fabs. Most input prices dropped by 60%–90% during the sample period, which is consistent with the 74% decrease in row 4 in Table 11. These improvements were possible because many of these inputs were relatively new products from the specialty chemical and electronic device industries, which engaged in their own innovations. The rate of price drop is slower for sputtering targets, sheet glass, and liquid crystal than for others.[37]

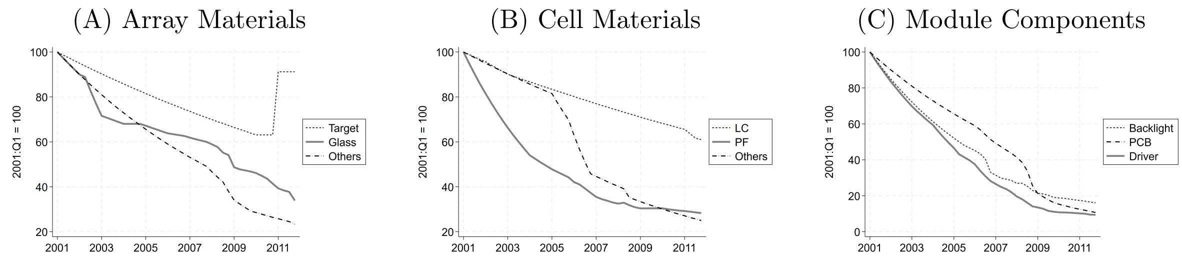
A.3 Fab Investments

Capacity by Generation. Figure 12 tracks the evolution of fab investments by technological generation. Panel A measures each fab's capacity by the number of input glass sheets that it can process. This measure is proportional to the number of machines and production lines within each fab. Meanwhile, Panel B measures capacity by the surface area of input glass, and hence accounts for the fact that more advanced fabs use larger glass sheets.

Both panels show that a new generation of fabs appeared every year or two—5G in 2002, 6G in 2004, 7G in 2005, 8G in 2006, 8.5G in 2007, and 10G in 2009. According to panel A, broadly similar numbers of machines went into production across all generations. However,

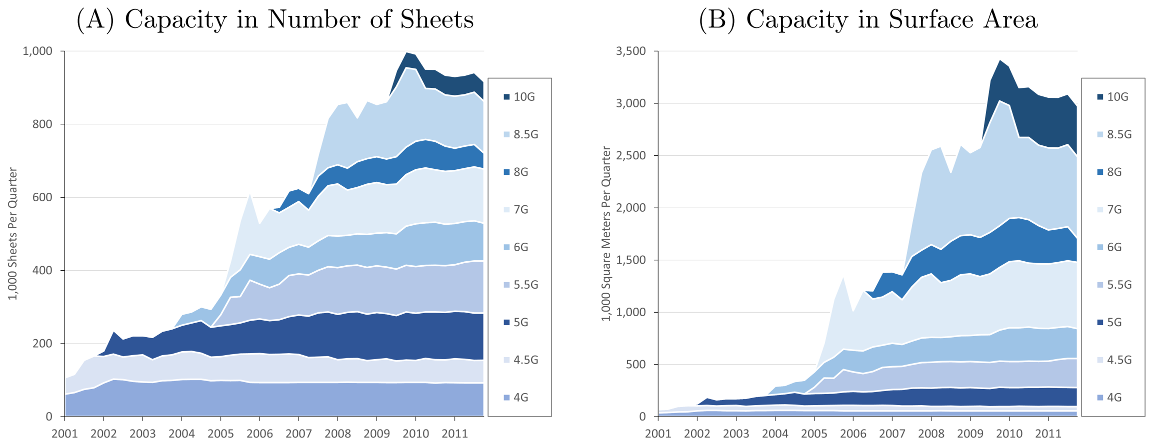
[37] We do not have any systematic information about these input markets, but our conjecture is as follows. First, the sputtering target is made of rare metals such as indium, molybdenum, and tungsten, the prices of which could fluctuate a lot and did not monotonically decrease over time. Second, sheet glass is manufactured by only a handful of specialty-glass makers, including Asahi Glass, Corning, Nippon Electric Glass, and their joint ventures. These oligopolistic suppliers might have had significant market power and retained some of the gains from their own innovations. Third, liquid crystal is a relatively simple raw material. Its production technology could have already matured, with limited room for further cost reductions.

Figure 11: Material and Component Prices (17-inch Monitor, 4.5G Fab)



Note: These graphs show the prices of materials and components that are used in three different stages of the manufacturing process (array, cell, and module). Input prices vary across products and fab generations; we show the prices for a 17-inch monitor panel (twisted-nematic technology, 1,280×1,024 pixels) manufactured at a 4.5G fab (730×920 mm input glass), for which data are available for the entire sample period. In Panel A, "target" refers to the sputtering target, "glass" is non-alkaline sheet glass, and "others" refer mostly to chemicals. In Panel B, "LC" is liquid crystal, and "PF" is polarizer film. In Panel C, "backlight" is CCFL backlight, "PCB" is printed circuit board, and "driver" is driver integrated circuit.

Figure 12: Fabrication Plants by Technological Generation



Note: Panel A measures fabs' capacities by the number of input glass sheets that can be processed per calendar quarter. Panel B measures fabs' capacities by the surface area of input glass per calendar quarter.

because more advanced fabs use larger input glass, the surface-area contribution from the later generations was disproportionately larger. For example, the combined share of 7G–10G fabs in 2011:Q4 was 42% in panel A but 72% in panel B. These fabs were also more expensive.

Dollar Amount by Firm. Table 12 lists the total dollar amount of investments by firm. Samsung and LG led 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), lagged behind, as they stopped investing in the mid-2000s. Sharp (\$9.8 billion) was the only Japanese firm with comparable footprints. "Others" are mostly fringe firms in Japan, with only \$5.5 billion of collective investments.

Table 12: 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.

A.4 Pass-Through of Wholesale Prices to Retail Prices

Did the reductions in panel prices benefit the final users of LCD products? To investigate the extent of pass-through, we manually constructed a supplementary dataset on the prices of final goods in the US retail markets, based on product-review articles in *AnandTech*, *CNET*, *PC Magazine,* and other online sources.[38] We matched these retail prices with the wholesale prices and manufacturing costs from Databases 1 and 2, which resulted in an unbalanced panel of 14 products (application-size categories) for 2001–2011.[39]

We estimate the pass-through rate of global wholesale prices to US retail prices using the following specification:

$$P_{gy} = \tilde{\rho} p_{gy} + \delta_g + \tau_y + \epsilon_{gy}, \tag{14}$$

where P_{gy} is the average US retail price of category-g product in year y, p_{gy} is the average global wholesale price, $\tilde{\rho}$ is the pass-through rate (e.g., $\tilde{\rho} = 1$ means 100% pass-through), δ_g and τ_y are fixed effects for products and years, respectively, and ϵ_{gy} is the error term, which we interpret as the measurement error in retail prices. To address potential endogeneity problems with p_{gy} (i.e., P_{gy} could affect p_{gy} because US sales account for a substantial fraction of global sales), we use the manufacturing cost, c_{gy}, as an instrumental variable (IV).

[38] We collected approximate retail prices for 12–13-inch, 14–15-inch, and 16–17-inch notebook PCs; 15, 17, 19, 20, 22, and 24-inch LCD monitors; and 32, 40, 46, 55, and 65-inch LCD TVs.

[39] The sampling frequency of the retail prices is annual. Accordingly, we aggregate the quarterly data from Databases 1 and 2 to the industry-wide annual averages.

Table 13: Pass-Through of Global Wholesale Prices to US Retail Prices

	(1)	(2)	(3)	(4)
Wholesale price	1.828	1.850	1.266	0.960
	(0.104)	(0.103)	(0.090)	(0.061)
Observations	124	124	124	124
First-stage F statistic	157.14	35.25	92.34	54.56
Year fixed effects	No	Yes	No	Yes
Product fixed effects	No	No	Yes	Yes

Note: An observation is a product-year, where a product is defined by an application-size combination (e.g., 15-inch monitor). The LHS variable is the average retail price in the United States. The RHS variables include the average wholesale price, which is instrumented by the average manufacturing cost in the 2SLS regression, as well as the dummy variables for years and/or products in columns 2–4. Heteroskedasticity-robust standard errors are in parentheses.

Table 13 reports our estimates. Column 1 presents the baseline results without fixed effects. A pass-through rate of 1.828 implies that a \$1 decrease in wholesale prices leads to a \$1.83 decrease in retail prices. Column 2 includes year fixed effects to flexibly control for time trends. Column 3 incorporates product fixed effects. Column 4 controls for both of them, with a pass-through estimate of 0.96 and the 95% confidence interval of $[0.841, 1.078]$. These results suggest an almost complete pass-through.[40] Our interpretation is that the frequent decreases in LCD prices made these trends highly predictable and transmittable. Furthermore, the downstream firms had strong incentives to sell LCD-based products as fast as possible because an inventory of older, more expensive products would lead to a loss.

A.5 First-Time versus Replacement Purchases

This section explains why first-time buyers are likely to account for most of the LCD TV purchases in our data.[41] We first focus on the case of Japan (for data availability reasons and its earlier timing of market expansion) and then consider the rest of the world.

First, the household surveys in Japan show that only 10% of the approximately 50 million households owned LCD TVs as of 2005, and that LCD TVs were used for 10.7 years on average.[42] In 2010, 25.48 million new TVs were sold. Even if all of the five million LCD TV owners in 2005 had decided to replace them in 2010, the fraction of replacement purchases would have been less than $5 \div 25.48 = 19.6\%$. A complete replacement of five-year-old LCD

[40]In the recent pass-through literature, similarly high rates were found by Fabra and Reguant (2014) in the Spanish electricity markets and by Besanko, Dubé, and Gupta (2005) in the US supermarket context.

[41]The underlying concern is that the installed base of LCD TVs could play the role of outside goods in consumers' choice. If the replacement of previously purchased devices accounts for a large fraction of new purchases, the true value of outside goods depends on the quality of those older products.

[42]Central Research Services, Report 738, https://www.crs.or.jp/backno/No738/7381.htm (accessed August 15, 2025). Cabinet Office, Government of Japan, *Consumer Confidence Survey*, March 2024.

TVs in a single year is an extreme assumption only to illustrate the logical upper bound; the actual fraction of replacement demand is estimated to be only a few percent or less, according to industry reports.

Second, the average number of years of use was similar in other developed countries and regions, including the United Kingdom, the United States, and continental Europe.[43] The timing of the expansion of the LCD TV market in these countries was at least a few years later than in Japan. Thus, the size of the installed base that could have potentially been replaced was smaller (as a fraction of new sales circa 2010) than in Japan.

Third, conventional (CRT) TVs remained mainstream in most developing countries throughout our sample period. Hence, virtually all LCD TV sales in those markets were first-time purchases.

In summary, first-time purchases accounted for most of the demand even in Japan, where LCD TVs became popular much earlier than in the rest of the world. Hence, our demand estimates seem unlikely to be biased by the lack of data on consumer holding of previously purchased goods.

B Supplements for Demand Estimation and Its Implications

B.1 Unobserved Quality and Outside Goods

We investigate the possibility of allowing the value of outside goods to vary over time, $u_{i0t} = \gamma_t + \varepsilon_{i0t}$, and separately identifying γ_t from the time fixed effects, τ_t, which represents the mean utility of the inside goods at t. Let $\tilde{\xi}_{jt} = \xi_{jt} + \tau_t$, and assume $E[\xi_{jt}|\mathbf{z}_{jt}] = 0$, when $\mathbf{z}_{jt}$ is a set of IVs. Pakes, Berry, and Levinsohn (1993) separately identify them by further assuming

$$\forall j \in \mathcal{J}_t^{cont} : E[\tilde{\xi}_{jt} - \tilde{\xi}_{j,t-1}] = E[(\tau_t - \tau_{t-1}) + (\xi_{jt} - \xi_{j,t-1})] = 0, \tag{15}$$

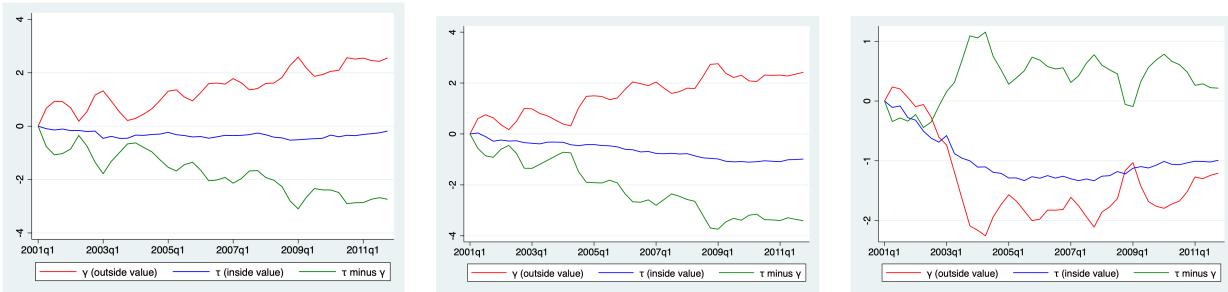
where $\mathcal{J}_t^{cont}$ is the set of continuing products offered in both t and $t-1$. In words, even though $\tilde{\xi}_{jt}$ can change over time, its mean change is assumed to be zero.

Figure 13 plots the net appeal of the inside goods ($\tau_t - \gamma_t$) and its two components (γ_t and τ_t) under these assumptions. In the notebook and monitor markets, net appeal follows a downward trend, suggesting that the inside goods became less attractive vis-à-vis the outside option. Most of this downward trend is due to the increasing appeal of the outside good (γ_t); τ_t exhibits either no trend (notebooks) or a slightly decreasing trend (monitors).

[43] E-scrap News, link; United States Environmental Protection Agency, link (accessed August 15, 2025).

Figure 13: Mean Values of Inside and Outside Goods

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



Note: See the main text for the details of the decomposition and interpretations.

The results are qualitatively different in the TV market. The net appeal of inside goods ($\tau_t - \gamma_t$) fluctuates in a vaguely cyclical pattern without any clear trend. Its decomposition shows that τ_t decreased in the first few years and never recovered afterward.

These decreasing (or non-increasing) trends in $\hat{\tau}_t$ are difficult to reconcile with the fact that LCD panels trended to improve over time in terms of the range of possible brightness, sharpness, response speed, viewing angle, and other physical determinants of picture quality. One possibility is that these improvements were highly collinear with the improvements in the observed characteristics and did not independently contribute to τ_t after we control for them. Another possibility is that the identification assumptions did not hold in the current data context, in which the definition of product is broader than the stock-keeping unit (SKU) and other granular ones.

B.2 Comparison of Price Indices

Table 14 compares four price indices to capture "real" changes between 2001:Q1 and 2011:Q4. First, the average unit price decreased by $100 - 38.59 = 61.41$ (%) across all applications. Second, price per surface area (m^2) controls for the systematic increase in panel size and records a much larger decrease of 87.24%. Third, we use hedonic regressions to control for improvements in resolution and backlights as well, and find a quality-adjusted price decrease of 89.46%. However, none of these indices incorporates the explosive growth in market size induced by these price decreases, thereby failing to account for the overall change in economic surplus. Our demand model allows us to construct an alternative cost-of-living index, which suggests that the other price indices underestimate the true economic impact of innovations by seven orders of magnitude.

Table 14: Comparison of Price Indices in 2011:Q4

Price index	Unit price	Price per m^2	Hedonic regression	Based on demand estimate
Notebook PC	19.60192132	19.15902865	16.02415363	0.00000136
Desktop monitor	15.44295343	11.18762981	8.15032812	0.00000176
TV	49.00838143	9.39348834	7.85855845	0.00000175
All applications	38.59314853	12.76146672	10.53916361	0.00000162

Note: All price indices are normalized to 100 in the base period (2001:Q1). Unit price and price per m^2 are the unweighted average nominal prices (per unit of LCD panel and per surface area, respectively). Hedonic estimates are based on the 2SLS regression of the natural logarithm of p_{jt} on the time dummies, $size_j$, $\ln(ppi_j)$, and led_j, with c_{jt} as an IV for $size_j$. The demand-model-based index uses our estimates and the method by Trajtenberg (1989, section 1.4 and Table 4.9); see section 5.2.

B.3 Paired t Tests for Price Comparison

We examine the competitive conduct of firms. Because we have detailed cost data, we can directly compare the actual price p_t with three theoretical benchmarks $(p_t^{mo}, p_t^{bn}, p_t^{sp})$.

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	392.63	14.46	56.02	361.61	423.65
Bertrand-Nash price, p_t^{bn}	15	289.89	9.23	35.73	270.11	309.68
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	4.94	12.86	49.79	-22.63	32.52
Difference 2, $p_t - p_t^{bn}$	15	107.68	10.40	40.31	85.36	130.00
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	383.43	10.98	59.15	360.93	405.93
Bertrand-Nash price, p_t^{bn}	29	240.51	11.29	60.81	217.38	263.64
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	−134.73	5.39	29.00	−145.76	−123.70
Difference 2, $p_t - p_t^{bn}$	29	8.20	4.93	26.54	−1.90	18.30
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.

Table 15 shows the summary statistics of the four prices and of the difference between p_t and each of $(p_t^{mo}, p_t^{bn}, p_t^{sp})$.[44] 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.

[44] 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 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. Panel A suggests that the actual price is more consistent with monopoly pricing than the other two in this subperiod. Panel B favors the assumption of Bertrand-Nash pricing in the later subperiod.

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, $p_t - p_t^{mo}$	0.3843	14	0.6467	0.7066	0.3533
Difference 2, $p_t - p_t^{bn}$	10.3458	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, $p_t - p_t^{mo}$	-25.0182	28	0.0000	0.0000	1.0000
Difference 2, $p_t - p_t^{bn}$	1.6635	28	0.9463	0.1074	0.0537
Difference 3, $p_t - p_t^{sp}$	7.6922	28	1.0000	0.0000	0.0000

B.4 Supplementary Tables Related to Demand Estimation

Tables 17 and 18 report the first-stage regressions of prices and within-nest market shares, respectively. Tables 19 and 20 report alternative demand estimates when the market size M_t (the number of potential buyers) is decreased and increased by 50%, respectively.

Table 17: First-Stage Regression: Prices

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Marginal cost	1.177	(0.034)	2.838	(0.058)	1.565	(0.020)
Cartel participation	3.866	(1.357)	−50.359	(7.833)	−64.246	(17.659)
Diff IV resolution (own)	2.547	(0.628)	−36.358	(3.643)	−0.955	(5.889)
Diff IV LED (own)	1.908	(0.663)	4.495	(7.355)	1.756	(5.866)
Diff IV size (own)	0.339	(0.082)	4.739	(0.378)	−1.039	(0.256)
Diff IV resolution×LED (own)	−0.729	(0.116)	−2.225	(0.833)	4.647	(1.595)
Diff IV resolution×size (own)	0.065	(0.037)	−0.095	(0.157)	−0.076	(0.151)
Diff IV LED×size (own)	0.027	(0.005)	0.073	(0.011)	−0.021	(0.004)
Diff IV resolution (others)	2.012	(0.222)	28.056	(2.323)	1.718	(1.210)
Diff IV LED (others)	−0.299	(0.157)	−2.257	(1.506)	0.639	(1.221)
Diff IV size (others)	0.387	(0.023)	−0.498	(0.103)	0.319	(0.053)
Diff IV resolution×LED (others)	0.157	(0.035)	0.315	(0.332)	1.723	(0.413)
Diff IV resolution×size (others)	−0.005	(0.007)	0.015	(0.031)	0.059	(0.031)
Diff IV LED×size (others)	0.030	(0.002)	0.013	(0.003)	0.008	(0.001)
Resolution	78.945	(2.464)	328.025	(22.193)	73.894	(19.791)
LED	−5.810	(0.957)	−6.448	(13.441)	−6.561	(11.476)
Size = 12”	−22.233	(2.581)				
Size = 13”	−11.647	(3.457)				
Size = 14”	−23.496	(3.777)			14.140	(37.090)
Size = 15”	−8.164	(3.979)				
Size = 15.4”	−11.675	(3.881)				
Size = 16”	−16.130	(3.939)	48.512	(13.487)	−30.743	(33.723)
Size = 17”	−20.738	(3.656)				
Size = 18”	−43.311	(3.860)	44.773	(14.932)	−58.971	(35.120)
Size = 20”			58.558	(17.011)	−66.719	(34.963)
Size = 22”			63.525	(18.478)	−71.484	(36.189)
Size = 24”			−8.081	(19.289)	−48.651	(37.088)
Size = 26”					−50.529	(38.027)
Size = 27”			−94.071	(17.916)		
Size = 28”					46.299	(46.536)
Size = 30”					−71.227	(43.427)
Size = 32”					−107.643	(40.456)
Size = 40”					−150.908	(42.097)
Size = 45”					−200.250	(44.011)
Size = 50”					−243.186	(44.092)
Size = 55”					−266.566	(46.693)
Size = 60”					174.121	(52.807)
Size = 65”					−26.755	(61.576)
Firm = Samsung	11.378	(1.103)	29.022	(6.227)	86.793	(10.533)
Firm = LG	8.004	(1.063)	16.673	(6.616)	73.560	(9.958)
Firm = CMO	−1.319	(1.198)	−10.194	(6.379)	−34.813	(10.486)
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−5.392	(1.477)	28.903	(10.500)	11.105	(11.457)
Firm = CPT	−8.853	(1.638)	−12.364	(7.769)	−6.511	(16.408)
Firm = HS	−7.081	(1.855)	5.517	(8.287)	28.275	(26.859)
Firm = Others	−8.734	(1.321)	−19.836	(6.443)	−62.218	(12.453)
Constant	−273.142	(11.073)	−1,707.820	(98.969)	−92.743	(102.896)
Time dummies	Yes		Yes		Yes	
Adjusted R^2	0.946		0.898		0.921	
F statistic	986.808		414.860		508.219	
Observations	4,140		3,374		3,582	

Table 18: First-Stage Regression: Within-Nest Shares

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Marginal cost	0.015	(0.003)	0.001	(0.001)	0.001	(0.000)
Cartel participation	−0.302	(0.113)	0.783	(0.152)	0.046	(0.149)
Diff IV resolution (own)	−0.169	(0.052)	0.305	(0.071)	−0.177	(0.050)
Diff IV LED (own)	−0.089	(0.055)	0.233	(0.142)	0.037	(0.050)
Diff IV size (own)	0.027	(0.007)	0.019	(0.007)	−0.003	(0.002)
Diff IV resolution×LED (own)	−0.058	(0.010)	−0.006	(0.016)	−0.001	(0.013)
Diff IV resolution×size (own)	0.002	(0.003)	−0.000	(0.003)	−0.001	(0.001)
Diff IV LED×size (own)	0.000	(0.000)	0.000	(0.000)	−0.000	(0.000)
Diff IV resolution (others)	−0.049	(0.018)	−0.300	(0.045)	−0.061	(0.010)
Diff IV LED (others)	0.023	(0.013)	0.040	(0.029)	0.004	(0.010)
Diff IV size (others)	−0.018	(0.002)	−0.009	(0.002)	−0.003	(0.000)
Diff IV resolution×LED (others)	−0.022	(0.003)	−0.062	(0.006)	−0.040	(0.003)
Diff IV resolution×size (others)	−0.002	(0.001)	0.002	(0.001)	0.001	(0.000)
Diff IV LED×size (others)	−0.000	(0.000)	0.000	(0.000)	−0.000	(0.000)
Resolution	−3.569	(0.204)	−0.644	(0.430)	−1.883	(0.167)
LED	−0.176	(0.079)	1.096	(0.260)	0.118	(0.097)
Size = 12”	−1.948	(0.214)				
Size = 13”	−2.248	(0.287)				
Size = 14”	−3.421	(0.313)			−1.164	(0.314)
Size = 15”	−3.451	(0.330)				
Size = 15.4”	−2.973	(0.322)				
Size = 16”	−3.347	(0.327)	−1.342	(0.261)	−1.713	(0.285)
Size = 17”	−2.965	(0.303)				
Size = 18”	−1.120	(0.320)	−1.747	(0.289)	−1.315	(0.297)
Size = 20”			−1.804	(0.329)	−2.833	(0.296)
Size = 22”			−1.186	(0.358)	−2.402	(0.306)
Size = 24”			−1.133	(0.373)	−1.978	(0.313)
Size = 26”					−3.176	(0.321)
Size = 27”			−3.014	(0.347)		
Size = 28”					−1.312	(0.393)
Size = 30”					−2.946	(0.367)
Size = 32”					−3.588	(0.342)
Size = 40”					−4.279	(0.356)
Size = 45”					−3.988	(0.372)
Size = 50”					−4.436	(0.373)
Size = 55”					−5.187	(0.395)
Size = 60”					−4.197	(0.446)
Size = 65”					−5.429	(0.520)
Firm = Samsung	0.410	(0.092)	−0.282	(0.121)	0.462	(0.089)
Firm = LG	0.452	(0.088)	0.112	(0.128)	0.423	(0.084)
Firm = CMO	−0.494	(0.099)	−0.503	(0.123)	0.141	(0.089)
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.650	(0.123)	−1.778	(0.203)	0.131	(0.097)
Firm = CPT	−1.143	(0.136)	−0.320	(0.150)	−1.084	(0.139)
Firm = HS	−1.674	(0.154)	−0.545	(0.160)	−1.872	(0.227)
Firm = Others	−0.849	(0.110)	−1.777	(0.125)	−0.971	(0.105)
Constant	13.978	(0.919)	1.713	(1.916)	8.241	(0.870)
Time dummies	Yes		Yes		Yes	
Adjusted R^2	0.325		0.273		0.329	
F Statistic	27.963		18.566		22.387	
Observations	4,140		3,374		3,582	

Table 19: Demand Estimates with 50% Reduction in M_t

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−108.359	14.218	−91.510	4.017	−34.831	2.096
Size nests (ρ)	0.795	0.026	0.759	0.026	0.888	0.027
Size = 12" (β^{12})	1.927	0.062	–	–	–	–
Size = 13" (β^{13})	2.083	0.074	–	–	–	–
Size = 14" (β^{14})	3.356	0.083	–	–	2.099	0.181
Size = 15" (β^{15})	3.071	0.095	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	3.004	0.089	–	–	–	–
Size = 16" (β^{16})	3.417	0.112	4.320	0.089	2.959	0.160
Size = 17" (β^{17})	2.516	0.085	–	–	–	–
Size = 18" (β^{18})	−0.006	0.132	5.303	0.109	2.111	0.180
Size = 20" (β^{20})	–	–	6.013	0.134	4.475	0.182
Size = 22" (β^{22})	–	–	5.420	0.138	3.770	0.196
Size = 24" (β^{24})	–	–	5.151	0.136	3.387	0.184
Size = 26" (β^{26})	–	–	–	–	4.888	0.198
Size = 27" (β^{27})	–	–	4.287	0.157	–	–
Size = 28" (β^{28})	–	–	–	–	3.493	0.268
Size = 30" (β^{30})	–	–	–	–	4.823	0.253
Size = 32" (β^{32})	–	–	–	–	6.639	0.212
Size = 40" (β^{40})	–	–	–	–	6.389	0.230
Size = 45" (β^{45})	–	–	–	–	6.109	0.234
Size = 50" (β^{50})	–	–	–	–	6.158	0.251
Size = 55" (β^{55})	–	–	–	–	6.211	0.283
Size = 60" (β^{60})	–	–	–	–	4.883	0.349
Size $\geq$ 65" (β^{65})	–	–	–	–	5.755	0.381
Resolution (β^r)	1.067	0.139	1.742	0.161	0.237	0.059
LED (β^b)	0.129	0.035	−0.108	0.047	0.365	0.034
Firm = Samsung	−0.038	0.046	0.014	0.043	0.104	0.039
Firm = LG	−0.082	0.048	0.118	0.039	0.062	0.034
Firm = CMO	−0.129	0.053	−0.177	0.044	−0.051	0.041
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.393	0.073	−0.218	0.073	−0.046	0.036
Firm = CPT	−0.046	0.062	−0.146	0.052	−0.093	0.064
Firm = HS	−0.167	0.072	−0.111	0.057	−0.464	0.103
Firm = Others	−0.234	0.045	−0.157	0.053	−0.160	0.045
Constant	−9.292	0.495	−13.386	0.670	−10.612	0.356
Time dummies	Yes		Yes		Yes	
Own elasticity	−6.28		−6.04		−8.73	
Observations	4,140		3,374		3,582	

Table 20: Demand Estimates with 50% Increase in M_t

Application	Notebook PC		Desktop monitor		TV	
Estimate	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Price (α)	−110.290	14.989	−93.709	4.317	−35.029	2.116
Size nests (ρ)	0.795	0.026	0.752	0.026	0.889	0.027
Size = 12" (β^{12})	1.927	0.063	–	–	–	–
Size = 13" (β^{13})	2.082	0.074	–	–	–	–
Size = 14" (β^{14})	3.354	0.083	–	–	2.102	0.181
Size = 15" (β^{15})	3.066	0.094	–	–	–	–
Size = 15.4" ($\beta^{15.4}$)	3.001	0.089	–	–	–	–
Size = 16" (β^{16})	3.415	0.112	4.307	0.090	2.965	0.160
Size = 17" (β^{17})	2.513	0.084	–	–	–	–
Size = 18" (β^{18})	−0.011	0.133	5.284	0.110	2.115	0.180
Size = 20" (β^{20})	–	–	5.984	0.135	4.482	0.182
Size = 22" (β^{22})	–	–	5.396	0.139	3.778	0.196
Size = 24" (β^{24})	–	–	5.126	0.137	3.392	0.184
Size = 26" (β^{26})	–	–	–	–	4.891	0.198
Size = 27" (β^{27})	–	–	4.264	0.158	–	–
Size = 28" (β^{28})	–	–	–	–	3.496	0.268
Size = 30" (β^{30})	–	–	–	–	4.830	0.253
Size = 32" (β^{32})	–	–	–	–	6.637	0.211
Size = 40" (β^{40})	–	–	–	–	6.382	0.229
Size = 45" (β^{45})	–	–	–	–	6.098	0.233
Size = 50" (β^{50})	–	–	–	–	6.140	0.249
Size = 55" (β^{55})	–	–	–	–	6.181	0.280
Size = 60" (β^{60})	–	–	–	–	4.830	0.344
Size $\geq$ 65" (β^{65})	–	–	–	–	5.703	0.376
Resolution (β^r)	1.060	0.138	1.729	0.163	0.236	0.059
LED (β^b)	0.129	0.035	−0.115	0.047	0.360	0.034
Firm = Samsung	−0.039	0.046	0.012	0.044	0.103	0.039
Firm = LG	−0.082	0.048	0.117	0.039	0.062	0.034
Firm = CMO	−0.130	0.053	−0.181	0.045	−0.052	0.041
Firm = AUO	–	–	–	–	–	–
Firm = Sharp	−0.393	0.073	−0.231	0.074	−0.046	0.036
Firm = CPT	−0.046	0.062	−0.151	0.052	−0.091	0.064
Firm = HS	−0.167	0.072	−0.114	0.058	−0.461	0.103
Firm = Others	−0.234	0.045	−0.168	0.054	−0.159	0.045
Constant	−10.366	0.495	−14.389	0.679	−11.698	0.356
Time dummies	Yes		Yes		Yes	
Own elasticity	−6.25		−5.86		−8.75	
Observations	4,140		3,374		3,582	

C Supplements Related to Counterfactual Simulations

C.1 Gains from Quality versus Variety

All discrete choice models of demand with individual taste for products (i.e., ε_{ijt} in equation 10) share a common property that the addition of any product will mechanically increase BS regardless of its characteristics. In this sense, the gains from new products in section 6.1 represent an upper bound that incorporates the gains from both better products (quality effect) and more products (variety effect). We assess the magnitude of this issue by computing a lower bound that eliminates the variety effect.[45]

Table 21 reports additional counterfactual results in which we keep the number (or composition) of products constant across simulations. First, our change-composition counterfactual keeps the number of products constant (i.e., 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.[46] 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, our 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 21 reuse the counterfactual histories of the reduced number of products in simulations (i), (ii), and (iii) in Table 4 in section 6.1, 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 report the mean TS 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, our change-both counterfactual alters both the number and composition of products, which is the same design as the original counterfactuals in section 6.1 and incorporates both the quality and variety effects. Both of them are quantitatively important, according to our results. In terms of relative magnitude, the quality effect is larger than the variety effect and represents more than half of the total effect in all three panels of Table 21.

We have also considered alternative approaches to mitigate the variety effect, including

[45] 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).

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

Table 21: Separating the Quality Effect and the Variety Effect of Product Innovations

Setting	Number of products	Composition of products	Total surplus $	Total surplus (% change from baseline)
Baseline	Actual	Actual	605.2	(0.0)
(i) Without larger new products				
Change composition	Actual	Without larger new products	443.7	(−26.7)
Change number	CF (i)	Actual	560.0	(−7.5)
Change both	CF (i)	Without larger new products	378.7	(−37.4)
(ii) Without other new products				
Change composition	Actual	Without other new products	451.8	(−25.4)
Change number	CF (ii)	Actual	511.0	(−15.6)
Change both	CF (ii)	Without other new products	412.9	(−31.8)
(iii) Without any new products				
Change composition	Actual	Without any new products	220.4	(−63.6)
Change number	CF (iii)	Actual	327.0	(−46.0)
Change both	CF (iii)	Without any new products	173.3	(−71.4)

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

the adjustment proposed by Ackerberg and Rysman (2005) and the pure characteristics model proposed by Berry and Pakes (2007). However, neither of them is particularly useful in our setting. Our baseline specification of demand already includes the time fixed effects, which makes the additional term in Ackerberg and Rysman (2005) redundant. The pure characteristics model is known to produce implausibly high estimates of the price-elasticity of demand, and its estimation algorithm faces severe computational limitations.[47]

C.2 Impact of New Technologies under Always-Bertrand Assumption

We report the gains from fab generations under the alternative conduct assumption of Bertrand competition throughout the sample period (Table 22). Results are similar to the baseline estimates in section 6.3.

C.3 Effects of Mergers in Dollar Terms

Table 23 reports the summary statistics of the effects of the 4,803 mergers that we simulate in section 7.2 in terms of dollar values.

[47] See Berry and Pakes (2007, Table 6), Song (2015, Table 5), and Song's (2006) computational note.

Table 22: Welfare Impact of New-Generation Fabs under Always-Bertrand Assumption

Welfare measure	Consumer surplus		Producer surplus		Social welfare	
Counterfactual simulation	$	(% change)	$	(% change)	$	(% change)
A. Notebook						
4G–4.5G only (baseline)	100.1	(±0)	21.3	(±0)	121.4	(±0)
4G–5G only	104.8	(4.7)	22.4	(5.4)	127.2	(4.8)
4G–5.5G only	105.4	(5.4)	22.6	(6.0)	128.0	(5.5)
4G–6G only	105.9	(5.9)	22.7	(6.4)	128.6	(6.0)
4G–8G only	106.2	(6.1)	22.7	(6.8)	129.0	(6.3)
4G–10G	106.3	(6.2)	22.8	(7.0)	129.1	(6.4)
B. Monitor						
4G–4.5G only (baseline)	151.5	(±0)	41.7	(±0)	193.2	(±0)
4G–5G only	166.6	(10.0)	45.4	(8.7)	212.0	(9.7)
4G–5.5G only	166.6	(10.0)	45.4	(8.7)	212.0	(9.7)
4G–6G only	168.2	(11.1)	45.8	(9.7)	214.0	(10.8)
4G–8G only	169.0	(11.6)	46.0	(10.3)	215.0	(11.3)
4G–10G	169.3	(11.7)	46.1	(10.4)	215.3	(11.5)
C. TV						
4G–4.5G only (baseline)	175.1	(±0)	22.2	(±0)	197.2	(±0)
4G–5G only	228.8	(30.7)	32.4	(46.3)	261.3	(32.5)
4G–5.5G only	231.9	(32.4)	33.4	(50.9)	265.3	(34.5)
4G–6G only	241.5	(37.9)	35.1	(58.3)	276.6	(40.2)
4G–8G only	244.7	(39.8)	35.9	(61.9)	280.6	(42.3)
4G–10G	245.6	(40.3)	36.1	(63.1)	281.8	(42.9)
D. All applications						
4G–4.5G only (baseline)	426.6	(±0)	85.2	(±0)	511.8	(±0)
4G–5G only	500.2	(17.3)	100.2	(17.7)	600.5	(17.3)
4G–5.5G only	503.9	(18.1)	101.4	(19.0)	605.3	(18.3)
4G–6G only	515.6	(20.9)	103.5	(21.6)	619.2	(21.0)
4G–8G only	519.9	(21.9)	104.6	(22.8)	624.5	(22.0)
4G–10G	521.2	(22.2)	105.0	(23.3)	626.2	(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.

C.4 Predicting the Outcomes of Merger Simulations

Table 24 reports regression results in which the left-hand-side (LHS) variable is ΔSII. Panel A uses the full sample of 4,803 mergers and shows that ΔSII is positively correlated with post-merger HHI, the change in HHI (ΔHHI), post-merger IHHI (the HHI of the dollar amount of fab investments), the change in IHHI (ΔIHHI), and upward pricing pressure (UPP) in columns (1)–(5), respectively; it is negatively correlated with the change in the DPV of TS, $\Delta DPV(TS)$, in column (6). Panel B excludes outliers and focuses on a subsample consisting of 4,533 mergers that are densely collocated in the two-dimensional plane defined by ΔSII and $\Delta DPV(TS)$—specifically, the subsample with $\Delta DPV(TS) \in [-3\%, 0\%]$. We find ΔSII is negatively correlated with HHI, IHHI, and $\Delta DPV(TS)$, but positively correlated with ΔHHI, ΔIHHI, and UPP.

Table 23: Summary of All Possible Mergers and Their Effects (in Dollar Values)

Merger from/to	Possible mergers	Welfare effect, $\Delta DPV(SW)$ Mean	Stdev	Min	Max	Incentive effect, ΔSII Mean	Med	Stdev	Min	Max	Frac < 0
7 to 6	21	−2.1	3.7	−15.6	−0.0	0.4	−0.0	1.0	−0.2	3.4	0.71
		(0.19)	(0.35)	(1.69)	(0.00)	(0.05)	(0.01)	(0.19)	(0.13)	(0.98)	(0.06)
6 to 5	315	−3.2	5.2	−29.5	−0.0	0.4	−0.0	1.2	−1.8	7.1	0.68
		(0.27)	(0.45)	(2.90)	(0.00)	(0.07)	(0.02)	(0.25)	(0.38)	(1.82)	(0.05)
5 to 4	1,400	−5.2	8.5	−80.0	−0.0	0.4	−0.1	1.6	−4.1	10.8	0.68
		(0.43)	(0.64)	(5.73)	(0.00)	(0.10)	(0.03)	(0.34)	(0.61)	(2.54)	(0.04)
4 to 3	2,100	−10.2	16.9	−135.2	−0.0	0.4	−0.3	3.3	−4.9	32.5	0.66
		(0.76)	(1.01)	(6.60)	(0.00)	(0.18)	(0.06)	(0.64)	(0.65)	(6.03)	(0.03)
3 to 2	903	−27.9	37.9	−155.7	−0.0	1.8	−1.1	8.3	−5.3	32.3	0.66
		(1.63)	(2.00)	(7.84)	(0.00)	(0.56)	(0.20)	(1.56)	(0.65)	(6.03)	(0.02)
2 to 1	63	−138.6	34.6	−162.6	−7.5	24.0	26.1	7.1	−3.5	30.4	0.05
		(7.02)	(1.87)	(8.20)	(0.87)	(4.92)	(5.37)	(1.36)	(0.21)	(6.10)	(0.00)
No Others	1	−190.5	–	−190.5	−190.5	−5.8	−5.8	–	−5.8	−5.8	1.00
		(13.14)	–	(13.14)	(13.14)	(0.97)	(0.97)	–	(0.97)	(0.97)	(0.00)
Total	4,803	−13.3	26.7	−190.5	0.0	0.9	−0.2	5.1	−5.8	32.5	0.66
		(0.83)	(1.39)	(13.14)	(0.00)	(0.27)	(0.04)	(1.00)	(0.85)	(6.03)	(0.03)

Note: "No Others" is a merger to perfect monopoly that consolidates Others. All effects are computed as discounted present values in billion US dollars as of 2001:Q1 at $r = 5\%$. Standard errors from 400 parametric bootstrap samples are in parentheses.

In Table 25, the LHS variable is $\Delta DPV(TS)$. The same set of regressors performs well in terms of fit—ΔHHI alone achieves the R^2 of 0.828 (panel B, column 2). Almost all of the coefficient estimates are negative and readily interpretable: greater concentration and/or market power reduces welfare.[48] Thus, the static-welfare effect of mergers is simpler and easier to predict than their innovation-incentive effect.

[48]The only two exceptions arise in the all-regressor specification of column 6 (panels A and B), which 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 25 demonstrates similarly good performance of UPP, thus empirically validating the simulation results of Miller, Remer, Ryan, and Sheu (2017).

Table 24: Predictors of the Effect of Mergers on Innovation Incentives

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Including Outliers							
Post-merger HHI	1.635						−0.429
	(0.040)						(0.086)
Change in HHI		2.791					−3.144
		(0.065)					(0.153)
Post-merger IHHI			1.145				−0.111
			(0.025)				(0.060)
Change in IHHI				1.864			−1.079
				(0.037)			(0.073)
UPP					4.659		4.888
					(0.090)		(0.218)
$\Delta DPV(TS)$						−14.492	−20.851
						(0.116)	(0.179)
Constant	−57.421	−13.649	−42.074	−13.949	−17.606	−7.333	16.649
	(1.562)	(0.567)	(1.074)	(0.511)	(0.559)	(0.228)	(1.227)
Number of observations	4,803	4,803	4,803	4,803	4,803	4,803	4,803
R^2	0.262	0.279	0.312	0.348	0.356	0.765	0.859
Adjusted R^2	0.262	0.279	0.312	0.347	0.356	0.765	0.859
B. Excluding Outliers							
Post-merger HHI	−0.044						−0.291
	(0.022)						(0.043)
Change in HHI		0.462					−4.086
		(0.033)					(0.083)
Post-merger IHHI			−0.046				−0.043
			(0.015)				(0.031)
Change in IHHI				0.245			−1.243
				(0.022)			(0.040)
UPP					1.220		5.933
					(0.048)		(0.136)
$\Delta DPV(TS)$						−8.016	−23.754
						(0.226)	(0.379)
Constant	1.386	−3.034	1.559	−2.414	−5.582	−4.125	10.540
	(0.824)	(0.253)	(0.603)	(0.249)	(0.257)	(0.179)	(0.644)
Number of observations	4,533	4,533	4,533	4,533	4,533	4,533	4,533
R^2	0.001	0.042	0.002	0.027	0.126	0.217	0.757
Adjusted R^2	0.001	0.041	0.002	0.027	0.126	0.217	0.757

Note: The dependent variable is ΔSII 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.

Table 25: Predictors of the Effect of Mergers on Total Surplus

Specification	(1)	(2)	(3)	(4)	(5)	(6)
A. Including Outliers						
Post-merger HHI	−0.145					−0.022
	(0.002)					(0.007)
Change in HHI		−0.247				0.169
		(0.003)				(0.012)
Post-merger IHHI			−0.098			−0.035
			(0.001)			(0.005)
Change in IHHI				−0.157		−0.070
				(0.002)		(0.006)
UPP					−0.378	−0.322
					(0.004)	(0.017)
Constant	4.681	0.802	3.185	0.754	0.988	2.565
	(0.072)	(0.026)	(0.048)	(0.022)	(0.025)	(0.092)
Number of observations	4,803	4,803	4,803	4,803	4,803	4,803
R^2	0.564	0.598	0.628	0.681	0.644	0.749
Adjusted R^2	0.564	0.598	0.628	0.681	0.644	0.749
B. Excluding Outliers						
Post-merger HHI	−0.053					−0.011
	(0.001)					(0.002)
Change in HHI		−0.120				0.028
		(0.001)				(0.003)
Post-merger IHHI			−0.037			−0.000
			(0.001)			(0.001)
Change in IHHI				−0.076		−0.009
				(0.001)		(0.002)
UPP					−0.187	−0.194
					(0.001)	(0.004)
Constant	1.474	0.241	0.946	0.191	0.335	0.698
	(0.038)	(0.006)	(0.027)	(0.007)	(0.006)	(0.023)
Number of observations	4,533	4,533	4,533	4,533	4,533	4,533
R^2	0.383	0.828	0.395	0.777	0.877	0.890
Adjusted R^2	0.383	0.828	0.395	0.777	0.877	0.890

Note: The dependent variable is $\Delta DPV(TS)$ 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.

References

[1] Ackerberg, D., and M. Rysman. 2005. "Unobserved product differentiation in discrete-choice models: estimating price elasticities and welfare effects." *RAND Journal of Economics*, 36(4): 771–788.

[2] Berry, S., and A. Pakes. 2007. "The Pure Characteristics Demand Model." *International Economic Review*, 48(4): 1193–1225.

[3] Besanko, D., J.-P. Dubé, and S. Gupta. 2005. "Own-Brand and Cross-Brand Retail Pass-Through." *Marketing Science*, 24(1): 123–137.

[4] Ciliberto, F., G. Moschini, and E.D. Perry. 2019. "Valuing Product Innovation: Genetically Engineered Varieties in U.S. Corn and Soybeans." *RAND Journal of Economics*, 50(3): 615–644.

[5] Dafny, L., K. Ho, and M. Varela. 2013. "Let Them Have Choice: Gains from Shifting Away from Employer-Sponsored Health Insurance and Toward an Individual Exchange." *American Economic Journal: Economic Policy*, 5(1):32–58.

[6] Fabra, N., and M. Reguant. 2014. "Pass-Through of Emissions Costs in Electricity Markets." *American Economic Review*, 104(9): 2872–2899.

[7] Grieco, P.L.E., C. Murry, and A. Yurukoglu. 2024. "The Evolution of Market Power in the U.S. Automobile Industry." *Quarterly Journal of Economics*, 139 (2): 1201–1253.

[8] Miller, N.H., M. Remer, C. Ryan, and G. Sheu. 2017. "Upward pricing pressure as a predictor of merger price effects." *International Journal of Industrial Organization*, 52: 216–247.

[9] Nocke, V., and M.D. Whinston. 2022. "Concentration Thresholds for Horizontal Mergers." *American Economic Review*, 112(6): 1915–1948.

[10] Song, M. 2006. "Estimating the Pure Characteristics Demand Model: A Computational Note." Manuscript, Georgia Institute of Technology.

[11] —. 2015. "A Hybrid Discrete Choice Model Of Differentiated Product Demand with An Application to Personal Computers." *International Economic Review*, 56(1): 265–301.