Mergers, Innovation, and Entry-Exit Dynamics: The Consolidation of the Hard Disk Drive Industry, 1996–2015*

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Abstract

We study the process of industry consolidation with endogenous mergers, innovation, and entry-exit. We develop an empirical model of a dynamic game with a random proposer of merger in each period, and estimate it using data from the hard disk drive industry. We find mergers became a dominant mode of exit and sometimes generated productivity improvement (i.e., synergies). Our counterfactual simulations feature antitrust policy regimes with alternative tolerance levels of mergers, and highlight a dynamic welfare tradeoff between the ex-post pro-competitive effects of blocking mergers and its negative side

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effects due to the destruction of ex-ante option values. The results suggest approximately four firms as the optimal regulatory threshold.

Keywords: Consolidation, Dynamic Oligopoly, Entry and Exit, Innovation, Merger, Productivity, Shakeout.

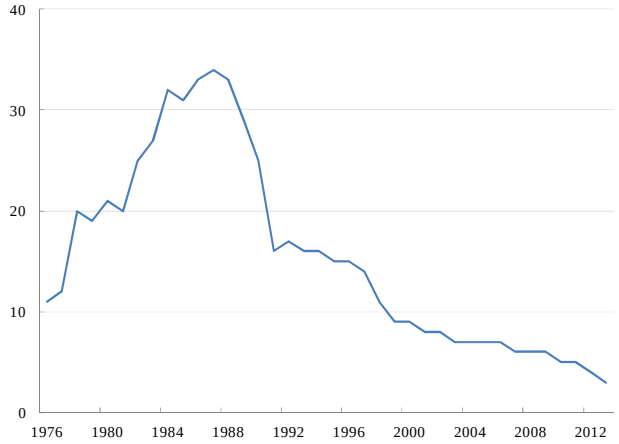
1 Introduction

The welfare analysis of horizontal mergers has traditionally focused on the static tradeoff between market power and productivity (e.g., Williamson 1968, Werden and Froeb 1994, Nevo 2000). However, both of these factors are likely to change in the longer run, partially in response to the rules governing mergers (e.g., Gilbert 2006, U.S. Department of Justice and the Federal Trade Commission 2010). Mergers change market structure, and in turn, the expectations about market structure affect firms' incentives to invest in continued operation, productivity improvement, as well as mergers and acquisitions. Thus a full understanding of the economic impact of mergers and competition policy requires an analytical framework that incorporates firms' forward-looking behaviors with respect to entry/exit, R&D investment, and mergers.

For these purposes, we develop an empirical model of a dynamic oligopoly game with endogenous mergers, innovation, and entry/exit. Our model captures the conventional, static tradeoff between market power and productivity by a period game featuring Cournot competition among firms with heterogeneous productivity levels. That is, mergers reduce the number of firms but may potentially improve the productivity of merged entities, so that the net welfare contribution can be either positive or negative. Moreover, by explicitly incorporating the dynamics of endogenous mergers, R&D, and entry/exit, we allow both market power and productivity to change over time through multiple channels. Specifically, market structure changes in response to entry/exit and mergers, whereas the productivity profile of firms evolves reflecting

their R&D investment and stochastic synergy from mergers. Thus the model can predict firms' equilibrium response to the change in antitrust policy, and allows for a fine decomposition of welfare impact into competition effect and innovation effect.

Figure 1: The Number of HDD Manufacturers in the World

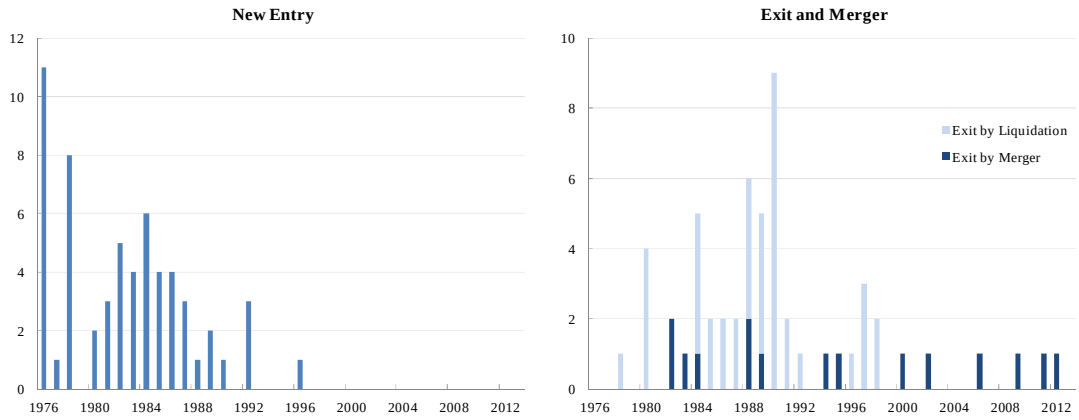


Note: The number of firms counts only the major firms with market shares exceeding one percent at some point of time. See Igami (2015a, 2015b) for the detailed analyses of product and process innovations during the first two decades of the sample period.

We use data from the hard disk drive (HDD) industry between 1976 and 2014, which has experienced a typical trajectory of markets for high-tech products in three phases (Figures 1 and 2). First, massive entry occurred during the first half of our sample period, when the demand grew fast as personal computers (PCs) were commercialized successfully. Second, the industry consolidation started around 1990 when new entry became rare and many fringe firms exited mostly through bankruptcy and liquidation: shakeout. Third, the final phase of consolidation began around 2000 when the nine major survivors started merging with each other, eventually down to three firms in the entire world. We estimate the dynamic model using this final subsample (in the current version of the paper).

Besides the availability of data that cover a long process of industry consolidation, we have two other reasons to study this market. One is that antitrust au-

Figure 2: Number of Entry and Exit



Note: The number of firms counts only the major firms with market shares exceeding one percent at some point of time.

thorities across the globe have seriously investigated these mergers for concerns over their potential impact on competition and innovation, which makes the HDD mergers policy-relevant. For example, the U.S. Federal Trade Commission (FTC) questioned the merit of Seagate Technology's takeover of Maxtor in 2006, mostly out of concerns over an allegedly negative effect of reduced competition on the incentives to innovate in the subsequent years. Likewise, the Ministry of Commerce (MOFCOM) of China spent a considerable amount of time before approving the merger of Western Digital Corporation and Hitachi Global Storage Technologies in 2012. The other reason to study the HDD industry is the magnitude of its contribution to general computing, which makes the case relevant for the economics of innovation. Without mass storage of data with high access speed and low cost, none of today's economic activities that rely on digital information could function properly, including app-based services, cloud computing, electronic commerce, online banking, search engines, social networking, as well as the estimation of a dynamic structural model.

Our empirical analysis proceeds as follows. First, we document the process of consolidation in the HDD industry, which was briefly described in the above. Second,

we estimate each firm's marginal cost in each time period (calendar quarter) by using data on HDD prices, quantities, market shares, and the HDD component prices, based on a static model of demand and Cournot competition among heterogeneous firms. Third, we embed the implied period profits into the dynamic oligopoly model, solve it by backward induction, and estimate its key parameters using a nested fixed-point (NFXP) algorithm. Finally, we use the estimated model to assess the welfare impact of a hypothetical antitrust policy in which five-to-four and four-to-three mergers are completely blocked, as opposed to the historical rule-of-thumb practice that has permitted mergers down to three firms.

The results suggest this counterfactual merger policy may not necessarily increase social welfare despite its pro-competitive effect, for three reasons. First, the reduction of merger opportunities decreases firms' expected continuation values, thereby encouraging them to exit (by liquidation) more often: the value-destruction effect. This exit-inducing side effect partially offsets the pro-competitive effect of blocking mergers. Second, in response to the reduced synergy opportunities, firms try to increase in-house R&D investment as a substitute for merger. However, this substitution effect is partially offset by the value-destruction effect mentioned above, which deflates the incentives to invest across the board. Moreover, the estimated equilibrium R&D strategy exhibits an inverse-U shape that plateaus when there exist three, four, or five firms in the market, and hence the policy-induced increase of competition does not increase their incentives to innovate. Consequently, the increased R&D does not fully make up for the forgone synergies, so that the counterfactual productivity growth underperforms the baseline outcome. Third, as a result of these countervailing forces, the pro-competitive effect of merger policy does not necessarily dominate its negative innovation effect, and its net impact on consumer surplus indicates a dynamic trade-off, featuring a non-monotonic pattern over time. Our decomposition of the welfare impact highlights these (hitherto unknown or under-explored) economic forces, as well as the importance of incorporating these dynamic margins of firms' response to

a policy change, without which a merger analysis would appear to overestimate the merit of the restrictive policy.

In the last part of the paper, we explore the optimal merger policy by investigating the welfare outcomes under alternative regulatory thresholds other than three or five, including more permissive regimes in which firms can merge to become monopoly or duopoly. The results suggest the optimal policy toward the HDD industry would stop mergers when the number of firms is between three and five, which coincides with the range of market structure that receives serious regulatory scrutiny. Thus the current practice of the antitrust agencies seems to have focused on the "right" range of targets. This research explains why this is the right range, both by conceptually clarifying the various competing forces in a unified model and by quantifying the dynamic welfare tradeoffs that are inherent in any antitrust policy.

1.1 Related Literature

This paper builds on a growing literature that studies endogenous mergers using dynamic models. Gowrisankaran's (1997 and 1999) computational work spearheaded the efforts to understand mergers in a dynamic and strategic environment. Gowrisankaran and Holmes (2005) proposed an alternative modeling approach to focus on a dominant firm that engages in mergers.

More recently, Mermelstein, Nocke, Satterthwaite, and Whinston (2014, henceforth MNSW) propose a computational theory of dynamic duopoly to assess the role of antitrust policy, which is probably the most closely related paper to ours. Both MNSW's and our models feature endogenous mergers, investment, entry/exit, as well as Cournot competition in a stage game, and we share their focus on the evaluation of merger policy. Our paper departs from MNSW in two respects. First, we study an N-firm oligopoly (with $N > 2$) for its relevance to the practice of antitrust policy, in which authorities typically approve mergers to four or three firms but block mergers to duopoly or monopoly. Second, we estimate an empirical model of endoge-

nous mergers using data from the high-tech industry in which antitrust authorities have actually been evaluating the merit of mergers with a strong emphasis on the likely impact on competition and innovation. Besides enhancing relevance to public policy, these two features of our research necessitate and entail nontrivial efforts to develop an empirical model that is sufficiently rich to capture the dynamics of mergers, innovation, and competition in a real industry while maintaining tractability and estimability.

Another important paper is Jeziorski's (2014) empirical analysis of the radio industry, in which he proposes a continuous-time model of mergers and product repositioning, as well as a two-step estimation procedure. His work, along with Stahl's (2011), is among the first to empirically study merger dynamics. Besides technical differences in the modeling and estimation approaches (which largely stem from the differences in data situations), our research differs substantively in that we focus on competition and innovation in a high-tech commodity industry, with endogenous entry/exit and investment, whereas his paper analyzes the dynamics of product-portfolio management in the canonical context of product differentiation among radio stations.

A growing body of literature specifically focuses on mergers and innovation, including Ozcan's (2015) empirical analysis with a two-sided matching model, Entezarkheir and Moshiriz's (2015) panel-data analysis, Marshall and Parra's (2015) theoretical investigation, and Hollenbeck's (2015) computational dynamic oligopoly.

Because mergers come out of bargaining among firms, we also build on the empirical bargaining literature. In particular, our bargaining game is similar to those in Ho (2009) and Crawford and Yurukoglu (2012). Other related work includes Fong and Lee (2013) and Collard-Wexler, Gowrisankaran, and Lee (2014). Fong and Lee (2013) lay out a framework for a dynamic network-formation game and bargaining, whereas Collard-Wexler, Gowrisankaran, and Lee (2014) provide a theoretical foundation for the use of Nash bargaining in empirical work, with emphasis on bilateral oligopoly of upstream and downstream industries.

2 Data: Consolidation of the HDD Industry

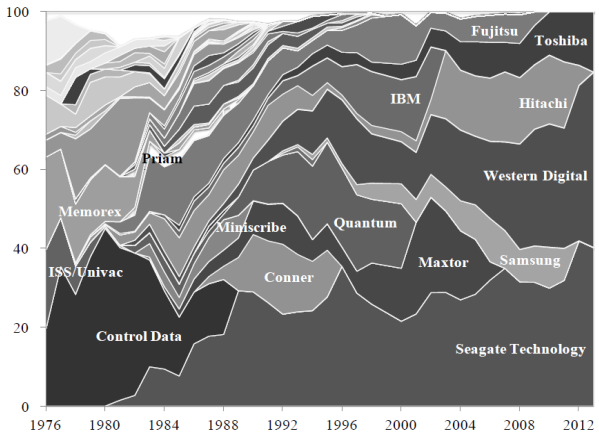
This section describes the process of industry consolidation. We have chosen to study the HDD industry because its fast pace of market structure evolution allows us to analyze the entire industry lifecycle. IBM manufactured prototypes of HDD in as early as 1956, but it was in the 1980s that its use became widespread with the arrival of personal computers (PCs). The first decade of our sample period witnessed the tripling of the number of HDD manufacturers (Figure 1). However, many of these firms failed to gain substantial market shares and lacked the capability or resources to keep up with competition and innovation, which led to a shakeout during the second decade. The number of HDD makers fell to nine by the end of the 20th century. In the final phase between 2000 and 2014, these nine major survivors merged with each other and the industry has consolidated into triopoly of Western Digital, Seagate Technology, and Toshiba.

Figure 2 shows the number of entry (right panel) and exit (left panel) to describe the patterns of firm turnover underlying Figure 1. The bar chart in the right panel is particularly important for the understanding of mergers, as it distinguishes two modes of exit, namely, plain exit by bankruptcy and liquidation (light color) and exit by mergers and acquisitions (dark color). Three patterns emerge. First, mergers have always accounted for a non-negligible fraction of exits since the first decade of the data. Second, plain exit occurred more frequently than exit by mergers during the first two decades, but it completely ceased since the mid 1990s. Third, as a result of these two patterns, mergers became the dominant mode of exit in the last 15 years of the data. Thus the early phase of industry consolidation proceeded mostly through the shakeout of fringe firms, whereas the late-stage consolidation proceeded through mergers among major survivors.

What explains these patterns of entry, exit, and mergers? A thorough analysis requires a dynamic oligopoly model and therefore has to be postponed until section 4, but some casual assessments are possible with descriptive analysis in section 3.

Massive entry is characteristic to a market for new products in which the demand is growing, and hence the first decade of our data is not a mystery. By contrast, a shakeout could occur in both declining and growing industries. Demand is shrinking in a declining industry almost by definition, which reduces profits and leads firms to exit, but the demand for HDDs had been growing at least until 2011 and hence does not serve as an obvious explanation for the mass exits in the 1980s and 1990s. An industry with growing demand may still experience a shakeout when the fixed or sunk cost of investment increases over time, either exogenously as a deterministic trajectory of the technology or endogenously through competitive dynamics as in Sutton's (1991 and 1998) models. This explanation seems to fit the HDD market better because the HDD makers' R&D expenditures have increased over time. Our interviews with the industry participants suggest many firms could not keep up with such investments.

Figure 3: Evolution of Global Market Shares

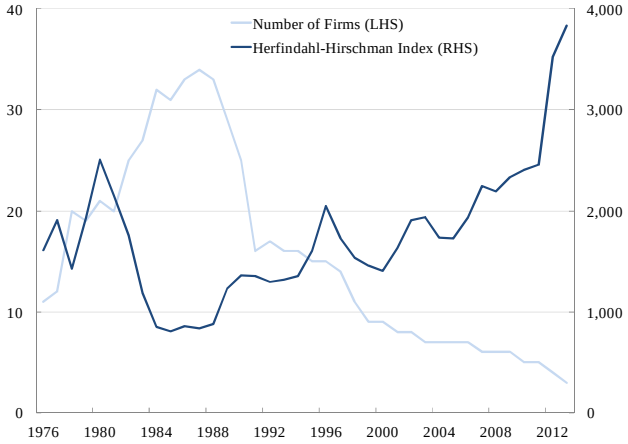


Note: Labels indicate the names of parties to most of the mergers. See Table 1 and 3 for information on the specific cases.

What was the antitrust implication of this industry consolidation? A full welfare analysis is the subject of the final sections of the paper, but our interviews with current and former practitioners of competition policy suggest the authorities typically

do not completely block a merger that creates a four- or three-firm oligopoly, whereas one that leads to a duopoly is not tolerated in the absence of special justification.[1] Consistent with this view, the mergers among HDD makers in the last decade faced some antitrust challenges but were eventually allowed to proceed, with some conditionalities such as asset divestiture, brand retention, and separate operation. Figure 3 depicts the evolution of market shares among all HDD makers, and Figure 4 overlays the Herfindahl-Hirschman Index (HHI) on the number of firms.

Figure 4: Herfindahl-Hirschman Index (HHI) of the Global HDD Market



Note: The HHI is the sum of the squares of the firm's market shares.

In summary, the HDD industry experienced phases of mass entry and exit, and has consolidated into triopoly mostly through mergers in the last two decades. The rising sunk cost of R&D investment, rather than a decline in demand, seems to underlie the overall tendency to consolidate. The antitrust authorities have made some limited interventions in recent cases but did not completely block any of the proposed mergers.

[1] We thank Joseph Farrell, Orie Shelef, and Lawrence Wu for these insights.

3 Static Structural Analysis

Before proceeding to develop a fully dynamic model of entry, exit, and mergers, let us pause and consider firms' incentives for mergers in this section. In section 3.1 we review the theoretical literature on the incentives to merge, which will guide our subsequent empirical analysis based on a static model in section 3.2.

3.1 Incentives to Merge

By definition, a merger reduces the effective number of competitors by concentrating the ownership of productive assets, and hence standard models of oligopoly predict increases in market power, markups, and profits. This market-power effect certainly exists, for example, in the traditional Cournot oligopoly with homogeneous goods and N identical firms, each of which faces linear demand, $P = a - \sum_i q_i$, and chooses output, q_i, to maximize profit, $\pi_i \equiv (P - c_i)\, q_i$, where c_i is constant marginal cost ($c_i = c \ \forall i$). In a symmetric Nash equilibrium, each firm's output and profit are $q_i = (a - c) / (N + 1)$ and $\pi_i = [(a - c) / (N + 1)]^2$, respectively, both of which will increase as N decreases. Thus the firms will enjoy increased market power, and this effect should provide a basic incentive for mergers.

However, the gains from mergers will be shared unevenly between merging parties ("insiders") and the rest of the industry ("outsiders"). Stigler (1950) argued that the insiders' combined market share may decrease after the merger, and that their joint profit may also decrease unless there exists a significant saving in fixed costs. Salant, Switzer, and Reynolds (1983) proved this conjecture in the symmetric Cournot setting (similar to the example in the above), showing that the outsiders will free-ride on the increased market power by expanding their outputs. Because outputs are strategic complements in a Cournot game, the insiders will have to best-respond by reducing their joint output, to the extent that mergers become unprofitable for the merging parties under most circumstances. The only exception is a merger that leads to a

monopoly because there will be no outsider. They also show the insiders' incentives to merge improves (i.e., become less negative) as N decreases because there will be less free-riders (outsiders). Qiu and Zhou (2007) articulate this intuition in a dynamic version of the Cournot game and discover that mergers are strategic complements.

Subsequent studies discovered that this free-riding effect does not necessarily dominate the market power effect in a Cournot game with heterogeneous firms (Perry and Porter 1985) and in a differentiated-good Bertrand game (Deneckere and Davidson 1985), but Stigler's argument still carries a useful insight that outsiders may benefit from a merger more than insiders, which could be a relevant lesson when we proceed to a fully dynamic analysis in which firms choose to stay alone or merge.

Another lesson from these papers is the importance of cost-heterogeneity across firms, depending on which insiders may increase or decrease their joint profit after mergers. Farrell and Shapiro (1990) further investigated the implications of cost-heterogeneity by analyzing two different modes of efficiency gains. One is "rationalization" of productive assets upon merger, by which the merged entity's marginal cost inherits the lowest of the two insiders' pre-merger marginal costs (i.e., $c^{IN} = min\{c^A, c^T\}$, where c^{IN}, c^A, and c^T denote marginal costs of the merged entity, acquiring firm, and target firm, respectively). The other is "synergies" between the insiders, by which the merged entity achieves the level of efficiency that is superior to both of the pre-merger insiders' (i.e., $c^{IN} < min\{c^A, c^T\}$) either through scale economies, knowledge spillovers, or some other channels. Their paper shows consumers will benefit from a merger only if some synergies materialize. Thus both the private and public gains from mergers depend on the extent of cost-heterogeneity as well as how these costs change as a result of mergers.

From these theoretical inquiries, we could gain the following three insights. First, there exists a tug-of-war between the market power effect and the free-riding effect. The former could increase the profits of insiders as well as outsiders, but the latter could tilt the distribution of such incremental profits in favor of outsiders, to the

extent that insiders may find a merger unprofitable. Second, the incentives to merge increase as the industry becomes more concentrated (i.e., as N decreases), because the market power effect grows larger and there will be less free-riders. Thus mergers are strategic complements, which explains some of the historical patterns in section 2 (see Figures 1 and 2) whereby mergers have become a dominant mode of exit over time. Third, the balance between the two forces critically depends on cost-heterogeneity across firms as well as how merged firms' cost structure change after mergers. For an empirical analysis of merger incentives, the relevant cost structure includes both the variable or marginal costs of production (i.e., rationalization and synergies, as defined by Farrell and Shapiro) and the fixed or sunk costs of operation, R&D, and capital expenditures.

We may translate these conceptual lessons into guidelines for our subsequent empirical analysis as follows. First, potential gains from an increase in market power can be measured by estimating the elasticity of demand. Second, the extent of free-riding effect should be visible in the data on market shares. Specifically, an inspection of the merging firms' combined market shares before and after mergers should provide a first indication of free-riding by outsiders. Third, we can estimate each firm's marginal cost in each period to investigate these patterns of cost-heterogeneity as well as the extent of rationalization or synergies due to merger. The combination of the demand and marginal cost estimates provides a more structural foundation to measure various incentives. Fourth, a similar analysis of fixed or sunk costs of operation and investments should complete the picture on how firms' cost structures change after mergers. Fifth, we may estimate the sunk costs of entry, exit, and merger, so that we can understand a full dynamics of merger incentives, including the option values and choice problems associated with entry/exit, staying alone, and merger. Most of the first four empirical objects are either directly observable in the data or estimable within a static model of demand and supply. The remainder of this section will engage in such a static analysis. By contrast, the last item in the above calls for

a dynamic model, which will be the subject of section 4.

Table 1: Market Shares Before/After Mergers (%)

Year	Target name	Acquiror name	ms^T Before	ms^A Before	$ms^T + ms^A$ Before	$ms^T + ms^A$ After
1982	Burroughs	Memorex	1.85	7.83	9.68	2.73
1983	ISS/Univac	Control Data	0.75	27.08	27.83	19.85
1984	Vertex	Priam	0.93	2.52	3.45	2.78
1988	Plus Dev.	Quantum	0.89	1.41	2.30	4.64
1988	Imprimis	Seagate	13.92	18.16	32.08	29.23
1989	MiniScribe	Maxtor	5.68	4.99	10.68	8.53
1994	DEC	Quantum	1.65	18.60	20.25	20.68
1995	Conner	Seagate	11.94	27.65	39.58	35.41
2001	Quantum	Maxtor	13.87	13.87	27.73	26.84
2002	IBM	Hitachi	13.86	3.64	17.50	17.37
2006	Maxtor	Seagate	8.19	29.49	37.67	35.27
2009	Fujitsu	Toshiba	4.41	10.32	14.72	11.26
2011	Samsung	Seagate	6.89	39.00	45.89	42.82
2012	Hitachi	Western Digital	20.32	24.14	44.46	44.27

Note: ms^T and ms^A denote the target and the acquiring firms' market shares, respectively. For each merger case, "before" refers to the last calendar quarter in which ms^T was recorded separately from ms^A, and "after" is four quarters after "before." Alternative time windows including 1, 8, and 12 quarters lead to similar patterns.

Source: *DISK/TREND* Reports (1977–99) and *TRENDFOCUS* Reports (1996–2014).

3.2 Market Shares Before and After Mergers

Table 1 shows the combined market share of the acquiring firm and the target firm declined after merger in each of the 14 cases, which suggests the theoretical prediction of free-riding by the non-merging parties is a real phenomenon. At the same time, the acquiring firms managed to achieve expansions relative to their individual pre-merger market shares, which is consistent with our interviews with the industry participants, in which they explained gaining market shares as the primary motivation for mergers. Finally, a larger firm acquires a smaller firm in most of the cases, which seems intuitive.

To gain further insights into the incentives to merge, we structurally interpret these market share data in terms of marginal costs which are heterogeneous across firms and change over time. Specifically, we first estimate a logit demand model, and

then recover from each firm's first-order condition its implied marginal cost in each period.

3.3 Product Characteristics and the Nature of Competition

HDDs are bundles of hard disks that provide data-storage capacity for computer users. Historically, many different capacity sizes (per HDD unit) have existed, but industry sales are concentrated in only a few "typical" or "average" capacity sizes at any point in time, and all active firms produce and sell practically all of these bundles (see Appendix A.1). Limited room for differentiation exists because all HDDs have similar, industry-standard access speed, and reliability is difficult to measure before purchase. An HDD either works or it does not. Reliability issues have occasionally dented some firms' reputations. Western Digital had bad times in the late 1990s; Seagate Technology had its share of problems in the early 2000s; and IBM-Hitachi (now HGST, owned by Western Digital) has had better reputation.

However, these product characteristics have such a limited variability that Peter Knight, the former senior vice president of Conner Peripherals and Seagate Technology, and the former president of Conner Technology, describes HDDs as "a completely undifferentiated product" in this respect. According to Mr. Knight, "there is no product differentiation. Everybody has the same (information storage) capacity and (speed) performance, and similar reliability, so the buyers want the cheapest drives with acceptable reliability. Cost is the single most important thing."[2] Moreover, direct sale to consumers represents only a small fraction of all trades, which leaves little room for brand-based horizontal differentiation. Thus HDDs are homogeneous "high-tech commodities" and the primary dimension of competition is in terms of (quality-adjusted) cost of production.

To capture these features of the HDD market, we have chosen to model the demand for HDDs as a log-linear demand function in terms of raw data-storage capacity

[2] Author's personal interview on June 30, 2015, in Cupertino, CA.

in bytes (i.e., bytes as homogeneous goods), and characterize the spot-market competition as a Cournot game among firms with heterogeneous marginal costs. The next two subsections will explain the details of our modeling and estimation of demand and spot-market competition, respectively.

3.4 Log-linear Demand for Data-storage Capacity

Given this technogical background, we specify the following log-linear demand function for raw data-storage capacity, which HDDs embody physically,

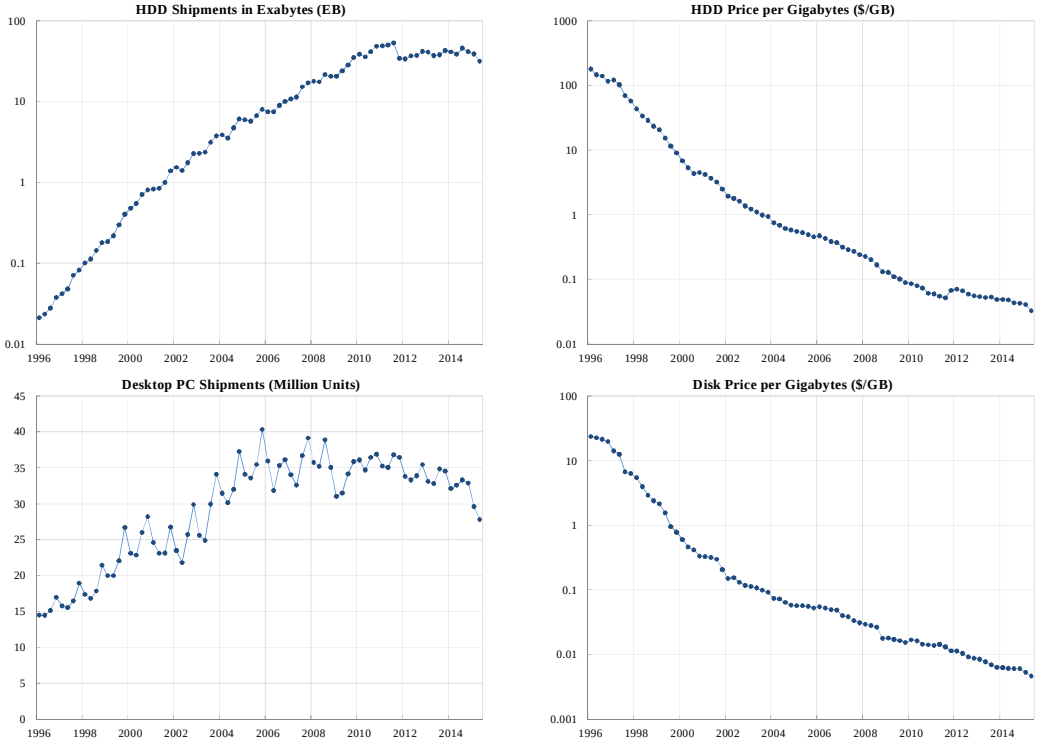
$$\log Q_t = \alpha_0 + \alpha_1 \log P_t + \alpha_2 \log X_t + \varepsilon_t, \tag{1}$$

where Q_t is the world's total HDD shipments in exabytes (EB, or one billion gigabytes), P_t is the average HDD price per gigabytes (\$/GB), X_t is the PC shipments (in million units) as a demand-shifter, and ε_t represents unobserved demand shocks. Because the equilibrium prices in the data may correlate with ε_t, we instrument P_t by Z_t, the average disk price per gigabytes (\$/GB). Disks are one of the main components of HDDs, and hence their price is an important cost-shifter for HDDs. The disks are made from substrates, which are in turn made of either aluminum or glass. The manufacturers of these key inputs are primarily in the business of processing materials, and only a small fraction of their revenues come from the HDD-related products. Thus we regard Z_t as exogenous to the developments within the HDD market.

Figure 5 summarizes the data patterns of these four variables for demand estimation, (Q_t, P_t, X_t, Z_t). The HDD shipment volume in EB (Q_t) has grown steadily on the back of PC shipments (X_t) as the upper- and lower-let panels show. The HDD price per GB (P_t) has been decreasing as a result of "Kryder's Law," which is an engineering regularity that says the recording density (and therefore storage capacity) of HDDs doubles approximately every 12 months, just like Moore's Law,

which says the circuit density (and therefore processing speeds) of semiconductor chips doubles every 18 to 24 months. With this secular trend in storage density, the disk price per GB (Z_t) has fallen dramatically, because more data can be stored on the disk surface of the same size. The upper- and lower-right panels capture these trends. Thus the downward trends in P_t and Z_t reflect both process innovation (i.e., lower marginal costs) and product innovation (i.e., higher "quality" or data-storage capacity per HDD unit) in this industry.[3]

Figure 5: Data for Demand Estimation at the Level of Gigabytes (GB)



Note: See sections 3.3 and 3.4 for technological details.

Table 2 shows the log-linear demand estimates. The price coefficient, α_1, is similar in both OLS and IV estimates, and also represents the price-elasticity of demand because of the log-log specification. This similarity of the estimates might suggest

[3]The modeling of Kryder's Law is outside the scope of this paper, and we regard this industry-wide trend as an exogenous technological process that progresses deterministically. Instead, we focus on how each firm's marginal cost deviates from this technological trend, in the subsequent sections.

most of the variation in HDD prices comes from cost shocks, such as Kryder's Law. The PC shipment is an important demand-shifter, increasing the HDD demand almost unit by unit (in the IV estimate). The fit is extremely high in both the first- and second-stage regressions partially because of the existence of trends (i.e., serial correlations) in these variables, which might generate some spurious correlations and which is an issue that we explore in **Appendix A.x**.[4] Nevertheless, given the technological nature of HDDs, including their direct use in PCs and Kryder's Law, these trends actually represent economic fundamentals of the market. In other words, we are not surprised by the fact that disk prices explain HDD prices well, or that PC shipments predict HDD shipments almost deterministically. Thus we feel comfortable in using the IV estimates in column 2 as our baseline demand function for the subsequent analyses.

Table 2: Demand Estimates

Dependent variable:	(1)	(2)	(3)
log total EB shipped	OLS	IV-1	IV-2
log price per GB (α_1)	$-.8549^{***}$	$-.8244^{***}$	$-.8446^{***}$
	(.0188)	(.0225)	(.0259)
log PC shipment (α_2)	$.8430^{***}$	1.0687^{***}	$.9198^{***}$
	(.1488)	(.1817)	(.2180)
Constant (α_0)	-1.6452^{***}	-2.4039^{***}	-1.9033^{***}
	(.4994)	(.6084)	(.7320)
Number of observations	78	78	78
Adjusted R^2	.9971	.9971	.9972
First stage regression			
IV for HDD price	–	*Disk price*	*Time trend*
F-value	–	3009.80	742.14
Adjusted R^2	–	.9889	.9469

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Before we move on to the supply side of the spot-market analysis, we discuss several other modeling considerations about the demand side, such as (1) linear specification, (2) product differentiation, (3) durability and repurchasing cycles, and (4) the downstream market of PCs.

[4]Future versions of the paper will feature such sensitivity analyses.

First, we estimated a linear demand (unreported) as an alternative specification, but found its fit less satisfying than the log-linear version, because the underlying data patterns exhibit exponential rates of change. The fact that we used log scales for Q_t, P_t, and Z_t in Figure 5 has already foreshadowed this result.

Second, we also estimated a differentiated-product version of the demand system, including a simple logit model as well as a random-coefficient logit specification (a.k.a. "BLP"). That is, we treat each "bundle" of GB as a different product (e.g., treating 500GB HDDs as differentiated from 1000GB HDDs), and estimate discrete-choice models of HDD buyers. Due to the absence of brand- or firm-level differentiation (see previous section), however, the result of the subsequent analyses remain mostly unchanged. We also point out the fact that prices per GB are similar across HDDs with different capacities. See Appendix A.1 for details.

Third, HDDs are physically durable for multiple years, and hence consumer's PC repurchasing cycles could potentially introduce dynamics into the determination of HDD demand in each period. However, consumers' PC repurchasing cycles are primarily driven by the generational changes in the semiconductor industry (e.g., the introductions of faster chips) and the operating-system software (e.g., the release of new editions of Windows), rather than by the factors that are specific to the HDD market. PCs typically feature stickers that prominently advertise the brands and the generations of CPUs (central processing units) and operating systems, such as "intel inside CORE i7" and "Windows 7." By contrast, the HDD makers' branding efforts have never achieved a comparable level of success. In other words, HDDs do not seem to drive consumers' PC purchasing behaviors, which makes PC demand exogenous to the HDD market. Once PC shipments (X_t) are controlled for, therefore, little room seems to exist for the physical durability of HDDs to play an important role.[5]

Fourth, PC makers comprise sizable fraction of the HDD buyers, which prompts us to consider at least three aspects of business-to-business relationships. The first

[5] Future versions of the paper will feature pictures HDDs, with detailed explanations about product specification information on the product label.

concern is the possibilities of long-term relationships between particular pairs of a HDD maker and a PC maker. One might even hear some HDD maker boasting about "exclusive contracts" with important PC makers. However, interviews with industry participants reveal such contracts are neither long-term or exclusive. Even if a particular model of PC product carries HDDs from certain suppliers, many comparable models exist and their product life cycles are short. Moreover, "second-sourcing" is historically a common practice in the computer industry, in which PC makers maintain multiple suppliers of the same product to guarantee steady supply of key components and to keep their prices in check. These trade practices appear closer to our characterization of spot-market competition as short-run transactions in an open market than long-term exclusive contracts.

The second PC-related concern is potential lumpiness of demand, because PC makers are not exactly atomistic buyers. However, although an average consumer might recognize only a few brands such as Lenovo, Dell, or HP, the overall concentration level of market shares is actually low or medium. The average five-firm concentration ratio (CR_5) between 1996 and 2014 is 49.5%, which is usually considered "low" for antitrust purposes. Moreover, the variety of PC product designs and models reflects ample heterogeneity among consumers, who purchase the final products and hence eventually underlies the PC makers' demand for HDDs. Thus the lumpiness of demand is not our primary modeling considerations.

Nevertheless, PC manufacturers have been experiencing their own process of consolidation, with CR_5 increasing from 34.8% in 1996 to 64.3% in 2014. Their speed is considerably slower than the consolidation of HDD makers, but the tendency is clear and steady. Such parallel processes of industry consolidations in vertically linked markets would deserve an independent research project. As long as spot-market transactions do not contain important dynamic elements, incorporating a bilateral oligopoly and bargaining model into the static part of our framework would be conceptually straightforward. However, additional data requirement and computation

burden persuaded us not to pursue this theme within our current paper.

3.5 Cournot Competition and Marginal Cost Estimates

Cournot competition with homogeneous goods and heterogeneous costs (by productivity levels) provides a useful approximation to the firms' spot-market behaviors in the HDD industry. Despite fierce competition with undifferentiated goods, accounting records indicate the HDD makers have enjoyed positive profit margins, which have widened considerably as the number of firms decreased (see Figure 6 below). Moreover, changes in production capacity take time, and hence price competition given installed capacities *à la* Kreps and Scheinkman (1983) is a physically realistic characterization of the spot market.

Firm i maximizes profits

$$\pi_{it} = (P_t - mc_{it})\, q_{it} \tag{2}$$

with respect to shipping quantity q_{it}, where P_t is the price of a representative HDD and mc_{it} is the marginal cost, which we assume is constant with respect to quantity. Firm i's first-order condition is

$$P_t + \frac{\partial P}{\partial Q} q_{it} = mc_{it}. \tag{3}$$

which provides one-to-one mapping between q_{it} (observed) and mc_{it} (implied) given P_t in the data and $\partial P/\partial Q$ from the demand estimates. Intuitively, the higher the firm's observed market share, the lower its implied marginal cost, which happens to coincide with the typical underlying assumption in the literature on firm heterogeneity and productivity (i.e., not limited to the game-theoretic IO literature).

Based on these marginal cost estimates, Table 3 shows the merging firms lowered their marginal costs at faster rates than the average trend of the rest of the industry in all but two cases. This evidence suggests the existence of synergies. In our interviews,

the industry participants indicated such synergies typically stem from more efficient uses of production facilities.

Table 3: Marginal Cost Estimates Before/After Mergers (US$)

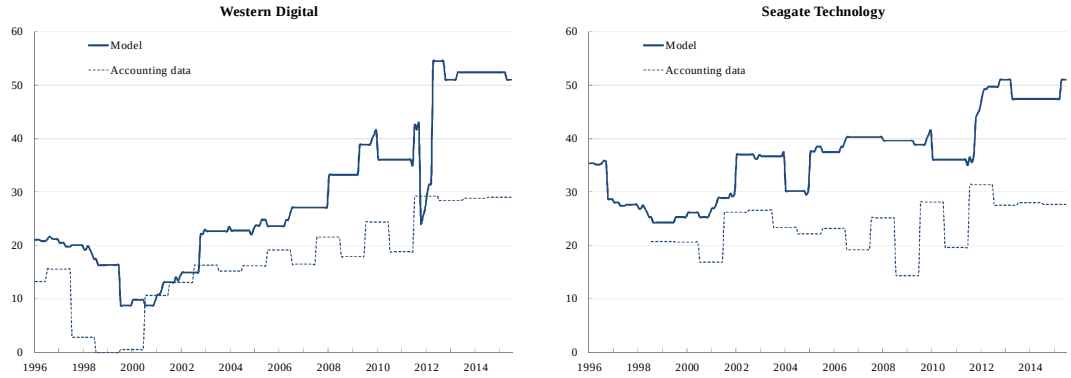
Year	Target name	Acquiror name	Target (c^T)	Acquiror (c^A)			Rivals ∇c^{OUT}	Relative change $\nabla c^{IN} - \nabla c^{OUT}$
				Before	After	∇c^{IN}		
1982	Burroughs	Memorex	2068.21	2044.52	1469.62	−574.90	−590.44	15.53
1983	ISS/Univac	Control Data	1475.65	1395.39	1024.25	−371.14	−393.17	22.03
1984	Vertex	Priam	1081.94	1077.10	959.96	−117.14	−116.34	−0.80
1988	Plus Dev.	Quantum	510.52	508.93	427.49	−81.44	−71.62	−9.83
1988	Imprimis	Seagate	470.79	457.88	352.52	−105.37	−71.62	−33.75
1989	MiniScribe	Maxtor	424.29	426.40	362.50	−63.91	−53.12	−10.79
1994	DEC	Quantum	239.96	188.30	165.19	−23.10	−16.76	−6.35
1995	Conner	Seagate	191.85	143.95	116.45	−27.51	−3.84	−23.67
2001	Quantum	Maxtor	91.81	91.81	70.61	−21.20	−17.52	−3.68
2002	IBM	Hitachi	67.35	70.27	59.53	−10.73	−6.79	−3.94
2006	Maxtor	Seagate	57.46	51.39	50.84	−0.55	0.22	−0.76
2009	Fujitsu	Toshiba	48.69	47.01	44.56	−2.44	−2.42	−0.02
2011	Samsung	Seagate	54.15	45.01	39.29	−5.72	−3.74	−1.98
2012	Hitachi	Western Digital	47.75	46.66	37.21	−9.45	−7.63	−1.81

Note: c^T and c^A denote the target and the acquiring firms' marginal costs, respectively. The definitions of "before" and "after" are the same as in Table 1 (i.e., 4-quarter time window). ∇c^{IN} and ∇c^{OUT} denote the changes in the insiders' and the outsiders' marginal costs, respectively.

As an informal assessment of the fit of the static part of the model (i.e., log-linear demand and Cournot competition), Figure 6 compares the model's predictions with accounting data, in terms of profit margins at Western Digital (left) and Seagate Technology (right), respectively. Our model takes as inputs the demand estimates and the marginal-cost estimates, and predicts equilibrium outputs, prices, and hence each firm's variable-profit margin in each year, under any market structure (i.e., the number of firms and their productivity levels). The solid lines represent such predictions of economic profit margins along the actual history of market structure, whereas the dotted lines represent "gross profit" margins (i.e., revenue minus "cost of revenues") in the firms' financial statements.

Economic profits and accounting profits do not necessarily coincide because they are different concepts, which explains the existence of gaps in the graphs. On average,

Figure 6: Comparison of Profit Margins (%) in the Model and Financial Statements



Note: The model predicts economic variable profits, whereas the financial statements report accounting profits (gross profits), and hence they are conceptually not comparable. The correlation coefficient between the model and the accounting data is .8398 for Western Digital, and .5407 for Seagate Technology. With a management buy-out in 2000, Seagate Technology was a private company until 2002, when it re-entered the public market. These events caused discontinuity in the financial record.

(economic) variable profit margins are higher than (accounting) gross profit margins by 11.4 and 13.8 percentage points at Western Digital and Seagate Technology, respectively, presumably because the former excludes fixed costs of operation and sunk costs of investment, whereas the latter includes some elements of fixed and sunk costs. For example, manufacturing operations in East Asia accounted for $41,304$, or 80.8%, of Seagate's $50,988$ employees on average between 2003 and 2015, whose wage bills constitute the labor component of the "cost of revenues" as a matter of accounting. However, some of these employees must have spent time and efforts on technological improvements, such as the re-tooling of manufacturing equipment for new products (i.e., product innovation), as well as the diagnosis and solution of a multitude of engineering challenges to improve the cost-effectiveness of manufacturing processes (i.e., process innovation), which should be characterized as some sorts of investment and innovation as a matter of economic interpretation. For these reasons, we regard this comparison as an informal assessment of the fit. Nevertheless, the correlation coefficient between the model's prediction and the accounting data is .8398 for Western Digital, and .5407 for Seagate Technology, which seems to confirm the overall

relevance of the static components of our model with respect to what the managers and the shareholders of these firms would have cared about.

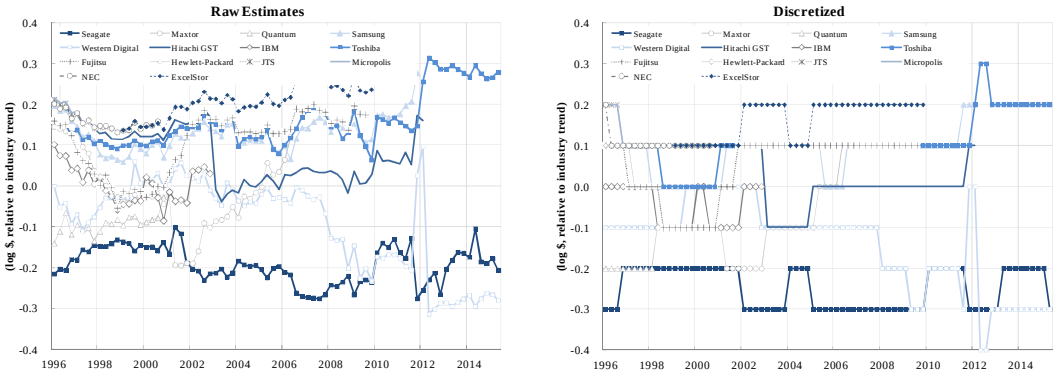
3.6 Discretization of Productivity Levels

These static analyses are interesting by themselves and provide a basis for welfare assessment of particular merger cases, as long as we are willing to take these mergers as exogenous shocks and assume away potential changes in investments and market structure. In reality, however, an antitrust policy (regime) is likely to affect not only the firms' spot-market behaviors but also their incentives for mergers, investments, as well as entry-exit, and hence the entire history of innovation and market structure. Thus a complete welfare analysis of industry consolidation requires endogenous mergers, innovation, and entry-exit dynamics, which will be the focus of the subsequent sections.

In anticipation of such dynamic analysis, we define the empirical state space by discretizing the levels of firm-specific productivity based on the marginal cost estimates from the previous subsection. Figure 7 (left) plots the trajectories of marginal costs at the firms that were active in the final process of industry consolidation between 1996 and 2015. Because the whole industry has historically experienced a secular trend of cost reduction, we de-trend these estimates and express them relative to the trajectory of Kryder's Law, in the natural logarithm of dollars.

To parameterize the dynamic oligopoly game parsimoniously (see next section) and keep it computationally tractable, we discretize this relative marginal-cost space as shown in Figure 7 (right). This discretization scheme eliminates small wiggles of productivity evolution but preserves the overall patterns of these firms' relative performances, including their major shifts as well as leader-follower differences (at least most of the persistent ones). Finer grids resulted in too many zig-zag patterns, frequently amplifying small wiggles which happened to cross the discretization thresholds. More coarse grids tended to eliminate such noises, but the transitions be-

Figure 7: Marginal Cost Estimates and Their Discretization



Note: The left panel plots our marginal cost estimates based on the empirical analysis in the previous subsections. The right panel displays its discretized version. See main text for details.

tween levels became too infrequent and each of such productivity changes became too impactful in terms of its profit implications via Cournot competition. After experimenting with these alternative grids, we have come to prefer the 0.1 log-dollar grid because it appears to strike the right balance between noise reduction and smooth transitions.

Henceforth these discretized marginal cost estimates (say, $\overline{mc}_{it}$s) span the state space of firm-specific productivity levels, which will be denoted by $\omega_{it} \in \{\bar{\omega}_1, \bar{\omega}_2, ..., \bar{\omega}_M\}$, where $M = 7$ with our preferred grid. Note that the ranking convention reverses as we redefine marginal costs as productivity levels. That is, a lower marginal cost will be referred to as a high productivity level in the subsequent sections.

4 Dynamic Structural Analysis

4.1 A Dynamic Model of Merger, Investment, and Entry/Exit

Setup Time is discrete with an infinite horizon, $t = 1, 2, ..., \infty$. There exist a finite number of firms, $i = 1, 2, ..., I$. Each firm's individual state is its productivity level,

$\omega_{it} \in \{\bar{\omega}_{00}, \bar{\omega}_0, \bar{\omega}_1, \bar{\omega}_2, ..., \bar{\omega}_M\}$, where $\bar{\omega}_{00}$ represents an absorbing state in which the firm is "dead" (upon exit or acquisition by a rival firm), $\bar{\omega}_0$ is a "potential entrant" state from which a firm may choose to become active in the product market, and $(\bar{\omega}_1, \bar{\omega}_2, ..., \bar{\omega}_M)$ indicate discrete productivity levels of active firms. The industry state is a collection of individual states across I firms, $\omega_t = \{\omega_{it}\}_{i=1}^{I}$. Payoffs depend on the profile of productivity levels but not on the identity of firms, and hence the distribution of the number of firms across productivity levels is a sufficient statistic for the industry state, $s_t = (n_{00}, n_0, n_1, n_2, ..., n_M)$. Because only active firms participate in the product-market competition and inactive firms (i.e., dead firms and potential entrants) do not, $(n_1, n_2, ..., n_M)$ completely determine each firm's period profit, $\pi_{it} = \pi(\omega_{it}, n_1, n_2, ..., n_M)$. This section focuses on the exposition of the dynamic part of the model and takes these period profits as given (i.e., as primitive inputs).

At the beginning of each period, nature randomly chooses one firm (say i) as a proposer of merger with the recognition probability $\rho_i(s_t) = 1/n_{\max}$, where $n_{\max}$ is the maximum number of firms. If i is already active, it becomes the proposer and may choose to exit, stay alone, invest in R&D, or propose merger to one of the active rivals, j. That is, an active firm at its turn-to-move chooses its action, a_{it}, from the choice set $A_i(s_t) = \{exit, stay, invest, merge(1), merge(2), ..., merge(M)\}$, where $merge(m)$ indicates proposing merger to a level-m rival firm, if such a firm exists in state s_t.

When i exits (by its own choice to liquidate and not by being acquired), it earns scrap value, κ^x, and exits forever (i.e., $\omega_{i,t+1} = \bar{\omega}_{00}$). When i stays alone, it pays the fixed cost of operation and equipment maintenance, κ^c, and its productivity remains the same (i.e., $\omega_{i.t+1} = \omega_{it}$). When i invests in a better process, it pays the sunk cost of innovation, κ^i, and its productivity increases by one level (i.e., $\omega_{i,t+1} = \omega_{it} + 1$), with $\bar{\omega}_M$ as the upper bound. When proposing merger, firm i ("acquiror") makes a take-it-or-leave-it (TIOLI) offer to j ("target"), $p_{ij}(s_t)$, which the latter may accept or reject. If the offer is accepted, acquiror i's productivity may potentially improve by

some increment, Δ_{ijt}, based on a draw from the Poisson distribution with mean $\lambda > 0$, which represents the realization of stochastic synergy from the combined assets (i.e., $\omega_{i,t+1} = \max\{\omega_{it}, \omega_{jt}\} + \Delta_{ijt}$), whereas target firm j collects the acquisition price, $p_{ij}(s_t)$, and exits forever (i.e., $\omega_{j,t+1} = \bar{\omega}_{00}$). If j rejects the offer instead, both i and j will stay independent, with $\omega_{i,t+1} = \omega_{it}$ and $\omega_{j,t+1} = \omega_{jt}$. We assume i sets $p_{ij}(s_t)$ slightly above j's outside option (i.e., j's expected value of staying alone), so that j will strictly prefer accepting the offer. Each of the other non-proposers (i.e., $k \neq i, j$) pays κ^c, and its productivity remains the same. At the end of each period, active firms are subject to stochastic depreciation of productive assets by one level, with probability δ.

If nature chooses a potential entrant (i.e., $\omega_{it} = \bar{\omega}_0$), this firm may choose to enter (or stay out of) the market: $a^0_{it} \in A^0 = \{enter, out\}$. Entry requires a sunk cost of investment, κ^e, to establish level-1 operation (i.e., $\omega_{i,t+1} = \bar{\omega}_1$ upon entry). Staying out does not cost anything, in which case the potential entrant remains outside the market (i.e., $\omega_{i,t+1} = \omega_{it} = \bar{\omega}_0$).

These discrete alternatives are accompanied by private cost shocks. For an active firm, $\varepsilon_{it} = \left(\varepsilon^x_{it}, \varepsilon^c_{it}, \varepsilon^i_{it}, \{\varepsilon^m_{it}\}_{m=1}^M\right)$, where ε^m_{it} corresponds to the choice of merging with a level-m rival. For a potential entrant, $\varepsilon^0_{it} = (\varepsilon^e_{it}, \varepsilon^o_{it})$. We assume these shocks are i.i.d. extreme value. Along with the (public) state s_t, these ε_{it}s constitute the payoff-relevant state of the proposer i.

Equilibrium Each firm maximizes its present value of expected future profit stream discounted by a common factor, $\beta \in (0, 1)$. We focus on a type-symmetric Markov perfect equilibrium (MPE) of this game, where a Markov strategy is a mapping from the firm's public and private state variables, $(s_{it}, s_{-it}, \varepsilon_{it})$, to its action, a_{it}. Because the game features a random proposer in each period, an equilibrium will be characterized by two sets of expected value functions, $EV_{it}(s_t)$ and $W^j_{it}(s_t)$, which correspond to periods in which nature chooses a focal firm i and someone else (i.e., $j \neq i$) as

proposers, respectively. We will refer to $EV_{it}(s_t)$ and $W_{it}^j(s_t)$ as "proposer" and "non-proposer" value functions, and construct them as follows.

When nature picks an active firm i as a proposer at time t, firm i earns its period profit, $\pi_i(s_t)$, draws private cost shocks, $\varepsilon_{it} = (\varepsilon_{it}^x, \varepsilon_{it}^c, \varepsilon_{it}^i, \varepsilon_{it}^m(s_t))$, and compares the following alternative-specific values,

$$\begin{aligned}
\bar{V}_i^x(s_t, \varepsilon_{it}^x) &= -\kappa^x + \varepsilon_{it}^x + \beta E\left[\Lambda_{i,t+1}(s_{t+1}) | s_t, a_{it} = exit\right], && (4)\\
\bar{V}_i^c(s_t, \varepsilon_{it}^c) &= -\kappa^c + \varepsilon_{it}^c + \beta E\left[\Lambda_{i,t+1}(s_{t+1}) | s_t, a_{it} = stay\right], && (5)\\
\bar{V}_i^i\left(s_t, \varepsilon_{it}^i\right) &= -\kappa^c - \kappa^i + \varepsilon_{it}^i + \beta E\left[\Lambda_{i,t+1}(s_{t+1}) | s_t, a_{it} = invest\right], \text{ and} && (6)\\
\bar{V}_{ij}^m\left(s_t, \varepsilon_{ijt}^m\right) &= -\kappa^c - \kappa^m + \varepsilon_{ijt}^m - p_{ij}(s_t) && (7)\\
&\quad + \beta E\left[\Lambda_{i,t+1}(s_{t+1}) | s_t, a_{it} = merge\ j\right],
\end{aligned}$$

for exiting, staying alone, investing, and merging with each of the active rivals (generically denoted by j), respectively. $\Lambda_{i,t+1}(s_{t+1})$ represents i's expected value at time $t+1$ (with expectation as of time t), that is, *before nature picks a proposer* for time $t+1$,

$$\Lambda_{i,t+1}(s_{t+1}) = \rho_i(s_{t+1}) EV_{i,t+1}(s_{t+1}) + \sum_{j \neq i} \rho_j(s_{t+1}) W_{i,t+1}^j(s_{t+1}). \quad (8)$$

As this equation clarifies, $\Lambda_{it}(s_t)$ is an "umbrella" expected value function that nests both "proposer" and "non-proposer" values, which is why $\Lambda_{it}(s_t)$ is a probability-weighted sum of $EV_{it}(s_t)$ and $W_{it}^j(s_t)$s. Proposer i's value *after* drawing ε_{it} is

$$V_{it}(s_t, \varepsilon_{it}) = \pi_i(s_t) + \max\left\{\bar{V}_{it}^x(s_t, \varepsilon_{it}^x), \bar{V}_{it}^c(s_t, \varepsilon_{it}^c), \bar{V}_i^i\left(s_t, \varepsilon_{it}^i\right), \left\{\bar{V}_{ijt}^m\left(s_t, \varepsilon_{ijt}^m\right)\right\}_j\right\}, \quad (9)$$

and its expected value *before* drawing ε_{it} is

$$\begin{aligned} EV_{it}(s_t) &= E_\varepsilon\left[V_{it}(s_t,\varepsilon_{it})\right] \qquad (10)\\ &= \pi_i(s_t)+\gamma+\ln\left[\exp\left(\tilde{V}^x_{it}\right)+\exp\left(\tilde{V}^c_{it}\right)+\exp\left(\tilde{V}^i_{it}\right)+\sum_{j\neq i}\exp\left(\tilde{V}^m_{ijt}\right)\right], \end{aligned}$$

where γ is Euler's constant and $\tilde{V}^{\cdot}_{it}$ is the deterministic part of $\bar{V}^{\cdot}_i(s_t,\varepsilon^{\cdot}_{it})$, that is, $\tilde{V}^{\cdot}_{it}\equiv\bar{V}^{\cdot}_i(s_t,\varepsilon^{\cdot}_{it})-\varepsilon^{\cdot}_{it}$.

Likewise, if nature picks a potential entrant i as a proposer, i draws $\varepsilon^0_{it}=(\varepsilon^e_{it},\varepsilon^o_{it})$ and chooses to enter or stay out, which entail the following alternative-specific values,

$$\bar{V}^e_i(s_t,\varepsilon^e_{it}) = -\kappa^e+\varepsilon^e_{it}+\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t,a_{it}=enter\right], \text{ and} \qquad (11)$$

$$\bar{V}^o_i(s_t,\varepsilon^o_{it}) = \varepsilon^o_{it}+\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t,a_{it}=out\right], \qquad (12)$$

respectively. Thus the potential entrant's "proposer" value *after* drawing ε^0_{it} is

$$V^0_{it}\left(s_t,\varepsilon^0_{it}\right)=\max\left\{\bar{V}^e_i(s_t,\varepsilon^e_{it}),\bar{V}^o_i(s_t,\varepsilon^o_{it})\right\}, \qquad (13)$$

and its expected value *before* drawing ε^0_{it} is

$$EV^0_{it}(s_t)=E_\varepsilon\left[V^0_{it}\left(s_t,\varepsilon^0_{it}\right)\right]=\gamma+\ln\left[\exp\left(\tilde{V}^e_{it}\right)+\exp\left(\tilde{V}^o_{it}\right)\right]. \qquad (14)$$

Next, we construct the "non-proposer" value functions, $W^j_{it}(s_t)$. When nature picks another active firm $j\neq i$ as a proposer, an active non-proposer i earns its period profit, $\pi_i(s_t)$ and waits for proposer j's action, a_{jt}, which depends on the realization of j's private cost shocks, ε_{jt}. Active non-proposer i's expected value

before j draws ε_{jt} is

$$\begin{aligned} W_{it}^{j}(s_t) &= \pi_i(s_t) - \kappa^c + \sigma_{it}(a_{jt} = exit)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = exit\right] \\ &\quad + \sigma_{it}(a_{jt} = stay)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = stay\right] \\ &\quad + \sigma_{it}(a_{jt} = invest)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = invest\right] \\ &\quad + \sigma_{it}(a_{jt} = merge\ i)\,p_{ji}(s_t) \\ &\quad + \sum_{k \neq i,j} \sigma_{it}(a_{jt} = merge\ k)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = merge\ k\right], \end{aligned} \tag{15}$$

where $\sigma_{it}(a_{jt} = \cdot)$ is i's belief over j's action (i.e., proposer j's choice probability, $\Pr(a_{jt} = \cdot)$, as perceived by non-proposer i). Our assumptions on the bargaining protocol simplifies the acquisition price as

$$p_{ji}(s_t) = E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = stay\right]. \tag{16}$$

When the non-proposer is a potential entrant, this "non-proposer" expected value is simpler than (15),

$$\begin{aligned} W_{it}^{0j}(s_t) &= \sigma_{it}(a_{jt} = exit)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = exit\right] \\ &\quad + \sigma_{it}(a_{jt} = stay)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = stay\right] \\ &\quad + \sigma_{it}(a_{jt} = invest)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = invest\right] \\ &\quad + \sum_{k \neq i,j} \sigma_{it}(a_{jt} = merge\ k)\,\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt} = merge\ k\right], \end{aligned} \tag{17}$$

because it does not earn profit, pay fixed cost, or become a merger target. When

nature picks a potential entrant j as a "proposer," (15) and (17) become

$$\begin{aligned} W_{it}^{j}(s_t) &= \pi_i(s_t) - \kappa^c \\ &\quad +\sigma_{it}\left(a_{jt}^0 = enter\right)\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt}^0 = enter\right] \\ &\quad +\sigma_{it}\left(a_{jt}^0 = out\right)\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt}^0 = out\right], \text{ and} \end{aligned} \tag{18}$$

$$\begin{aligned} W_{it}^{0j}(s_t) &= \sigma_{it}\left(a_{jt}^0 = enter\right)\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt}^0 = enter\right] \\ &\quad +\sigma_{it}\left(a_{jt}^0 = out\right)\beta E\left[\Lambda_{i,t+1}(s_{t+1})\,|s_t, a_{jt}^0 = out\right] \end{aligned} \tag{19}$$

for an active non-proposer and a potential entrant non-proposer, respectively.

These value functions entail the following optimal choice probabilities before proposer i draws ε_{it} (or ε_{it}^0 if i is a potential entrant),

$$\Pr(a_{it} = action) = \frac{\exp\left(\tilde{V}_{it}^{action}\right)}{\exp\left(\tilde{V}_{it}^{x}\right) + \exp\left(\tilde{V}_{it}^{c}\right) + \exp\left(\tilde{V}_{it}^{i}\right) + \sum_{j\neq i}\exp\left(\tilde{V}_{ijt}^{m}\right)} \tag{20}$$

$$\Pr\left(a_{it}^0 = action\right) = \frac{\exp\left(\tilde{V}_{it}^{action}\right)}{\exp\left(\tilde{V}_{it}^{e}\right) + \exp\left(\tilde{V}_{it}^{o}\right)}, \tag{21}$$

for an active firm and a potential entrant, respectively. In equilibrium, these probabilities also constitute the non-proposers' beliefs over the proposer's actions (i.e., $\sigma_{it}(a_{jt} = action)$ in equations 15, 17, 18, and 19), because of rational expectations. We will use these optimal choice probabilities to construct a likelihood function for estimation purposes.

4.2 Estimation

The parameters of the model include the discount factor β (which we set to .975 per calendar quarter, so that it is approximately .9 per year), the depreciation probability δ, the mean synergy λ, and the sunk costs of entry κ^e (which is assumed to be prohibitively high in our current analysis of the period 2000–14), exit κ^x (which we

set to zero), staying alone κ^c (which we observe in our data), investment κ^i, and merger κ^m. Our data contain each firm's state s_{it} and action a_{it}, as well as κ^c and period profit π_{it}. We can estimate δ and λ directly from the transition frequencies of ω_{it} in data as well. Thus our main econometric problem is to estimate κ^i and κ^m from the observations of states and actions.

The contribution of firm i at time t to the likelihood is

$$l_{it}\left(a_{it}|s_t;\kappa\right) = \rho_i(s_t) \prod_{action \in A_{it}(s_t)} \Pr\left(a_{it} = action\right)^{1\{a_{it}=action\}}, \tag{22}$$

where $1\{\cdot\}$ is an indicator function. The maximum likelihood estimate (MLE) is

$$\hat{\kappa} = \arg\max_{(\kappa^i,\kappa^m)} \frac{1}{T}\frac{1}{I}\sum_t \sum_i \ln\left[l_{it}\left(a_{it}|s_t;\kappa\right)\right], \tag{23}$$

where T is the number of sample periods and I is the number of firms.

The realizations of turns-to-move are not always evident in the data, and hence the implementation of MLE needs to distinguish "active" periods in which some firm took an action (such as exit, merger, or entry) and altered s_t, and "quiet" periods in which no such proactive moves were made by any firm. Specifically, we incorporate the random turns-to-move by setting

$$\hat{\rho}_i\left(s_t\right) = \begin{cases} 1 & \text{if } a_{it} \in \{exit, merger, enter\}, \text{ and} \\ \frac{1}{n_{\max}} \Pr\left(a_{it} = stay, out\right) & \text{if } a_{it} \in \{stay, out\} \ \forall i. \end{cases} \tag{24}$$

That is, when exit, merge, or entry is recorded in the data, we may assign probability 1 to the turn-to-move of the firm that took the action, whereas in a "quiet" period, nature may have picked any one of the firms, who subsequently decided to stay alone (or stay out) and did not alter s_t.

We use the nested fixed-point (NFXP) algorithm as in Rust (1987), in which we calculate the optimal choice probabilities and the joint likelihood for each candidate

parameter value, until the maximum is reached. We solve the model from the end of our sample period, $T = 2014Q1$, by assuming the industry state will remain constant afterward and calculating the terminal (or continuation) values from period-T profits, $\pi_T(s_T)$. Backward induction allows us to solve the model for a unique equilibrium of (the non-stationary version of) this extensive-form game, because the game has an effective terminal period, only a single decision-maker exists in each period, and the private cost shocks break the tie between multiple discrete alternatives.

4.3 Results

We estimate the dynamic model using data for the sub-sample period between 2000 Q1 and 2014 Q1 (in the current version of the paper) because the data set is complete with calendar-quarter frequency of observation. This period also spans the entire phase of industry dynamics in which all recorded exits occurred through mergers, the main focus of the paper. *We are currently in the process of: (1) extending the TRENDFOCUS's quarterly data to 1996 Q1–2015 Q2, (2) "de-coupling" the time-period frequencies in the data (quarterly) and the model (monthly), and (3) speeding up the run time of our MATLAB code by converting several subroutines into C.*

Table 4: ML Estimates of the Dynamic Parameters

Parameter	Estimate	Confidence Interval
κ^i	3.5250	(under construction)
κ^m	6.4214	(under construction)

Note: The confidence intervals are constructed from the likelihood-ratio tests.

We set the exit cost or scrap value to zero (i.e., $\kappa^x = 0$) because productive assets for HDD manufacturing quickly depreciate due to fast obsolescence and fast turnover of key personnel, and because industry outsiders would find little use. We also set the fixed cost of continued operation to the sum of SGA (selling, general, and administrative) expenses and capital expenditure, which is in the range of \$0.1 billion

and \$0.5 billion in each quarter (i.e., $\kappa^c \in (0.1, 0.5)$). The period 2000 Q1–2014 Q1 has not seen any new entry, and hence we do not use the entry part of our model and assume entry cost, κ^e, is prohibitively high (for now). The transition patterns of $\{\omega_{it}\}$ in data indicate $\delta = .0634$ and $\lambda = 1.1667$. Thus the costs of innovation and merger, κ^i and κ^m, will be the main dynamic parameters to be estimated.

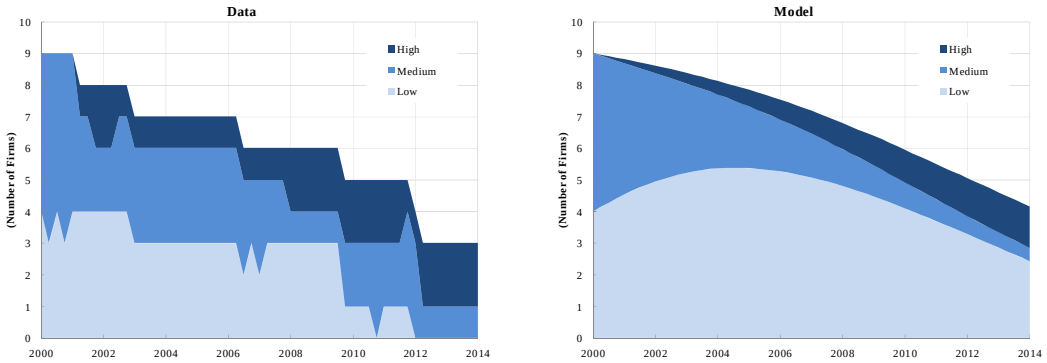
Table 4 shows the innovation cost (κ^i) estimate of \$3.5 billion. This cost estimate is close to the range of cumulative R&D expenditure in data over 12 calendar quarters (between \$2 billion and \$3 billion), which is the average frequency of productivity improvement due to in-house investment. The merger cost (κ^m) estimate of \$6.4 billion is comparable to the acquisition price for a medium-productivity firm, which suggests the actual economic cost of integrating two firms and reorganizing various activities is as big as the direct financial cost of acquisition. This finding is consistent with our interviews with industry veterans, who indicated the total economic cost of consolidating manufacturing facilities, product portfolios, R&D teams, intellectual properties, as well as forgone revenues due to glitches in reorganization could easily surpass a few billion dollars.

Figure 8 demonstrates the estimated model fits the data well in terms of reproducing the declining trajectory of the total number of firms, N_t. The composition of N_t by productivity level is also replicated with respect to both the gradual decline of less productive firms and the occasional emergence of more productive firms as a result of mergers and investments.[6]

We conduct another sanity check, with respect to enterprise values and acquisition prices. Figure 9 plots our firm value estimates along the path of market structure in the data, and overlays the actual transaction prices in the six merger cases from

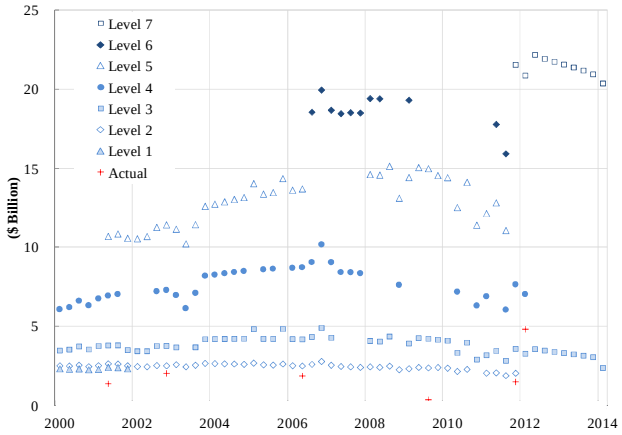
[6] The model-generated path features an initial increase of less productive firms until 2004, which is an artifact of exogenous stochastic depreciation, the rate of which is assumed constant over time and happens to be higher than the (endogenous) innovation rate during the first four years. Eliminating this assumption improves the fit of the productivity distribution of firms but does not alter our main findings from the simulation analysis in the next session. We are currently exploring more satisfying specifications of depreciation.

Figure 8: Fit of the Estimated Model (Number of Firms)



Note: The model outcome is the average of 10,000 simulations based on the estimated model. The productivity categories in the bottom panels are originally defined on a discretized grid of levels 1 through 7, each step of which corresponds to a \$2 reduction in marginal cost. For the purpose of visual illustration, we then aggregate these underlying productivity levels into three coarser categories as follows: low (levels 1 and 2), middle (levels 3 and 4), and high (levels 5, 6, and 7).

Figure 9: Firm Value Estimates and Actual Acquisition Prices



Note: Red crosses represent the actual acquisition prices in the six merger cases from *Thomson* database. The other seven markers represent our estimates of equilibrium firm values along the path of market structure in the data.

Thomson's financial data (marked by red crosses). Because target firms' stand-alone values underpin their equilibrium acquisition prices in our model, comparison of the

estimated values and the actual acquisition prices provides a ballpark assessment of the fit in terms of dollar values. Each of the acquisition prices is located close to the estimated value of firms with the corresponding productivity level (1, 2, 3, or 4) and stays within the range of the focal level and its adjacent level. Thus we regard the estimated model as a reasonable benchmark with which we may compare our counterfactual simulation to assess the impacts of a hypothetical merger policy, in the next section.

Figure 10: Equilibrium R&D Strategy and Competition

Note: This figure summarizes the overall patterns of R&D investment incentives. Our empirical analysis provides structural estimates of the equilibrium choice probabilities of each type (i.e., productivity level) of firms ω_{it}, in each market structure s_t, in each period t. Each graph pools these equilibrium investment probabilities across ω_{it} and s_t within a 5-year period and fits a nonparametric curve with local polynomials. Thus these graphs are descriptive summaries of the structural estimates rather than the estimates themselves.

Figure 10 summarizes how the firms' incentives to innovate change in response to competition, which we visualize by the number of active firms in the market. Because the graphs are based on the structural estimates of the firms' equilibrium strategies, we may interpret these competition-innovation relationships as causal. The famous "inverted U" shape emerges, indicating the equilibrium R&D probability peaks at around 3, 4, and 5 firms. The "replacement effect" (Arrow 1962) dominates when $N_t = 1$ because the monopolist is not under high competitive pressure to improve

productivity. The "efficiency effect" and preemptive motives (Gilbert and Newbery 1982) kick in with $N_t = 2$ and 3 because oligopolistic settings reward relatively more productive players with disproportionately larger market shares and wider profit margins at the expense of less productive rivals. But eventually the "rent dissipation effect" of increased competition (Dasgupta and Stiglitz 1980) starts to dominate, so that the positive impact of competition plateaus and tapers off with $N_t > 5$. These inverted-U shapes with plateaus at $N_t = 3$, 4, and 5 foreshadow part of our subsequent findings that blocking the consolidation of five firms to four and three would not accelerate innovation, in the next section.[7]

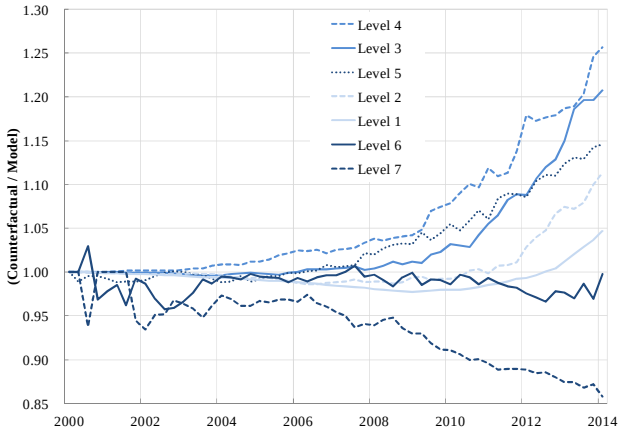
5 Impact of a More Restrictive Merger Policy

This section evaluates the welfare impact of a hypothetical competition policy in which the antitrust authorities block any merger proposal once the number of firms reaches five or less, instead of three or less, which the HDD industry participants have perceived as a historical rule of thumb. The motivation for this policy experiment is to understand how the explicit consideration of industry dynamics would alter the implications of antitrust interventions, which have traditionally been framed in static models.

Figure 11 shows how the evolution of counterfactual (CF) market structure differs from the baseline model (BL), by dividing the CF number of firms, n^{CF}, by the BL number of firms, n^{BL}, in each of the seven productivity levels. Nuanced patterns emerge. First, the CF features more medium-productivity firms and less high-productivity firms than the BL. Second, n^{CF} of low-productivity firms is lower than n^{BL} for most of the sample period and then starts overshooting after 2010. These patterns suggest both the competition effect and the innovation effect of the CF policy may exhibit complicated dynamics.

[7] We conduct more detailed decompositions of the inverted-U relationships in a separate paper (under construction).

Figure 11: Counterfactual Number of Firms by Productivity Level



Note: The model and counterfactual outcomes are the averages of 10,000 simulations based on the estimated model and the counterfactual model, respectively.

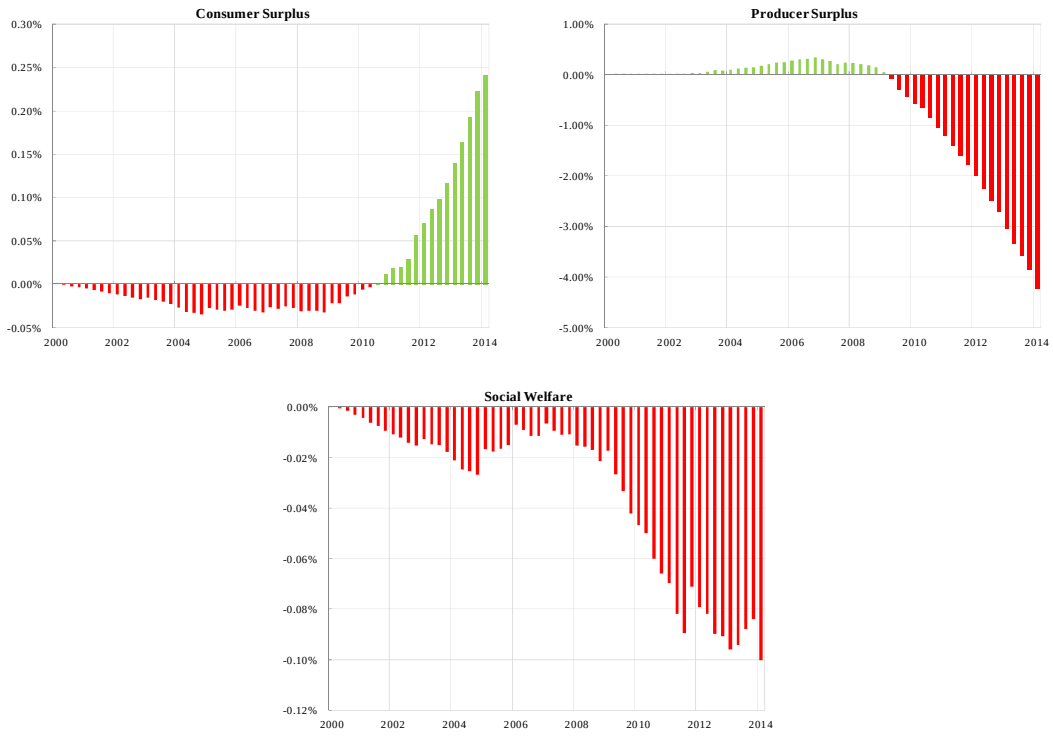
5.1 Welfare Performance

Figure 12 summarizes the welfare impact. In terms of consumer surplus (CS), the CF policy slightly underperforms the BL policy until 2010 and then outperforms it. By contrast, the CF producer surplus (PS) is higher than the baseline until 2009, when it starts deteriorating precipitously. The rate of change of PS is an order of magnitude larger than that of CS because the CF features a reduced number of high-productivity firms, which accounted for a disproportionately large portion of industry-wide profits under the BL policy. The net impact on social welfare (SW) is slightly negative throughout the sample period, including the last few years in which the CF policy had a positive impact on CS. Although CS is a larger component of SW than PS, the latter decreased in a sufficiently drastic manner to offset the improvement in CS.

5.2 Why Reduction of Mergers May Not Improve Welfare

Let us investigate the changes of CS in greater detail because the antitrust agencies typically focus on CS rather than SW in practice. Both the BL and CF models share

Figure 12: Counterfactual Welfare Outcomes



Note: The model and counterfactual outcomes are the averages of 10,000 simulations based on the estimated model and the counterfactual model, respectively.

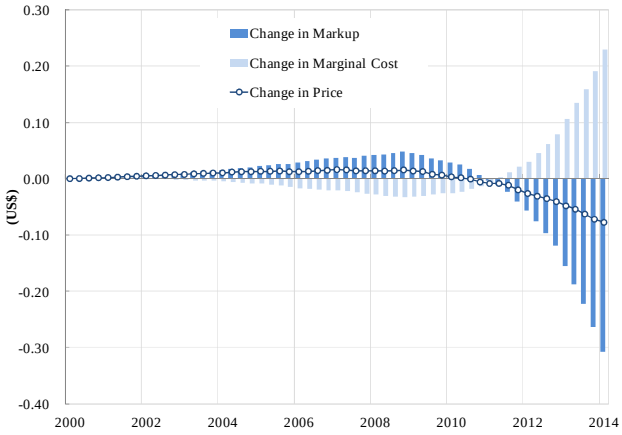
exactly the same demand structure, and hence the difference in prices completely determines the difference in CS. In other words, price is a sufficient statistic for us to judge whether the policy's impact on CS is positive or negative.

Figure 13 plots the difference in prices (i.e., $\Delta p \equiv p^{CF} - p^{BL}$) and decomposes it into two factors: the changes in markup (i.e., $\Delta m \equiv m^{CF} - m^{BL} = \left(p^{CF} - mc^{CF}\right) - \left(p^{BL} - mc^{BL}\right)$ and marginal cost (i.e., $\Delta mc \equiv mc^{CF} - mc^{BL}$).[8]

Negative Innovation Effect Partially Offsets Positive Competition Effect: Δm and Δmc reflect the changes in market power and productivity, respectively, and

[8] We use the (un-weighted) average marginal cost across firms. Alternative summary statistics such as the minimum or market share-weighted average do not qualitatively alter the decomposition patterns.

Figure 13: Decomposition of the Price Change into Competition and Innovation Effects



Note: We use the (un-weighted) average marginal cost across firms. Alternative summary statistics such as the minimum or market share-weighted average do not qualitatively alter the decomposition patterns.

hence we refer to them as the "competition effect" and the "innovation effect" of the CF merger policy.

The decomposition in Figure 13 conveys three messages. First, the magnitude of price changes appears relatively small, which explains the small impact of the CF policy on CS (in Figure 12). Second, this small difference in prices masks larger changes in the two underlying forces. The net change in price may be small, but that is because the competition effect and the innovation effect offset each other, with the former dominating the latter by a small margin most of the time. Third, each of these two forces evolves non-monotonically. The competition effect is "negative" from the perspective of CS-promotion until 2011, when it turns "positive." That is, the CF markup first increases and then decreases relative to the BL trajectory. Likewise, the innovation effect is "positive" for the first eleven years and then turns "negative."

This dual non-monotonicity is not a mere coincidence but a manifestation of the dynamic policy impact, the direction of which differs before and after the merger regulation becomes binding (i.e., when the number of firms reaches five). In the

following, we analyze these underlying mechanisms in greater detail.

Exit-promotion Effect Attenuates Pro-competitive Impact: To understand the root causes of these patterns, let us further investigate the determinants of the two forces. Specifically, we can explain the competition effect (Δm) and the innovation effect (Δmc) by the changes in firms' exit, investment, and merger.

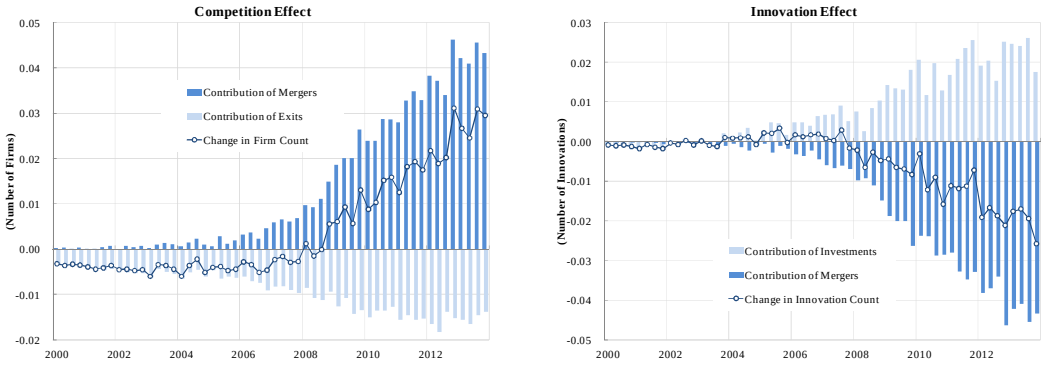
A key determinant of markup (or the competition effect) is the number of firms, which is in turn driven by exits and mergers. Figure 14 (left) decomposes the change in the number of firms into the contributions of exits and mergers.

The contribution of exits is negative throughout the sample period because more firms choose to exit (and hence the number of firms decreases) under the CF policy. Exits (by liquidation) increase because the CF policy reduces the opportunities for mergers, and with them the possibilities of more profitable exit (for target firms) as well as gains from higher productivity and market power (for acquiring firms). That is, the reduction of potential mergers leads to the deflation of enterprise values across the board and the increase in exit rate: the value-destruction effect of limited consolidation.

This "exit promotion" effect grows stronger in later years as the merger regulation becomes binding, but more noteworthy from the industry viewpoint is that the anticipation effect is present from the beginning. Forward-looking firms tend to exit more often when they expect lower continuation values down the road.

By contrast, the contribution of mergers is positive because the CF policy reduces mergers by design. The effect grows stronger in later years, when the authorities actually start blocking mergers. This is the kind of policy impact that static merger simulations have traditionally focused on. However, the explicit consideration of industry dynamics suggests the existence of the countervailing "exit promotion" effect, which dominates until 2008 and continues attenuating the positive impact of merger reductions thereafter.

Figure 14: Accounting for Competition and Innovation by Exit, Investment, and Merger



Note: These counts of firms and innovations do not distinguish the productivity levels of firms that engage in exit, investment, and merger, depending on which the eventual impact on welfare varies.

In-house Investment Substitutes for Synergy Only Imperfectly: Let us turn to the study of the innovation effect of the CF policy. The overall productivity of the industry is determined by individual firms' productivity levels, which firms can improve through either in-house R&D investment or synergy from mergers. Thus we can decompose the changes in the count of innovation into the contributions of investments and mergers, as shown in Figure 14 (right). Because the CF policy reduces mergers, mergers' contribution to productivity is negative, especially in the later years. By contrast, investments' contribution is mostly positive because in-house R&D becomes the only way to achieve higher productivity and firms try to make up for the forgone synergy through this channel. That is, firms substitute investments for mergers.

This positive change in investments, however, does not completely offset reduced synergies. The ex-post R&D incentives do not materially increase partly because the equilibrium R&D strategy exhibits an inverse-U shape with a plateau at $N_t = 3$, 4, and 5, so that keeping five firms in the market (instead of letting them consolidate into three) does not induce much difference in this respect. Moreover, investments'

contribution is slightly negative in the first few years. The underlying cause of these mediocre contributions from investments is the overall deflation of continuation values due to the reduced merger opportunities. This is another manifestation of the value-destruction effect of limited consolidation.

As a result of these competing forces, the CF merger policy affects the industry's productivity in a nuanced, non-monotonic manner. The net impact on innovation counts begins in a slightly negative range, then turns slightly positive, and finally negative again when the merger-blocking policy becomes binding and eliminates the possibilities of synergy.

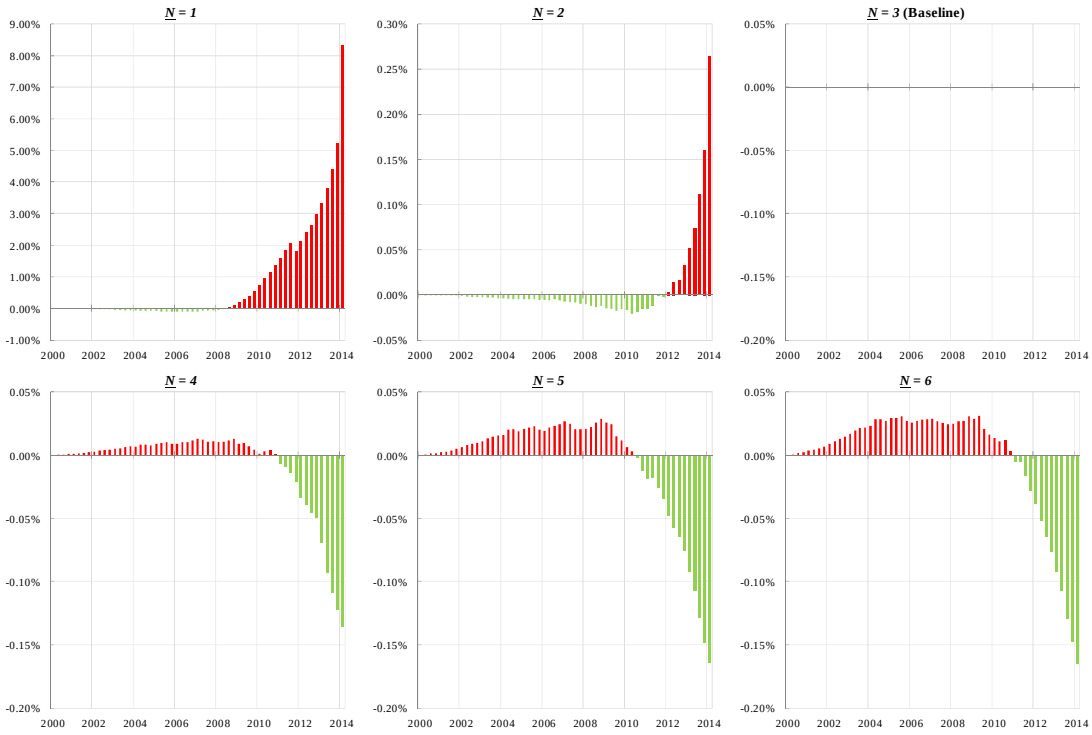
5.3 Optimal Merger Policy

Having understood the mechanism through which merger policy affects welfare, we may now ask what the optimal merger policy would be. Specifically, should the antitrust authorities permit mergers to monopoly or duopoly (i.e., $\underline{N} = 1$ or 2) instead of the current rule of thumb ($\underline{N} = 3$), or should they block mergers more aggressively (e.g., $\underline{N} = 4, 5$, or 6)?

Figure 15 shows the comparison of counterfactual HDD prices in terms of percentage change from the baseline policy regime with $\underline{N} = 3$, which is why the top-right panel ($\underline{N} = 3$) exhibits no change (i.e., $\pm 0\%$). Allowing mergers to monopoly ($\underline{N} = 1$) is a bad idea. Consolidation would proceed much faster than in reality, eventually raising prices by more than 5%, and any pro-consumer changes in the first eight years appear too small to offset the harm from consolidated market power in the last five years. In comparison, allowing mergers to duopoly ($\underline{N} = 2$) entails less dramatic consequences, but the eventual harm to consumers seems greater than the pro-investment benefits in the first twelve years. Thus, unless under special circumstances, the authorities would see little reason to relax the current regime with $\underline{N} = 3$.

If a more laid-back stance is not an attractive option, how about more restrictive merger policies, such as $\underline{N} = 4, 5$, or 6? The previous subsection has already assessed

Figure 15: Counterfactual HDD Prices Relative to the Baseline Policy



Note: Each panel shows the average of 10,000 simulations based on the estimated model under an alternative policy regime.

the performance of the $\underline{N} = 5$ policy, relative to the $\underline{N} = 3$ benchmark, and found the dynamic welfare tradeoff a close call. That is, the ex-ante value-destruction effect seems approximately in balance with the ex-post pro-competitive of blocking additional mergers. Under the $\underline{N} = 4$ regime, this dynamic tradeoff tilts slightly in favor of the ex-post pro-competitive effect, because the value-destruction side effects appear less pronounced while the main, pro-competitive effect remains visible. By contrast, the $\underline{N} = 6$ policy increases the negative side effects without visible improvements in the ex-post positive impact. Thus three, four, and five firms represent reasonable lower bounds for the enforcement of antitrust policy, and hence the regulatory agencies seem to have focused on investigating the right range of cases. Our analysis has clarified *in what sense* these are the "right" regulatory thresholds.

Before concluding this section on policy implications, we wish to delineate our framework's domain of usefulness and applicability. First, the static and the dynamic parts of our model are "modular" or "detachable." That is, an analyst can use different models of demand and spot-market competition other than what we have used, such as a discrete-choice demand model for differentiated products and Bertrand competition. Our choice of log-linear demand for homogeneous goods and a Cournot game with heterogeneous costs simply reflects our efforts to tailor the model to the specific context of the HDD market. One can preserve this modularity as long as the spot-market transactions do not contain dynamic elements of first-order importance. If the spot-market transactions do contain important dynamic elements, one has to estimate the entire model all at once, which would call for a different estimation procedure. Nevertheless, the outline of our dynamic model of mergers and innovation can still be used as a basic component.

Second, our model incorporates firms' incentives to invest in in-house R&D, both before and after the authorities approve the "final" merger (i.e., the merger that reduces the number of firms to the regulatory threshold). Innovations in the technological context of HDDs encompass both process and product innovations, in the sense that a higher data-storage density (i.e., the underlying technological progress) lowers manufacturing costs (via lower component counts) and improves product quality (i.e., storage capacity per HDD unit) at the same time. Thus the "productivity" of firms in our empirical analysis captures both of these notions of innovation. Applications of this framework to other high-tech contexts can accommodate either or both of them, depending on the technological feature of the industries.

Third, we allow market structure to evolve with endogenous entry and exit. Moreover, our empirical implementation accommodates the nonstationary economic environment surrounding the HDD industry, such as the growth of demand (i.e., the proliferation of PCs and servers), the steady improvement in engineering expertise (i.e., Kryder's Law), and the rising cost of keeping up with such technological trend

(i.e., the upward trend in the fixed costs of operation, which translates into ever higher effective sunk costs of entry). Such nonstationarity is inherent in innovative industries, and we designed our empirical approach specifically to reflect these features. Because of this flexibility, applications of our method to the computer industry and the various segments of the semiconductor industry would be straightforward, for example.

Fourth, the main focus of this paper is to explicitly incorporate endogenous mergers in the context of these industry dynamics. We designed our framework specifically to evaluate the long-run welfare consequence of alternative policy regimes. The HDD industry has already consolidated to three firms in reality, and hence whether to allow the next potential merger (to duopoly) might appear to be the most exciting question for practitioners, in the short run. Nevertheless, it is still important to step back and ask what if the policy regime had been different, with a range of alternative regulatory thresholds, including not only $\underline{N} = 2$ but also $\underline{N} = 1, 4, 5$, and 6. Only now have economists started to assess various competing forces in such a complex and realistic environment. Because these forces are general and expected to operate in industries other than HDDs as well, these counterfactual simulations would provide a useful starting point for assessing and calibrating merger policy toward other innovative industries.

6 Conclusion

Merger policy faces a dynamic welfare tradeoff. Our counterfactual policy simulation (of a more restrictive antitrust regime with $\underline{N} = 5$) demonstrates the value-destruction side effects of restricting consolidation, highlighting the importance of incorporating the dynamics of entry-exit and investment in the analysis of mergers. We decomposed the impact of a more restrictive merger policy on prices (and hence consumer surplus) into the competition effect and the innovation effect. We further accounted for these

two effects by the contributions of entry-exit, investment, and mergers. These decomposition exercises clarify that the pro-competitive effect of the policy is partially offset by the negative contribution of increased exits, as well as the negative innovation effect of reduced synergies, which in-house R&D investment cannot entirely substitute for.

A more relaxed policy is not desirable, either, because allowing mergers to monopoly or duopoly would decisively tilt the dynamic welfare tradeoff into a negative territory. In fact, our search for the optimal merger policy indicates three to five firms as the desirable regulatory thresholds, which are close to the current practice of antitrust enforcement. This paper has explained why these thresholds represent the "right" range of merger policy, by incorporating various economic factors into a cohesive dynamic model and by actually measuring the dynamic welfare tradeoffs in a real and relevant empirical setting of the HDD industry.

We leave for future research two important aspects of mergers, competition, and innovation. First, mergers and the resulting concentration might facilitate collusion, leading to an increase in market power that is greater than what usual models would predict. We do not know of any collusion episode in the HDD industry, and our interviewees repeatedly described the industry's culture as "cutthroat" and "bad at coordinating." Hence we do not see an immediate need to model collusion in this paper, nor do we know of any empirically useful model of collusion. Nevertheless, theory suggests such possibilities exist (e.g., Stigler 1964, and Selten 1973), and Miller and Weinberg (2015) found evidence of collusion following a big merger in the U.S. beer industry, so mergers with collusion represent an interesting and relevant topic.

Second, we have focused on innovations and productivity differences at the firm level, while taking the industry-wide engineering trend (i.e., Kryder's Law) as a deterministic, exogenous process. Recasting Kryder's Law as an endogenous process would be conceptually straightforward, because doing so is a matter of simply expanding the state space. But we have consciously chosen to model HDD innovations

in the way we did, because Kryder's Law does appear to be a secular trend in our data, and a larger state space would slow down computation without clear benefits in this context. We plan to investigate such technological trends of semi-macroeconomic scale in a separate project.

A.1 Log-linear Demand Estimates by Subsample

Our baseline demand estimates used the entire sample period, implicitly assuming that the demand function remained constant over time. However, changing uses of digital technology could have altered the consumers' willingness to pay for the same amount of data storage. To investigate this possibility, we estimate our demand model using two subsamples (i.e., the first and the second halves). Table 5 shows the first-half and the second-half estimates for the main parameter, the price coefficient (α_1), are within the 95% confidence intervals of each other, across all of the three specifications. Thus consumers' valuation for gigabytes of data storage has not changed in a statistically significant manner.

Table 5: Demand Estimates by Subsample

Dependent variable:	(1)		(2)		(3)	
log total EB shipped	OLS		IV-1		IV-2	
Subsample period:	First half	Second half	First half	Second half	First half	Second half
log price per GB (α_1)	$-.8165^{***}$	$-.8594^{***}$	$-.8188^{***}$	$-.8504^{***}$	$-.8959^{***}$	$-.8624^{***}$
	(.0246)	(.0264)	(.0172)	(.0233)	(.0484)	(.0249)
log PC shipment (α_2)	$.8053^{***}$	1.6302^{***}	$.7896^{***}$	1.6191^{***}	.2773	1.6340^{***}
	(.1728)	(.2422)	(.1222)	(.3809)	(.3191)	(.3797)
Constant (α_0)	-1.6405^{***}	-4.3901^{***}	-1.5868^{***}	-4.3337^{***}	.1649	-4.4094^{***}
	(.5863)	(.8718)	(.4102)	(1.3306)	(1.0895)	(1.3275)
Number of observations	39	39	39	39	39	39
Adjusted R^2	.9972	.9746	.9973	.9765	.9966	.9766
First stage regression						
IV for HDD price	–	–	*Disk price*	*Disk price*	*Time trend*	*Time trend*
F-value	–	–	2973.32	536.17	350.51	1056.23
Adjusted R^2	–	–	.9944	.9638	.9346	.9824

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

A.2 Differentiated-product Demand Estimates

Our baseline demand model in the main text used a log-linear specification at the level of data-storage unit in terms of gigabytes (GB), which are homogeneous goods in our view. Nevertheless, actual HDD products on the market are sold in "bundles" of GBs (e.g., 500GB or 1000GB) in the form of HDD units. This section explores alternative demand specifications to fully accommodate this aspect by using standard differentiated-product demand models, such as (plain) logit and random-coefficient logit. This exercise requires an alternative version of the dataset, which records HDD sales, prices, storage capacity (GB per HDD unit), and disk prices at the level of product categories (i.e., "bundles" of different sizes). Figure 16 summarizes these variables at the aggregate level across all categories, but note that the underlying data are recorded at the product-category level.

The current empirical context departs from typical applications of differentiated-product demand models, which would denote firms and brand by j, because HDDs are standardized products with little room for brand differentiation within each quality category (j denotes this dimension, and *not* firm or brand, in this paper). Thus a buyer h purchasing an HDD of *category* j in period t enjoys utility

$$u_{hjt} = c + \alpha p_{jt} + \beta x_{jt} + \xi_{jt} + \epsilon_{hjt}, \tag{25}$$
with j subscript denoting product category (and *not* firm or brand),

where c is constant, p_{jt} is the price, x_{jt} is quality (log of storage capacity in gigabytes), α and β are their coefficients, ξ_{jt} is the unobserved characteristics, and ϵ_{hjt} is the idiosyncratic taste shock that is assumed iid extreme value (over h, j, and t). The outside goods offer the normalized utility $u_{h0t} \equiv 0$, which represent other "secondary storage devices" or not using them at all.

Let $\bar{u}_{jt} \equiv c + \alpha p_{jt} + \beta x_{jt} + \xi_{jt}$ represent the mean utility from a category-j HDD whose market share is $ms_{jt} = \exp(\bar{u}_{jt}) / \sum_l \exp(\bar{u}_{lt})$. The shipment quantity is

Figure 16: Data for Demand Estimation at the Level of HDD Units

Note: See main text for explanations.

$Q_{jt} = ms_{jt}M_t$, where M_t is the size of the computer market. Berry's (1994) inversion provides the linear relationship,

$$\ln\left(\frac{ms_{jt}}{ms_{0t}}\right) = \alpha p_{jt} + \beta x_{jt} + \xi_{jt}, \tag{26}$$

which is our estimation equation underlying the demand estimates in Table 6.

Because p_{jt} might respond to ξ_{jt} and lead to an endogeneity problem, we instrument p_{jt} by the cost shifter, z_{jt}, which consists of the prices of aluminum and glass substrates (i.e., disks, the main component, for each HDD category j) and appear to be a strong IV. Thus we use the IV estimates in the subsequent analyses. See Berry and Haile (2014) for nonparametric identification of discrete-choice demand models

Table 6: Demand Estimates at the Level of HDD Units

Model:	Plain logit		Random-coefficient logit	
Estimation:	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Price (α)	$-.0322^{***}$	$-.0351^{***}$	–	-0.0241
	(.0029)	(.0031)	–	(.0085)
Quality (β)	1.3109^{***}	1.4241^{***}	–	1.726
	(.1214)	(.1287)	–	(.3224)
Year dummies	Yes	Yes	–	Yes
Quarter dummies	Yes	Yes	–	Yes
Num. of observations	476	476	–	476
Adjusted R^2	.3687	.3667	–	–
First stage regression				
F-value	–	129.39	–	–
Adjusted R^2	–	.9044	–	–

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

in general.

Column 1 and 2 report the estimates based on the (plain) logit spericication, whereas columns 3 and 4 report those based on a random-coefficient version, in which buyers are heterogeneous in terms of β_h (instead of common $\beta\ \forall h$). Our baseline (log-linear) demand model in the main text emphasized the "commodity" aspect of HDDs, whereas the random-coefficient discrete-choice version in this section tries to capture richer substitution patterns between different categories of HDDs.

Regardless of the demand specifications, an important data constraint exists as we try to analyze the supply side of the HDD spot market. Our data sources publish prices and quantities at the product category level (p_{jt} and q_{jt}) or the firm level (q_{it}) but not by product-firm (p_{ijt} or q_{ijt}). This reporting convention partially reflects the confidentiality agreements between the HDD makers and the data vendors, but another, more fundamental reason is that HDDs are so standardized and homogeneous within each category that such brand-level details would be redundant. The historical fact that these data publication businesses have been commercially viable for four decades suggests the limited disclosure is not a commercially relevant issue. Moreover,

although multiple categories of HDDs were available in the market, the majority of sales was concentrated in only a few,[9] because most of the computers on sale at any point in time came equipped with "typical" HDDs of the time, which were produced by most HDD makers. For these reasons, eventually, we will need to collapse multiple categories of HDDs into a single "composite" or "representative" HDD category with the average data-storage capacity in each period.

[9] Future versions of the paper will feature a graph that summarizes HDD sales by category, either across all years or in detail at five-year intervals. Another piece of evidence for HDDs' homogeneity would be the uniformity of price/GB across different categories.

References

[1] Arrow, Kenneth J. (1962) "Economic Welfare and the Allocation of Resources to Invention," in R.R. Nelson (Ed.), *The Rate and Direction of Economic Activity*. N.Y., Princeton University Press.

[2] Berry, Steven T. (1994) "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, Vol. 25, No. 2, pp. 242-262.

[3] ——— and Philip A. Haile (2014) "Identification in Differentiated Products Markets Using Market Level Data," *Econometrica*, Vol. 82, No. 5, pp. 1749–97.

[4] Collard-Wexler, Allan, Gautam Gowrisankaran, and Robin S. Lee (2015) "An Alternating Offers Representation of the Nash-in-Nash Bargaining Solution," mimeo.

[5] Dasgupta, Partha and Joseph Stiglitz (1980) "Industrial Structure and the Nature of Innovative Activity," *Economic Journal*, Vol. 90, No. 358, pp. 266-293.

[6] Deneckere, Raymond and Carl Davidson (1985) "Incentives to Form Coalitions with Bertrand Competition," *RAND Journal of Economics*, Vol. 16, pp. 473-86.

[7] Entezarkheir, Mahdiyeh, and Saeed Moshiriz (2015) "Merger Induced Changes of Innovation: Evidence from a Panel of U.S. Firms," mimeo.

[8] Farrell, Joseph and Carl Shapiro (1990) "Horizontal Mergers: An Equilibrium Analysis," *American Economic Review*, Vol. 80, pp. 107-26.

[9] Gilbert, Richard (2006) "Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?" in Adam B. Jaffe, Josh Lerner, and Scott Stern, eds., *Innovation Policy and the Economy*, Vol. 6, Cambridge, MA: The MIT Press.

[10] ——— and David Newbery (1982) "Preemptive Patenting and the Persistence of Monopoly," *American Economic Review*, 72(2): 514–26.

[11] Gowrisankaran, Gautam (1999) "A Dynamic Model of Endogenous Horizontal Mergers," *RAND Journal of Economics*, Vol. 30, pp. 56-83.

[12] ——— and Thomas J. Holmes (2004) "Mergers and the Evolution of Industry Concentration: Results from the Dominant Firm Model," *RAND Journal of Economics*, Vol. 35, pp. 561–82.

[13] Ho, Kate (2009) "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, Vol. 99, pp. 393-430.

[14] Hollenbeck, Brett (2015) "Horizontal Mergers and Innovation in Concentrated Industries," mimeo.

[15] Igami, Mitsuru (2015a) "Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998," mimeo.

[16] ——— (2015b) "Industry Dynamics of Offshoring: The Case of Hard Disk Drives," mimeo.

[17] Jeziorski, Przemyslaw (2014) "Empirical Model of Dynamic Merger Enforcement: Choosing Ownership Caps in U.S. Radio," mimeo.

[18] Kreps, David M. and Jose A. Scheinkman (1983) "Quantity precommitment and Bertrand competition yield Cournot outcomes," *The Bell Journal of Economics*, Vol. 14, No. 2, pp. 326–37.

[19] Mermelstein, Ben, Volker Nocke, Mark A. Satterthwaite, and Michael D. Whinston (2014) "Internal Versus External Growth in Industries with Scale Economies: A Computational Model of Optimal Oligopoly Policy," mimeo.

[20] Lee, Robin S. and Kyna Fong (2013) "Markov-Perfect Network Formation," mimeo.

[21] Marshall, Guillermo, and Álvaro Parra (2015) "Mergers in Innovative Industries," mimeo.

[22] Miller, Nathan H., and Matthew C. Weinberg (2015) "Mergers Facilitate Tacit Collusion: Empirical Evidencefrom the U.S. Brewing Industry," mimeo.

[23] Nevo, Aviv (2000) "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry," *RAND Journal of Economics*, Vol. 31, No. 3, pp. 395-421.

[24] Ozcan, Yasin (2015) "Innovation and Acquisition: Two-Sided Matching in M&A Markets," mimeo.

[25] Perry, Martin K. and Robert H. Porter (1985) "Oligopoly and the Incentive for Horizontal Merger," *American Economic Review*, Vol. 75, pp. 219-27.

[26] Qiu, Larry and Wen Zhou (2007) "Merger Waves: a Model of Endogenous Mergers," *RAND Journal of Economics*, Vol. 38, pp. 214-226.

[27] Rubinstein, Ariel (1982) "Perfect Equilibrium in a Bargaining Model," *Econometrica*, Vol. 50, pp. 97-110.

[28] Rust, John (1987) "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, Vol. 55, pp. 999-1033.

[29] Salant, Stephen W., Sheldon Switzer, and Robert J. Reynolds (1983) "Losses from Horizontal Merger: The Effects of an Exogenous Change in Industry Structure on Cournot-Nash Equilibrium," *Quarterly Journal of Economics*, Vol. 98, pp. 185-199.

[30] Selten, Richard (1973) "A Simple Model of Imperfect Competition, where 4 Are Few and 6 Are Many," *International Journal of Game Theory*, 2(1): 141–201.

[31] Stahl, C. Jessica (2011) "A Dynamic Analysis of Consolidation in the Broadcast Television Industry," mimeo.

[32] Stigler, George J. (1964) "A Theory of Oligopoly," *Journal of Political Economy*, 72(1): 44–61.

[33] Sutton, John (1991) "Sunk Costs and Market Structure : Price Competition, Advertising, and the Evolution of Concentration," MIT Press, Cambridge, Mass.

[34] Sutton, John (1997) "Game-Theoretic Models of Market Structure," *Advances in Economics and Econometrics: Theory and Applications: Seventh World Congress,* Kreps, David M and Wallis, Kenneth F, (eds.), Cambridge University Press, Cambridge.

[35] U.S. Department of Justice and the Federal Trade Commission (2010), *Horizontal Merger Guidelines*.

[36] Werden, Gregory J. and Luke M. Froeb (1994) "The Effects of Mergers in Differentiated Products Industries: Logit Demand and Merger Policy," *Journal of Law, Economics, & Organization*, Vol. 10, No. 2, pp. 407-426.

[37] Williamson, Oliver E. (1968) "Economies as an Antitrust Defense: The Welfare Tradeoffs," *American Economic Review*, Vol. 58, No. 1, pp. 18-36.

[38] Yurukoglu, Ali and Gregory S. Crawford (2012) "The Welfare Effects of Bundling in Multichannel Television Markets," *American Economic Review*, Vol. 102, pp. 643-85.