Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry

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Abstract

Why do incumbent firms innovate more slowly than entrants? This incumbent-entrant timing gap is the key to understanding the industry dynamics of "creative destruction." Theories predict cannibalization between existing and new products delays incumbents' innovation, whereas preemptive motives accelerate it, and incumbents' cost (dis)advantage would further reinforce these tendencies. To empirically quantify these three forces, I develop and estimate a dynamic oligopoly model using a unique panel dataset of hard disk drive (HDD) manufacturers (1981–98), which I constructed from industry publications. The results suggest that despite strong preemptive motives and a substantial cost *advantage* over entrants, incumbents are reluctant to innovate early because of cannibalization, which can explain at least 51% of the timing gap. I then discuss managerial implications of the findings, as well as welfare consequences of broad patents, trade barriers, and other competition/innovation policies.

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1 Introduction

"In the long run we are all dead,"[1] and firms and technologies are no exception. Netflix's movie download service has grown fast, whereas Blockbuster, a once-dominant DVD rental chain, filed for bankruptcy protection in 2010 after a reluctant pursuit of an online distribution service. Amazon is now selling everything from electronic books to disposable diapers, whereas Borders, America's number-two book retailer, liquidated its shops in 2011 after belated efforts to introduce its own electronic reader. These examples may seem extreme, but even when introducing a new technology is not too difficult, "the old winners tend not to adapt well; the new entrants face lower cost of entry, and quickly become successful," as a former CEO of Intel warned based on the experience of the world's biggest chip maker (Grove 1996). Some incumbents never introduce a new technology/product despite shrinking demand for their existing products, a puzzling phenomenon called "the innovator's dilemma" (Christensen 1997). This paper asks why incumbent firms are slower than entrants to innovate, and empirically tests three theoretical determinants of incumbents' innovation.[2]

So why do incumbents delay innovation? Viewed from a microeconomic perspective, the determinants of innovation timing include (1) cannibalization, (2) different costs, (3) preemption, and (4) institutional environment (Hall 2004, Stoneman and Battisti 2010). First, the benefits of introducing a new product are smaller for incumbents than for entrants because of cannibalization, to the extent that the old and new goods substitute for each other. By introducing new goods, incumbents are merely replacing their old source of profits, so Arrow (1962) calls this mechanism the "replacement effect." Second, incumbents may face higher costs of innovation because of organizational inertia. Economic theory, as well as case studies, suggest that as firms grow larger and older, their R&D efficiency diminishes (e.g., Schumpeter 1934);[3] although, *a priori*, hypothesizing that incumbency confers some advantages due to accumulated R&D capital is equally plausible (e.g., Schumpeter 1942). Hence, whether incumbents have a cost advantage or disadvantage is an open empirical question. Third, market structure dynamics play an important, countervailing role, as theories predict incumbents should innovate more aggressively than entrants to preempt potential rivals (e.g., Gilbert and Newbury 1982) under various oligopolistic settings. Finally, the impact of

[1] John Maynard Keynes, *A Tract on Monetary Reform* (1923), Ch. 3.

[2] I use the words innovation, diffusion, and technology adoption/choice interchangeably in this paper because I am studying a case of technological transition that exhibits all of these features. Alternatively, innovation can be more narrowly defined as invention and its first commercialization, as distinct from its subsequent spread, but such a distinction does not seem adequate for the situation in the HDD industry, where a technological roadmap is widely shared among engineers and managers throughout the industry.

[3] The existing literature suggests various reasons for incumbents' inertia, such as bureaucratization (Schumpeter 1934), hierarchy (Sah and Stiglitz 1986), the loss of managerial control (Scherer and Ross 1990), and informational, cognitive, or relationship reasons (Grove 1996, Christensen 1997).

these three determinants will change under different institutional contexts, such as the rules governing patents, non-compete clauses,[4] R&D subsidies, or international trade. In total, these three competing forces (plus institutional contexts) determine innovation timing. Cannibalization delays incumbents' innovation, whereas preemptive motives accelerate it, and incumbents' cost (dis)advantage would further reinforce these tendencies. Given this "tug of war" between the three theoretical forces, I propose to explicitly incorporate them into a unified model and estimate how much each of them matters empirically.

The goal of this paper is to empirically quantify these competing forces behind "the innovator's dilemma" in the hard disk drive industry, which is a highly relevant setting. This industry is a canonical case of "creative destruction" (Schumpeter 1942) or "disruptive innovation" (Christensen 1997), where cohorts of firms come and go with the generational transitions of technologies. I construct a unique dataset from the industry publications, *DISK/TREND Reports* (1977–99), which record a comprehensive set of firms (both incumbents and potential entrants) for more than two decades. First, I build and estimate a dynamic oligopoly model that explicitly incorporates cannibalization, heterogeneous sunk costs, and preemption (dynamic strategic interactions), all of which endogenously determine the timing of innovation and the evolution of market structure. Then I measure the effects of the three forces (i.e., estimate the innovator's dilemma) by contrasting the outcome of the estimated model with those of three counterfactual simulations in which firms ignore each of these incentives, respectively. Finally, to study broader implications of the phenomena, I simulate evolutions of the industry under four alternative institutional settings: (1) a broad patent regime, (2) a ban on non-compete clauses, (3) R&D subsidies for incumbents, and (4) a ban on foreign goods.

The estimation results suggest that despite strong preemptive motives and a substantial cost *advantage* over entrants, incumbents are reluctant to innovate early because of cannibalization, which can explain at least 51% of the timing gap. The results from the four policy simulations highlight the pro-innovation effect of competition, even though the overall effectiveness of public policies seems somewhat limited. These findings represent a contribution to the innovation literature in three respects (Hall 2004, Stoneman and Battisti 2010, Cohen 2010). First, through the modeling of strategic "creative destruction," I provide an empirically tractable microeconomic foundation of the phenomena that are central to both innovation and industry evolution.[5] Second, by quantifying the three determinants of innova-

[4] A non-compete clause is a type of employment contract that restricts employees from competing with their former employer firms. Such contracts work as entry barriers when the employees of existing firms leave their employers to start new businesses (called "spin-outs").

[5] In concluding her literature survey on innovation and diffusion, Hall (2004) suggests "there is room for an approach that is more structural and grounded in the choice problem actually faced by the adopter." This

tion timing (and its heterogeneity between incumbents and entrants), I separately measure the importance of each of these theoretical incentives in an actual industry setting. The most interesting finding is that incumbents may lag behind entrants, despite their advantage in innovation costs, which suggests a substantial part of what researchers have previously understood as organizational inertia could potentially be reinterpreted as an effect of cannibalization. Third, by simulating alternative competitive environments, I derive implications for both managerial and public policies. For example, I find a ban on international trade discourages innovation and hurt consumers. However, social welfare sometimes improves under *anti*-competitive policies, such as broad patents. Ironically, welfare improves not through promotion of innovation but through cost savings from preventing "excess" entry/innovation.

The timing of innovation in general and the incumbent-entrant timing gap in particular are important for both businesses and policymakers. Who innovates and survives better (and why) is a central question for individual firms. The timing gap also has broader implications for public policies because it is a symptom of the fundamental heterogeneity between incumbents and entrants. Discussing pro-innovation competition policies, Bresnahan (2003) stresses the importance of innovation by industry outsiders and new entrants that often results in Schumpeterian changes: "For society to have a rapid rate of technical progress, we need innovative competition from outsiders as well as innovation incentives for incumbents." Depending on how incumbents' and entrants' incentives differ, competition and innovation policies will have different consequences. Understanding the determinants of the timing gap is the first step toward designing a pro-innovation competition policy. For these purposes, I have chosen to study the HDD industry.

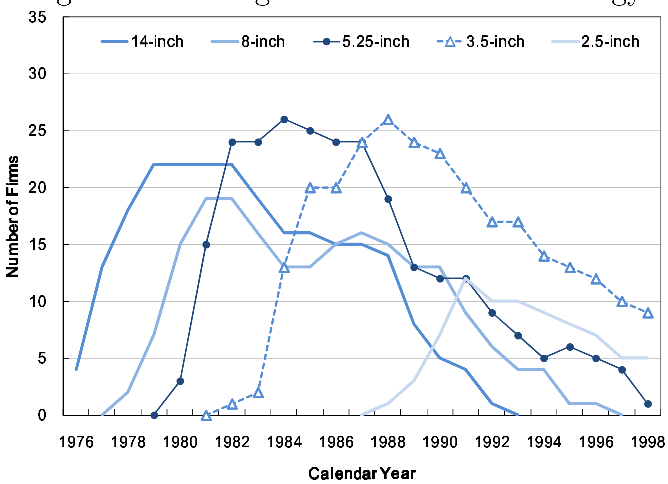
An HDD is a component of a personal computer (PC) that stores information. Desktop PCs used 5.25-inch HDDs during the 1980s, but 3.5-inch HDDs became popular during the 1990s, so those firms that exclusively manufactured 5.25-inch HDDs disappeared by the turn of the century (see Figure 1). For studying the long-run dynamics of firms and technologies, the HDD industry is ideal for three reasons. First, both technologies and firms are empirically tractable (i.e., the old and new technologies/products are different enough to represent distinct investment opportunities for firms, yet similar enough to compete within the same market as the "secondary information storage device" in desktop PCs).[6] That many firms competed, both incumbents and entrants, is also helpful for econometric purposes. Second, an unusually long panel dataset is available in the form of an annual industry publication series, the *DISK/TREND Reports* (1977–99). I obtained hard copies of the 23 volumes, in-

paper implements her recommendations in this respect. The following two contributions are the fruits of this approach.

[6]The *primary* device is memory chips (semiconductors), which provide smaller amounts of information storage with faster access speed, for temporary use.

terviewed the editor, and manually digitized the quantitative as well as qualitative contents. This 23-year period is long enough to cover the rises and falls of multiple generations of technologies and firms. Third, this industry is suitable for assessing the welfare impacts of public policies in competition and innovation, because contentious policy issues arose during its history, such as (frivolous) claims of patent infringement and restrictions on spin-out activities based on non-compete clauses.

Figure 1: Shifting Generations of Technology



Note: Shipment-based recognition of firms. Major firms only.

The task of quantifying the three forces calls for a structural approach, because incentives to innovate are sensitive to the technological and institutional context of an industry. Moreover, these incentives all interact with each other in a complex manner, are not directly observable, and create a situation in which both innovative activities and market structure evolve endogenously. Hence, absenting natural experiment-like episodes, some modeling is needed to identify these factors. In addition, policy evaluation at an industry level must address the Lucas critique (i.e., one cannot predict how innovation and competition would evolve under hypothetical policies, such as an alternative patent system, without estimating structural parameters). For these reasons, this paper takes a structural approach. I build, estimate, and simulate a model that incorporates the technological and institutional features of the HDD industry, as well as the three theoretical forces.

My empirical analysis proceeds in three steps as follows. First, I estimate demand using a standard discrete choice model for differentiated goods (the old- and new-generation HDDs). That is, I let the data tell the degree of substitution between the old and new goods and hence of cannibalization. Second, I recover marginal costs of production, implied from the first-order conditions of static competition (multi-product Cournot). From these demand and cost estimates, I calculate the static equilibrium profits in every state of the industry, that is, given any number of active firms in the market. These profit estimates embody the relationship between market structure and profitability and hence give a preliminary indication of the extent to which preemption motivates firms' introduction of a new technology/product. Third, I feed these static (period) profits into a dynamic model to estimate the sunk costs of innovation. The model features two types of firms, incumbents and entrants, so I estimate the sunk costs separately for each type. I explicitly incorporate firms' dynamic discrete choice between entering, exiting, continuing operation with the old product, or introducing the new product. I fully incorporate preemptive motives, because firms interact strategically and are forward-looking with rational expectations over the endogenous evolution of market structure. To reflect the computer industry's ever-changing nature, I make my model non-stationary, allowing demand, costs, and hence value and policy functions to change over years.

Conceptually, this third step is simple. I employ maximum likelihood estimation (MLE) to find the sunk cost parameter values that would maximize the likelihood of observing the actual innovation and entry/exit behaviors in the data. Intuitively, I invoke a "revealed preference" argument for every firm-year observation, comparing the benefits and costs of different alternatives and then inferring the sunk-cost size that is consistent with the observed action. Computationally, however, this procedure poses two technical challenges. One is the possibility of multiple equilibria. I address this issue through parsimonious modeling (small choice sets, a small state space, and period-by-period solutions) to guarantee the uniqueness of equilibrium under certain configurations. The other problem is the computational burden of calculating the equilibrium strategies (choice probabilities) and expected values. That is, for each set of candidate parameter values in the MLE procedure, I need to solve the dynamic game for its equilibrium play. I address this issue by coding the most computationally intensive routines (the calculation of expected values) in the C language within the MATLAB platform.

I have organized the rest of the paper as follows. The remainder of this section explains how this research contributes to the literature on innovation and industry dynamics. Section 2 summarizes the technological and institutional background of the HDD industry. Section 3 describes the model. Sections 4 and 5 explain the estimation procedure and results. In section 6, I quantify the three economic forces behind "the innovator's dilemma." In section 7, I evaluate welfare consequences of four different policies in innovation and competition. Section 8 concludes with a discussion of the implications for managerial practices and public policies.

1.1 Related Literature

This paper studies innovation and industry dynamics using a structural approach. As such, three bodies of literature motivate this study: competition and innovation, market structure dynamics, and the structural estimation of dynamic games. I aim to enhance the first two bodies by providing a microeconomic foundation of the "disruptive innovation" phenomena (i.e., the generational transitions of technologies and firms) and by quantifying the four incentives to innovate that have been prominent in theory but have few empirical counterparts. In doing so, I build on and extend the frameworks developed in the third body of literature by featuring a radical product innovation and incumbent-entrant heterogeneity (hence entry/exit dynamics as well) in a dynamic oligopoly model. I summarize the findings and remaining tasks of the literature in the following section.

Innovation

Many papers, both theoretical and empirical, have studied the relationship between competition and innovation, with mixed predictions and inconclusive evidence (see Gilbert [2006] and Cohen [2010] for detailed surveys). Arrow (1962) predicted an incumbent monopolist has less incentive to innovate than perfect competitors because of the "replacement effect" (i.e., the substitution between the old and new technologies), against which others theorized the preemptive motive for an incumbent monopolist to innovate more aggressively than an entrant (e.g., Gilbert and Newbery 1982, Reinganum 1983, Fudenberg and Tirole 1986). Empirical works have simplified and recast these predictions as two competing hypotheses regarding the effect of market structure on innovation, typically regressing R&D spending (or other measures of innovative activities) on the market share concentration (or measures of market power such as markups) in a cross-sectional dataset of industry-/firm-level observations. The findings are mixed. Horowitz (1962), Hamberg (1964), Scherer (1967), and Mansfield (1968) were the first among many to find a positive relationship, whereas Williamson (1965), Bozeman and Link (1983), Mukhopadhyay (1985), and Blundell et al. (1999) found a negative effect of concentration. Moreover, Scherer (1967) found a nonlinear, "inverted-U" relationship, later replicated by Scott (1984), Levin et al. (1985), and Aghion et al. (2005). Gilbert (2006) attributed the inconclusiveness of evidence to (1) the failure to control for contingencies highlighted by theorists, (2) the presence of fundamental heterogeneities across industries, and (3) the shortcomings of data and methods.

Another limitation was that whereas theories emphasized the heterogeneity of incentives to innovate between incumbents and entrants, the earlier data analyses considered the behavior of incumbents alone. This omission was problematic also from an empirical perspective because "there is abundant evidence from case studies (...) new entrants contribute a disproportionately high share of all really revolutionary new industrial products and processes" (Scherer 1980). Geroski (1989, 1991, 1994), Acs and Audretsch (1991), and Gans et al. (2002) partially filled this gap by analyzing the relationship among entry, competition, and innovation. However, rather than showing simple effects of one on the others, Geroski's studies suggested other industry characteristics such as technological opportunity and appropriability simultaneously determined these three variables. Thus, to the list of concerns Gilbert (2006) raised, Cohen (2010) added a fundamental critique that market structure was a function of innovation itself, and entry, competition, and innovation were simultaneously determined by more structural factors such as demand and technological opportunities. Some papers employed instrumental variables to address this simultaneity problem (Howe and McFetridge 1976, Levin et al. 1985, Blundell et al. 1999, Aghion et al. 2005), but Cohen (2010) concluded "cross-sectional analyses (...) have offered little insight into the actual role of these industry-level factors." The consideration of the underlying industry dynamics remains a major challenge as well. This paper addresses these issues by focusing on a specific high-tech industry, explicitly incorporating the technological context of the industry into a dynamic model, and estimating the structural parameters of the model.

Industry Evolution (Market Structure Dynamics)

The co-evolution of technology and competition has played a central role in the studies of industry evolution, or market structure dynamics, which is the second body of literature that motivates this study. Theoretical models and qualitative case studies constitute the bulk of this literature, whereas data analyses are scarce due to data limitations and the simultaneity issue. Prominent models include those of Nelson and Winter (1978, 1982), Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), Klepper (1996), and Sutton (1998). Researchers developed these theories alongside the documentation of empirical regularities (e.g., Mueller and Tilton 1969, Abernathy 1978, Abernathy and Utterback 1978, Utterback 1979, Gort and Klepper 1982, Klepper and Graddy 1990, and Klepper and Simons 2005).

Technology and market structure evolve particularly closely in a moment of "disruptive innovation," when an industry experiences the generational transitions of firms and technologies. Numerous case studies record such instances: Tushman and Anderson (1986), Mitchell (1989), Henderson and Clark (1990), Henderson (1993), Ehrnberg and Sjöberg (1995), Christensen (1997), and Tripsas (1997). More recent papers formally model these generational transitions, such as Adner and Zemsky (2005) and Klepper and Thompson (2006). However, a quantitative empirical work has not yet been released, probably because the drastic nature of the phenomena poses challenges to both data collection and empirical methods. Given the context of this literature, I propose a formal empirical analysis by developing a structural model of the Ericson-Pakes (1995) class and applying it to data from the HDD industry, the canonical case of "disruptive innovation" studied by Christensen (1993, 1997), Chesbrough (1999), and King and Tucci (2002).

Structural Estimation of Industry Dynamics

Structural analysis of industry dynamics is the third body of literature on which this study builds (for an overview, see Ackerberg et al. [2007] and Doraszelski and Pakes [2007]). The purpose of developing and estimating a structural model is to consider both theory and data explicitly, so invisible, theoretical effects and their welfare implications could be quantified through counterfactual simulations. Two approaches exist to estimate Markov-perfect equilibrium (MPE) models of the Ericson-Pakes (1995) class. The "full-solution" approach started with Rust's (1987) analysis of investment under uncertainty (bus engine replacement), whereas Hotz and Miller (1993) pioneered the "two-step" approach. The first approach requires intensive computation because a full solution of a dynamic programming problem is needed for each set of candidate parameter values; the second approach demands a large dataset to alleviate such a computational burden by a first-stage non-parametric estimation procedure. The first approach has been pursued by Su and Judd (2008), who proposed a re-formulation of the problem as Mathematical Programming with Equilibrium Constraints (MPEC) and the use of state-of-the-art solvers, by Besanko et al. (2010), who used a homotopy or path-following algorithm to trace the entire set of equilibria, and by Weintraub et al. (2008a, 2008b), who proposed oblivious equilibrium (OE) as a more tractable approximation concept for MPE. The second approach has been further developed by Aguirregabiria and Mira (2007), Bajari et al. (2007), Pakes et al. (2007), and Pesendorfer and Schmidt-Dengler (2008), who proposed various two-step estimators for dynamic games. I have chosen to follow the first approach by alleviating the computational burden through parsimonious modeling (symmetry among the same type of firms, relatively small choice sets and state space, and a finite-horizon environment). Since I study a geographically globalized industry, the dataset does not contain a large number of independent markets, which is an empirical setting where non-parametric estimation in the second approach might not function properly.

These dynamic structural frameworks have been applied to study both innovation and entry/exit (i.e., evolution of market structure), but only independently. I propose to incorporate both simultaneously, in order to study generational transitions of technologies and firms. Four recent papers studied various forms of innovation. Schmidt-Dengler (2006) took a full-solution approach to analyze U.S. hospitals' adoption timing of magnetic resonance imaging (MRI) technology. Goettler and Gordon (2011) also took the same approach to study the introduction of faster microprocessors by Intel and AMD. Xu (2008) applied an OE framework to the cost reduction among Korean electric motor makers. Finally, Eizenberg (2009) studied the introduction of PCs with faster chips. I follow Schmidt-Dengler (2006) and Goettler and Gordon (2011) in taking a full-solution approach in estimating a dynamic oligopoly; to investigate incumbent-entrant heterogeneity as well as market structure dynamics, I extend the scope of analysis to include entry/exit.

Structural analysis of entry/exit started from the estimation of static models (e.g., Berry 1992, Mazzeo 2002, Seim 2006, Jia 2008). More recent papers employed dynamic models: Ryan (2011) studied the cost of environmental regulation in the cement industry, Collard-Wexler (2010) studied the role of demand fluctuations in the concrete industry, Dunne et al. (2009) studied several retail industries, and Kalouptsidi (2010) focused on time to build in the bulk shipping industry. This paper shares the focus on industry evolution with the second strand of literature, but my empirical approach also builds on the first strand, namely, Seim's (2006) characterization of an entry/exit game. Specifically, I employ a finite-horizon setup to reflect the HDD industry's non-stationary environment, which allows me to solve for an industry equilibrium by backward induction, one (static) subgame at a time. More substantively, I extend the framework for analyzing entry/exit to incorporate incumbents' technology adoption, so I can study their technology choice in relation to entry/exit behavior and incumbent-entrant heterogeneity.

In short, this paper presents the first structural analysis of "disruptive innovation" (to my knowledge), bridging the frameworks to analyze innovation and entry/exit in a simple model. This model is empirically tractable and motivated by Christensen's (1993, 1997) case study as well as my own reading of the original data source. The next section summarizes the institutional background of the HDD industry.

2 Industry and Data

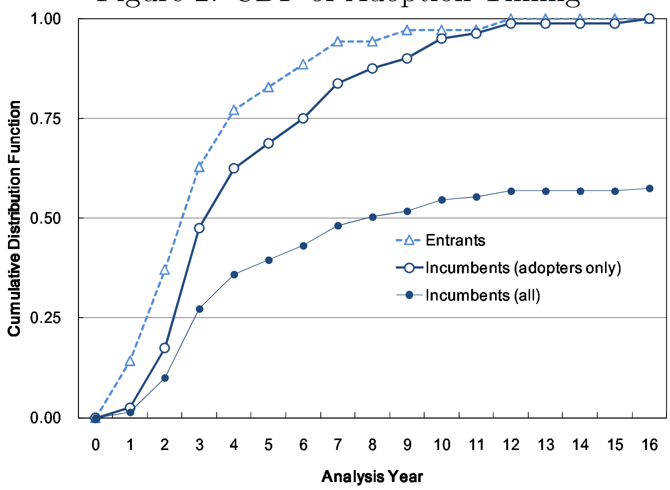
This section describes the key features of the HDD industry and explains why it is particularly suitable for the study of innovation and industry evolution.

2.1 HDD Industry: Canonical Case of Innovation and Evolution

The HDD industry provides a particularly fruitful example for the study of technological change and industry dynamics.

First, the HDD industry is the canonical example of "disruptive innovation." Multiple generations of technologies were born, matured, and died within a decade or two. A generation was defined by the diameter of disks used: 14-, 8-, 5.25-, 3.5-, and 2.5-inch (see Figure 1). The introduction of a new HDD of smaller diameters required a significant technological investment because each firm had to go through a process of trial and error in determining the adequate configuration of components, then build new assembly lines, and finally establish a reliable process for volume production. Along with each generation, a cohort of firms came and went, many of which delayed the adoption of a newer technology. Pooling the observations across five generations (4 transitions), Figure 2 plots the timing of innovation separately for incumbents (i.e., firms already active in the previous generation) and entrants (i.e., firms that appeared for the first time as the producer of new-generation HDDs). Only about a half of all incumbents ever innovated into a new generation. Even among those that did, their timing was approximately two years later than entrants. Those that never adapted gradually disappeared along with the shrinking demand for the old products. Changes in technology and market structure are pervasive in many industries, but the HDD market has witnessed one of the fastest, most unrelenting, and most easily measurable turnovers of products and firms.

Figure 2: CDF of Adoption Timing



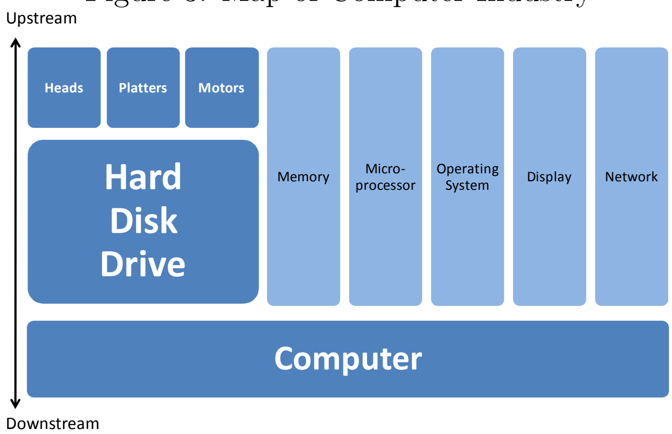
Note: Shipment-based recognition of technology adoption. Major firms only. Total of all diameters (14-, 8-, 5.25-, 3.5-, and 2.5-inch).

Second, a detailed industry data book series, the *DISK/TREND Reports* (1977–99), is available for this industry. From the original reports, I construct a comprehensive panel of the world's HDD manufacturers by digitizing each firm-year observation. The sample period is long enough to capture five generations of technologies, two of which I analyze in detail.

Third, a high-tech manufacturing sector with rapid growth and innovation is precisely the type of industry that is most relevant to the discussion of pro-innovation public policies. Moreover, the HDD market's fairly competitive structure (a total of 178 unique firms over 23 years) and geographical outreach (firms from the Americas, Asia, and Europe compete in a global market) underline the potential generalizability of the findings.

Figure 3 depicts the position of HDD manufacturing within the broader context of the computer industry. The market structure of the HDD industry was less concentrated than in other sub-sectors such as memory (which Samsung Electronics dominated), microprocessors (Intel and AMD), display (Samsung), operating systems (Microsoft), or various internet services (e.g., Google in search, or Facebook and Twitter in social media). Monopolies and duopolies are interesting subjects, but the performances of these "outlier" firms were so remarkable that a researcher would need to focus on their idiosyncrasies in great detail. By contrast, the HDD industry saw such a massive wave of new entries that the number of firms (pooled across all generations) reached over 100 in the late 1980s. Many of them later exited in a "shakeout" phase, which is a typical development in many sectors, including manufacturing and services, as documented by Carroll and Hannan (2000). Still, the top maker's market share in 1998, the final year of my dataset, was below 20%.

Figure 3: Map of Computer Industry



Note: For illustration purposes only. The box sizes do not necessarily reflect revenues or profits.

Another attractive feature of the HDD industry is that these firms originate from all over the world, not just Silicon Valley. The dataset allows comparison of firms from different regions. Moreover, perhaps because HDDs are not as directly exposed to consumers as are cars, computers, or other household electronics products, the sector largely avoided government interventions. Except in Brazil and France, national governments did not intervene as a matter of trade or industrial policies.[7] Thus the dataset is reasonably free from political complications.

My analysis of the HDD industry takes the developments in the global PC market (i.e., HDD's "downstream" industry) as given for the following reasons. First, the growth in PC demand was primarily driven by hobbyists during the 1980s and then by office automation

[7]As a separate issue, the governments of Singapore and other South East Asian countries actively promoted their territories as foreign firms' offshore production sites. I plan to incorporate firms' offshoring decisions as a form of radical process innovation in separate future work.

and growing popularity among households during the 1990s. Second, the price and performance of the central processing unit (CPU) and operating system (OS) determined most of the cost and perceived quality of PCs, and hence the overall demand for PCs and their replacement purchase cycles. Although the quality improvement of HDDs contributed to the enhanced performance of PCs in terms of storage capacity, Intel and Microsoft ("Wintel") were perceived to be the leaders of the PC industry. Third, the market structure of PC makers is rather competitive, with more than 100 firms across the globe. As Table 1 shows, even the combined market share of the top five makers was less than 50%. Moreover, the vendors (brands) and manufacturers of PCs were often different; that is, many less well-known manufacturers made products for famous brands such as Compaq and Hewlett-Packard. Hence the market structure of actual manufacturers is less concentrated than what vendors' market share suggests.

Table 1: Global PC Market Share by Units (%)

Rank	1981		1986		1991		1996	
1	Sinclair	23.9	IBM	12.3	IBM	11.4	Compaq	10.0
2	Apple	13.6	Commodore	11.4	Apple	9.1	IBM	8.6
3	Commodore	13.0	Apple	7.8	Commodore	8.3	Packard-Bell NEC	6.0
4	Tandy	12.8	Amstrad	5.9	NEC	5.8	Apple	5.9
5	Atari	4.5	NEC	5.3	Compaq	4.0	HP	N/A
Others		32.3		57.2		61.5		69.5

Note: Market share based on worldwide unit shipments.

Source: Gartner Dataquest, Wikipedia.

Likewise, I do not explicitly model the developments in the "upstream" industry: HDD components, such as read-write heads, platters, and motors. Some HDD manufacturers make these components in-house, whereas others procure them from electronics parts makers. According to James Porter, the editor of *DISK/TREND Reports*, there is no clear advantage/disadvantage concerning whether to make or to buy.

2.2 Data Source

I manually construct the panel data of 1,378 firm-year observations from *DISK/TREND Reports* (1977–99), an annual publication series edited by the HDD experts in Silicon Valley. I digitize each firm-year observation, which is accompanied by half a page of qualitative descriptions (on the characteristics of the firm, managers, funding, products, production locations, as well as major actions taken in that year with their reasons) in the original publication. Not all information is amenable to quantitative analysis, but some of the firms' characteristics are suitable for regressions. For example, firms' age and size (in terms of revenues and profits, either company-wide or specifically for the HDD business) are readily codifiable.[8] Firms' organizational forms, regions of origin, and the initial HDD generations in which they started manufacturing, are also digitized as categorical variables.

As a preliminary, descriptive analysis, I regress the timing of innovation (i.e., the shipment of new-generation HDDs) on these firm characteristics. Table 2 reports the estimation results based on a standard duration model (Cox proportional hazard estimates). The estimates suggest incumbents are 50% less likely than entrants to innovate in a given year, even after controlling for all of the observed characteristics.[9]

An auxiliary dataset, also from *DISK/TREND Reports*, containing the prices and shipment quantities of HDDs, accompanies this panel data of firms. For each year, the reports record the average transaction price and total quantity for each of the generation-quality categories (5 generations and 14 quality levels in total).

Researchers in both economics and management repeatedly confirm the accuracy, relevance, and comprehensiveness of the record.[10]

2.3 Focus: Transition from 5.25- to 3.5-inch Generations

I analyze the technological transition from the 5.25- to 3.5-inch generations, which I will call the "old" and "new" generations henceforth. This subsample of the dataset spans 18 years (1981–98) and 259 firm-years. I concentrate on these generations because they competed directly with each other in the desktop PC market. Although transitions between the other generations showed similar developments, 14-, 8-, and 2.5-inch HDDs were used in different

[8]However, age is not necessarily comparable across firms that had roots in different industries (e.g., manufacturers of card punchers, typewriters, automobile components, or coin laundries). Not all firms disclosed division-level revenue/profit information. For these reasons, I omit these variables in the following regressions.

[9]I employ two different definitions of entrants in these regressions. The first definition is data-driven and narrower: a potential entrant is recognized when a new firm announces the product specifications without actually manufacturing or shipping them. The second definition is more conceptually motivated and broader: for all of the potential entrants that announced or shipped HDDs, I count as "time at risk (of innovation)" all years since the industry-wide establishment of new-generation standards. That is, regardless of whether these new firms were already incorporated or not, I interpret that their founders were considering the innovation and entry, from the moment the industry consensus emerged on the physical size of new-generation HDDs.

Econometrically, regressions based on the first definition would over-estimate the entrants' propensity to innovate because this definition recognizes entrants only when they were most serious about innovation. In contrast, regressions based on the second definition would probably under-estimate entrants' propensity to innovate because all years until actual shipments are interpreted as evidence against their innovativeness, regardless of whether they existed as firms or not. Table 2 reports only the results based on the second definition, in order to show that entrants were twice more likely to innovate than incumbents, even when I use the definition that would bias against such findings.

[10]Christensen (1993, 1997); Lerner (1997); McKendrick, Donner, and Haggard (2000); and Franco and Filson (2006).

Table 2: Preliminary Regressions of Innovation Timing on Firm Characteristics

	Duration model (Cox proportional hazard estimates)					
Dependent variable: Decision to Innovate	(1)		(2)		(3)	
Firm characteristics						
Incumbent	.41***	(.06)	.53***	(.09)	.50***	(.09)
Initial generation of entry						
5.25-inch	–	(–)	.84	(.18)	.71	(.19)
3.5-inch	–	(–)	.52***	(.12)	.46***	(.12)
2.5-inch	–	(–)	.34***	(.10)	.91	(.40)
Organizational Form						
Specialized HDD start-up	–	(–)	1.04	(.22)	1.01	(.22)
Computer maker (“backward” integration)	–	(–)	1.39	(.29)	1.32	(.28)
HDD component maker (“forward” integration)	–	(–)	.55	(.21)	.54*	(.20)
Region of Origin						
U.S.	–	(–)	1.04	(.32)	1.18	(.37)
Asia	–	(–)	1.91**	(.58)	1.90**	(.58)
Europe (West)	–	(–)	1.01	(.37)	1.20	(.45)
Europe (East)	–	(–)	.14*	(.15)	.16*	(.17)
Industry state						
Number of firms	–	(–)	–	(–)	1.16***	(.05)
Number of firms squared	–	(–)	–	(–)	.99***	(.00)
Number of subjects (firms)	437		437		437	
Number of innovations	190		190		190	
Time at risk of innovation	2,591		2,591		2,591	
Number of observations	1,842		1,842		1,842	
Log likelihood	−1,018		−997		−990	

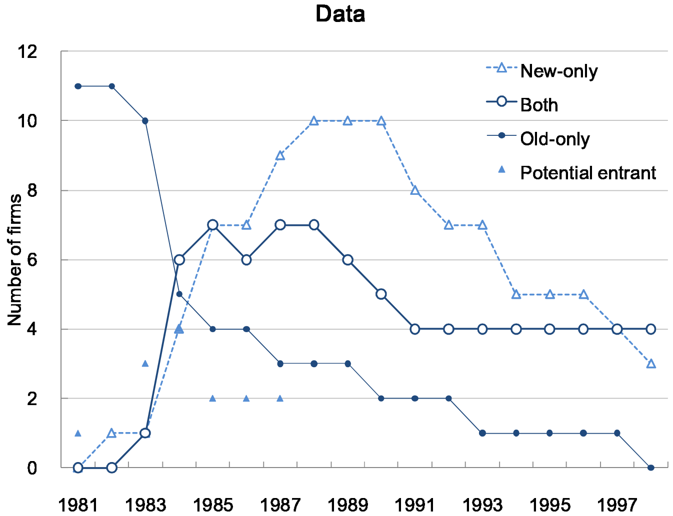
Note: Coefficients greater (less) than 1 indicate higher (lower) propensities to innovate. Omitted categories are “Potential entrant,” “8-inch,” “Other electronics maker (horizontal diversification),” and “Brazil.” ***, **, and * indicate signifiance at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses.

segments of the computer industry, that is, 14-inch for mainframe computers, 8-inch for minicomputers, and 2.5-inch for notebook PCs. By focusing on 5.25- and 3.5-inch generations, I avoid confounding factors that might originate from diverging trends in different segments downstream. These two generations were also historically the most important of all generations in terms of volume and revenue.

Figure 4 shows the numbers of firms in four different states: (1) “old-only,” (2) “both,” (3) “new-only,” and (4) “potential entrant.” Incumbents start as (1) and become (2) upon the adoption of new technology. Entrants start as (4) and become (3) upon adoption (entry).

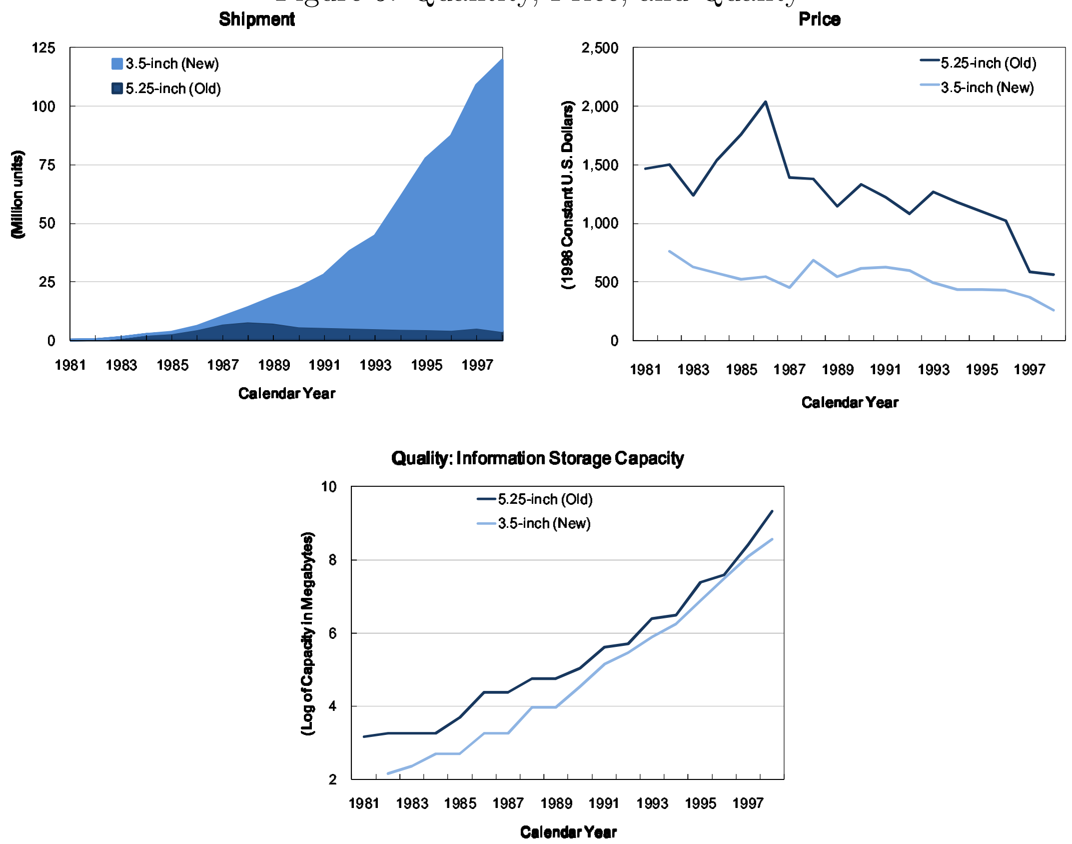
The two generations of HDD experienced a fast growth in volume and a steady decline in price (Figure 5, top). Over the years, the average quality (information storage capacity) of HDDs improved at an approximately constant rate (Figure 5, bottom). These developments were typical of those in many computer-related industries.

Figure 4: Evolution of the Industry Composition



Note: "Old-only" and "new-only" firms produce 5.25- and 3.5-inch HDDs, respectively. "Both" represents incumbents that adopted the new technology, hence producing both of the two generations. "Potential entrant" is identified by the announcement of product specifications (without actual shipment).

Figure 5: Quantity, Price, and Quality



Note: Both 5.25- and 3.5-inch HDDs serve the same market, namely, desktop personal computers. Quality is measured by average capacity per unit for each generation.

3 Model

This section presents my industry equilibrium model. The first subsection outlines the dynamic game of technology adoption and entry/exit. The second subsection explains the demand side. The third subsection explains the spot-market competition. The fourth subsection shows how I solve the dynamic part of the model by backward induction.

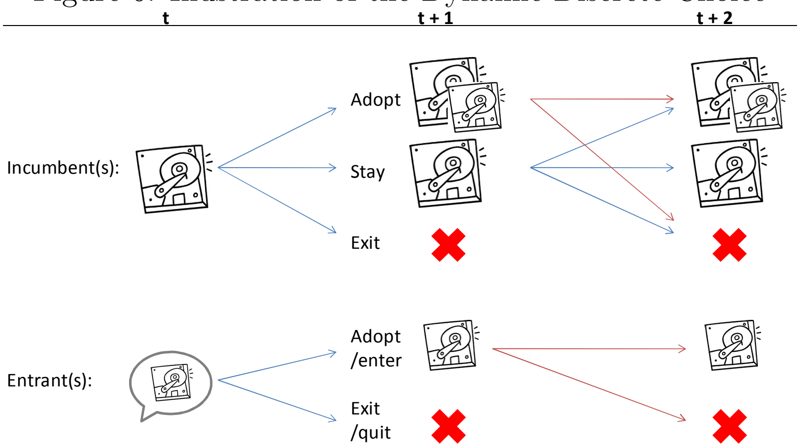
3.1 Setup: Dynamic Discrete-Choice Game

Time is discrete with finite horizon $t = 0, 1, 2, ..., T$. Two goods, old and new, are imperfect substitutes from the buyers' viewpoint. Each of these goods requires a specific generation of technology for production, old and new.

Two Types, Four States

There are two types of firms ("incumbents" and "entrants") and four individual states ("old-only," "both," "new-only," and "potential entrant"), as illustrated in Figure 6.

Figure 6: Illustration of the Dynamic Discrete Choice



Note: "Old-only" and "New-only" firms produce 5.25- and 3.5-inch HDDs exclusively. "Both" represents incumbents that adopted the new technology, hence producing both of the two generations. "Potential entrant" is identified by the annoucement of product specifications without actual shipment.

"Incumbents" produce old goods from time 0, using the old-generation technology. In any time period, an incumbent may choose to adopt the new-generation technology by paying a sunk cost and starting to produce both old and new goods from the next period. Hence an incumbent starts in the "old-only" state (a production technology status in which a firm can produce only old goods) and may elect to transition to the "both" state (a status in which a firm can produce both old and new goods).

"Entrants" are the other type of firms. They are not active in the market at time 0. Each of them appears in a predetermined year (observed in data), at which moment they may choose to adopt new technology and enter the market, or quit the prospect of entry. That is, by paying a sunk cost, a potential entrant becomes an actual entrant in the subsequent period in the "new-only" state, a production technology status in which a firm can produce only new goods.[11]

Hence a firm belongs to any one of the four states, $s_{it} \in \{old, both, new, pe\}$. The industry state summarizes all firms' states, $s_t = \left(N_t^{old}, N_t^{both}, N_t^{new}, N_t^{pe}\right)$, as the numbers of firms in each of three states. Let $s_{-i,t}$ denote the numbers of competitors for firm i, which is simply s_t minus 1 in firm i's own category.

Period Profit

Firm i's single-period profit, $\pi\left(s_{it}, s_{-i,t}, W_t\right)$, depends on its own state s_{it}, its competitors' state $s_{-i,t}$, and the characteristics of demand and cost W_t. s_{it} and $s_{-i,t}$ change endogenously as a result of each firm's dynamic decision, whereas W_t evolves exogenously. Old and new goods are imperfect substitutes; that is, products are differentiated *across* generations. The logit demand system characterizes their substitution pattern (section 3.2). Products are homogeneous *within* each generation, with the spot-market competition characterized by a symmetric Cournot game.

Dynamic Discrete-choice Problem

Each firm aims to maximize its expected present value. The interest rate is assumed to be positive and constant over time, resulting in a constant discount factor $\beta \in (0, 1)$ per period. In each period, events occur in the following order:

1. Each active firm observes its private cost shocks ε_{it}^0 and ε_{it}^1, associated with exiting and staying, respectively. If a firm's state is *old*, it additionally draws ε_{it}^2, which is associated with technology adoption. A potential entrant draws ε_{it}^0 (for quitting) and ε_{it}^2 (for adoption/entry) but not ε_{it}^1 because it cannot wait on the sidelines.

2. Firms make dynamic decisions, namely exit/quit, stay, or adopt/enter.

3. Active firms compete in the spot market and earn profits, $\pi\left(s_{it}, s_{-i,t}, W_t\right)$.

4. Dynamic decisions are implemented. Specifically, exiting firms exit and receive their sell-off values $\phi + \varepsilon_{it}^0$. Staying firms receive ε_{it}^1. Adopting incumbents pay $\delta^t \kappa^{inc} - \varepsilon_{it}^2$. Potential entrants receive ε_{it}^0 (if they quit) or pay $\delta^t \kappa^{ent} - \varepsilon_{it}^2$ (if they adopt/enter) to become active.

[11] I do not consider entrants' adoption of the old technology because it rarely happens in the data once the new technology becomes available. For the same reason, I rule out the alternative to "wait."

5. The industry takes on a new state, $s_{t+1} = \left(N_{t+1}^{old}, N_{t+1}^{both}, N_{t+1}^{new}, N_{t+1}^{pe}\right)$.

Hence the decision problems for active firms in each of the three states are

$$\begin{aligned}
V_t^{old}(s_t) &= \pi_t^{old}(s_t) + \max\left\{\begin{array}{c} \phi + \varepsilon_{it}^0, \\ \beta E\left[V_{t+1}^{old}(s_{t+1})\,|s_t\right] + \varepsilon_{it}^1, \\ \beta E\left[V_{t+1}^{both}(s_{t+1})\,|s_t\right] - \delta^t \kappa^{inc} + \varepsilon_{it}^2 \end{array}\right\}, \qquad (1) \\
V_t^{both}(s_t) &= \pi_t^{both}(s_t) + \max\left\{\begin{array}{c} \phi + \varepsilon_{it}^0, \\ \beta E\left[V_{t+1}^{both}(s_{t+1})\,|s_t\right] + \varepsilon_{it}^1 \end{array}\right\}, \text{ and} \\
V_t^{new}(s_t) &= \pi_t^{new}(s_t) + \max\left\{\begin{array}{c} \phi + \varepsilon_{it}^0, \\ \beta E\left[V_{t+1}^{new}(s_{t+1})\,|s_t\right] + \varepsilon_{it}^1 \end{array}\right\},
\end{aligned}$$

subject to the perceived law of motion governing the industry state, s_t (see below). For a potential entrant, the problem is simply

$$\max\left\{\varepsilon_{it}^0, \beta E\left[V_{t+1}^{new}(s_{t+1})\,|s_t\right] - \delta^t \kappa^{ent} + \varepsilon_{it}^2\right\}.$$

Solution Concept

Possible equilibrium concepts for use include Subgame-perfect equilibrium (SPE), Markov-perfect equilibrium (MPE), and (non-stationary) Oblivious Equilibrium (OE). I proceed with SPE because the environment is non-stationary and strategic.

Recent applications of dynamic game and its estimation techniques often use MPE, which is adequate for a stationary environment. In contrast, I am studying a topic and industry whose chief characteristics are non-stationary. That is, the old technology eventually dies and new technology becomes mainstream. The research question is how much each of the four theoretical forces determines whether and when incumbents decide to adopt new technology. Given the motivation and dataset, I choose to model the industry's non-stationary evolution as is rather than try to stationarize the environment and apply techniques suitable for MPE.

I assume the HDD industry reaches its terminal state in 1998, when the state stops evolving. I solve the model backward over 18 years for SPE. In reality, the industry keeps evolving after the sample period, but the point is that the 5.25-inch HDDs all but disappeared by 1998. Since my purpose is to analyze the economic incentives surrounding the transition from the 5.25- to 3.5-inch HDDs and firms' turnover, I believe the finite-horizon setup is a reasonable representation of history during the sample period.

Beliefs (Perceived Law of Motion)

For rules governing firms' expectations, alternatives include rational expectations and perfect foresight.[12] Regarding firms' beliefs about rivals' moves, $s_{-i,t+1}$, I assume rational expectations. That is, a firm correctly perceives how its rivals make dynamic decisions *up to private cost shocks*, $(\varepsilon_{it}^0, \varepsilon_{it}^1, \varepsilon_{it}^2)$ iid extreme value. This setup allows for dynamic strategic interactions, which are a prerequisite for incorporating cannibalization and preemptive motives into the model. I "knock out" this feature in one of the counterfactuals (no-preemption case, in section 6.4), where firms instead perceive the industry state as evolving exogenously, in the spirit of non-stationary OE (Weintraub, Benkard, Jeziorski, and Van Roy 2008).

An additional benefit lies in these private cost shocks, which, as Seim (2006) shows, ensures uniqueness and hence identification of entry/exit games. This advantage reinforces the rationale for modeling the industry dynamics as a finite-horizon game. The multiplicity of MPE is the common cause of concern in the studies of dynamic oligopoly, which motivated the development of the two-step estimation methodologies that bypass the issue. Here I propose an alternative bypass route via finite-horizon setup and its solution for SPE by backward induction. My approach reduces the task of solving full dynamics into numerous but tractable period-by-period (and state-by-state) solutions of a static entry/exit game with private information.

With respect to the evolution of demand and production costs, I assume firms' perfect foresight. From the theoretical perspective, this choice reflects my analytical focus on strategic interactions and adoption costs rather than informational factors related to demand uncertainty. I do not intend to disregard the role of information in studying investment under uncertainty. Rather, the issue is the empirical tractability of informational factors given the current dataset.[13] In my view, this assumption is simplistic but not distortionary because firms' beliefs are homogeneous regardless of their types or individual state in any given period. Hence it is unlikely to affect the incumbent-entrant asymmetry this paper tries to explain.

Model Primitives

There are dynamic and static components of model primitives. Dynamic primitives are the discount factor β, the mean sell-off value ϕ, the base sunk costs of technology adoption κ^{inc} and κ^{ent}, the annual rate of sunk cost change δ, a dynamic equilibrium concept, and the informational assumptions made on firms' perceived law of motion for the industry state.

[12] Adaptive expectations might be another interesting modeling choice.

[13] Although they are beyond the scope of this paper, information-related topics present fascinating directions for future research, including (1) beliefs about new HDDs' profitability that are potentially heterogeneous across firms, and (2) the updating of these beliefs through own experimentation and learning from rivals.

Static primitives determine the period profit function: demand parameters, cost parameters, and a static equilibrium concept. The next two subsections explain the details of these static model components.

3.2 Demand

I capture the substitution pattern across generations of HDDs using the logit model of differentiated products. The dynamic discrete-choice model (section 3.1) captures HDDs' differentiation *across* generations and assumes homogeneity *within* each generation.

A buyer k purchasing an HDD of generation g enjoys utility,[14]

$$u_{kg} = \alpha_0 + \alpha_1 p_g + \alpha_2 I\left(g = new\right) + \alpha_3 x_g + \xi_g + \epsilon_{kg}, \tag{2}$$

where p_g is the price, $I\left(g = new\right)$ is the indicator of new generation, ξ_g is the unobserved characteristics (most importantly, "design popularity" among buyers, as well as other unobserved attributes such as "reliability"), and ϵ_{kg} is the idiosyncratic taste shock over generations. The outside goods offer the normalized utility $u_{k0} \equiv 0$, which represent *removable* HDDs (as opposed to *fixed* HDDs) and other storage devices.[15]

Let $\bar{u}_g \equiv \alpha_0 + \alpha_1 p_g + \alpha_2 I\left(g = new\right) + \alpha_3 x_g + \xi_g$ represent the mean utility from a generation-g HDD whose market share is

$$ms_g = \frac{\exp\left(\bar{u}_g\right)}{\sum_l \exp\left(\bar{u}_l\right)}. \tag{3}$$

The shipment quantity of generation-g HDDs is

$$Q_g = ms_g M,$$

where M is the size of the HDD market including the outside goods (removable HDDs and other storage devices). Practically, M reflects all desktop PCs to be manufactured globally in a given year.

Berry's (1994) inversion provides the linear relationship,

$$\ln\left(\frac{ms_g}{ms_0}\right) = \alpha_1 p_g + \alpha_2 I\left(g = new\right) + \alpha_3 x_g + \xi_g, \tag{4}$$

[14] I suppress the time subscript t for the simplicity of notation. The demand side is static in the sense that buyers make new purchasing decisions every year. This assumption is not restrictive because multi-year contracting is not common and there are hundreds of buyers (computer makers) during the sample period.

[15] Tape recorders, optical disk drives, and flash memory.

where s_g represents the market share of HDDs of generation g, and ms_0 is the market share of outside goods (removable HDDs and other devices). The inverse demand is

$$p_g = \frac{1}{-\alpha_1}\left[-\ln\left(\frac{ms_g}{ms_0}\right) + \alpha_2 I\left(g = new\right) + \alpha_3 x_g + \xi_g\right]. \tag{5}$$

3.3 Period Competition

The spot-market competition is characterized by multi-product (i.e., old and new goods) Cournot competition. Marginal costs of producing old and new goods, mc^{old} and mc^{new}, are assumed to be common across firms and constant with respect to quantity. Firm i maximizes profits

$$\pi_i = \sum_{g \in A_i} \pi_{ig} = \sum_{g \in A_i} \left(p_g - mc_g\right) q_{ig}$$

with respect to shipping quantity q_{ig} $\forall g \in A_i$, where π_{ig} is the profit of firm i in generation g, and A_i is the set of generations produced by firm i. Firm i's first-order condition with respect to its output q_{ig} is

$$p_g + \frac{\partial p_g}{\partial Q_g} q_{ig} + \frac{\partial p_h}{\partial Q_g} q_{ih} = mc_g, \tag{6}$$

with $g, h \in \{old, new\}$, $g \neq h$, if firm i produces both old and new HDDs. The third term on the left-hand side is dropped if a firm makes only one generation.

3.4 Solution of Dynamic Game by Backward Induction

I assume the state stops evolving after year T. Hence the terminal values associated with a firm's states, $s_{iT} \in \{old, both, new\}$, are

$$\left(V_T^{old}, V_T^{both}, V_T^{new}\right) = \left(\sum_{\tau=T}^{\infty} \beta^\tau \pi_T^{old}\left(s_T\right), \sum_{\tau=T}^{\infty} \beta^\tau \pi_T^{both}\left(s_T\right), \sum_{\tau=T}^{\infty} \beta^\tau \pi_T^{new}\left(s_T\right)\right).^{16} \tag{7}$$

In year $T-1$, an old-only firm's problem (aside from maximizing its period profit) is

$$\max\left\{\phi + \varepsilon_{i,T-1}^0, \beta E\left[V_T^{old}\left(s_T\right)|s_{T-1}\right] + \varepsilon_{i,T-1}^1, \beta E\left[V_T^{both}\left(s_T\right)|s_{T-1}\right] - \delta^{T-1}\kappa^{inc} + \varepsilon_{i,T-1}^2\right\}.$$

I follow Rust (1987) to exploit the property of the logit errors, $\varepsilon_{it} = (\varepsilon_{it}^0, \varepsilon_{it}^1, \varepsilon_{it}^2)$, and their (conditional) independence over time, to obtan a closed-form expression for the expected

[16] Alternatively, I might consider anchoring the terminal values to some auxiliary data that would cover the periods after 1998, the final year of my data set.

value before observing ε_{it},

$$E_{\varepsilon_{i,T-1}}\left[V_{T-1}^{old}\left(s_{T-1},\varepsilon_{i,T-1}\right)|s_{T-1}\right]=\pi_{T-1}^{old}\left(s_{T-1}\right)+\gamma$$
$$+\ln\left[\exp\left(\phi\right)+\exp\left(\beta E\left[V_{T}^{old}\left(s_{T}\right)|s_{T-1}\right]\right)+\exp\left(\beta E\left[V_{T}^{both}\left(s_{T}\right)|s_{T-1}\right]-\delta^{T-1}\kappa^{inc}\right)\right],$$

where γ is the Euler constant (0.5772). Similar expressions hold for the other two types:

$$E_{\varepsilon_{i,T-1}}\left[V_{T-1}^{both}\left(s_{T-1},\varepsilon_{i,T-1}\right)|s_{T-1}\right]=\pi_{T-1}^{both}\left(s_{T-1}\right)+\gamma$$
$$+\ln\left[\exp\left(\phi\right)+\exp\left(\beta E\left[V_{T}^{both}\left(s_{T}\right)|s_{T-1}\right]\right)\right],$$

and

$$E_{\varepsilon_{i,T-1}}\left[V_{T-1}^{new}\left(s_{T-1},\varepsilon_{i,T-1}\right)|s_{T-1}\right]=\pi_{T-1}^{new}\left(s_{T-1}\right)+\gamma$$
$$+\ln\left[\exp\left(\phi\right)+\exp\left(\beta E\left[V_{T}^{new}\left(s_{T}\right)|s_{T-1}\right]\right)\right].$$

In this manner, I can write the expected value functions from year T all the way back to year 0. The associated choice probabilities (policy functions) will provide a basis for the maximum likelihood estimation (in section 4.3).

4 Estimation

My empirical approach takes three steps. First, I estimate the system of demand for differentiated products. Second, I recover the marginal costs of production implied by the demand estimates and the first-order conditions of the firms' period-profit maximization. These two steps generate the measure of period profit in each year and state, which forms the basis for estimating the dynamic parameters. Third, I estimate the dynamic parameters (the sunk costs of technology adoption/entry and the sell-off value upon exit) using the solution to my dynamic model.

4.1 Estimation: Demand

The empirical demand analysis proceeds at the level that is more detailed than generation g. The purpose is to facilitate identification and control of HDD product attributes other than g, such as observed quality x and unobserved "popularity" ξ.

In data, the unit of observation is the combination of generation, quality, buyer category (PC makers and distributors/end-users), geographical regions (U.S. and non-U.S.), and year

t. For notational simplicity, I denote the generation-quality pair by "product category" j and suppress subscripts for the latter three dimensions. I estimate the simple logit model as well as its nested version (with nests on generations) so as to empirically confirm the economic significance of substitution across generations.

These empirical considerations lead to the following recasting of the demand model. A buyer k purchasing an HDD of product category j, that is, a combination of generation g (diameter) and quality x (storage capacity in megabytes), enjoys utility

$$u_{kj} = \alpha_0 + \alpha_1 p_j + \alpha_2 g_j + \alpha_3 x_j + \xi_j + \sigma \zeta_{kg_j} + (1 - \sigma)\,\epsilon_{kj}, \tag{8}$$

where p_j is the price, ξ_j is the unobserved characteristics, ζ_{kg_j} is the idiosyncratic taste shock over generations of HDDs, and ϵ_{kj} is the idiosyncratic taste shock over generation-quality bins.

The coefficients, α_0 through α_3 and σ, are the taste parameters to be estimated. The nest parameter $\sigma \in [0, 1]$ measures the importance of substitution *within* generation g relative to that *across* generations. For example, $\sigma = 1$ indicates substitution is only within g, whereas $\sigma = 0$ indicates a plain logit model without nests. ϵ_{kj} is iid extreme value (over buyers and bins); that is, its cumulative distribution function is $F(\epsilon_{kj}) = \exp(-\exp(-\epsilon_{kj}))$. ζ_{kg_j} is distributed such that the marginal distribution of the composite error term, $\sigma \zeta_{kg_j} + (1 - \sigma)\,\epsilon_{kj}$, is also iid extreme value.

I estimate the logit and nested logit models of demand using OLS and instrumental variables (IVs). Berry's (1994) inversion allows the econometrician to run a linear regression,

$$\ln\left(\frac{ms_j}{ms_0}\right) = \alpha_1 p_j + \alpha_2 g_j + \alpha_3 x_j + \sigma \ln\left(ms_{j|g_j}\right) + \xi_j, \tag{9}$$

for the estimation of the nested logit model, where ms_j represents the market share of HDDs of category j, ms_0 is the market share of outside goods (removable HDDs), and $ms_{j|g_j}$ is the market share of category-j HDDs *within* its generation g_j.

Identification

The demand parameters are identified by the time-series and cross-sectional variations in data (subscripts omitted for notational simplicity) as well as the (nested) logit functional form. The sample period is the 18 years between 1981 and 1998. There are three sources of cross-sectional variation. First, an HDD's product category (denoted by j) is a pair of generation (diameter, or form-factor) and quality (information storage capacity in megabytes). There are two generations and 14 discrete quality levels according to the industry convention. Second, data are recorded by buyer category, PC makers and distributors/end-users.

Third, data are recorded by geographical category, U.S., and non-U.S.

The OLS estimation relies on the assumption that $E[\xi_j | p_j, g_j, x_j] = 0$; that is, the price of a category-j HDD is uncorrelated with that particular category's unobserved attractiveness to the buyers. However, one might suspect a positive correlation between them because an attractive product category would command both higher willingness to pay and higher cost of production.

In the IV estimation, I use the following variables as instruments for p_j (and also $ms_{j|g_j}$ in nested logit): (1) the prices in the other region and user category, (2) the number of product models and firms, and (3) the number of years since first introduction. The first IV is used by Hausman (1996) and then by Nevo (2001). The identifying assumption is that production cost shocks are correlated across markets, whereas taste shocks are not. This assumption is consistent with the industry context that HDD makers from across the globe compete in both the United States and elsewhere, whereas end users of HDDs (and hence of PCs) are more isolated geographically.

The second IV was used by Bresnahan (1981) and Berry et al. (1995) and exploits the proximity of rival products (in product space), that is, the negative correlation between the number of models/firms, markup, and price in oligopolies. The identifying assumption is that taste shocks in any given period are not correlated with the number of models/firms in a particular product category j. Firms need to make product-introduction decisions in prior years, without observing taste shocks in particular regions/user types in the following years. More importantly, such dynamic decisions are driven by the sum of discounted present values of future profits, which is affected only negligibly by taste shocks in any single period and for particular regions/user types. Hence this identifying assumption is plausible as long as particular regions'/user types' taste shocks are not extremely serially correlated.

The third IV relies on steady declines in the marginal costs of production over years. In the HDD industry, costs dropped because of design improvements, reduced costs of key components, and offshore production in Singapore, Malaysia, Thailand, and the Philippines. This overall tendency holds at the product category level as well. The identifying assumption is that taste shocks are not correlated with such time patterns on the cost side, which may or may not be the case.

Thus the first IV is the most preferable and so is used in most IV estimations, whereas the second and third IVs are used in the case where the first IV is not available, namely, the robustness check with an alternative market definition.

4.2 Estimation: Marginal Costs

For each year, we can infer the marginal costs of production, mc_{old} and mc_{new}, from equation (6), namely, the first-order conditions for the firms' static profit maximization problems. Because the unit observation in the HDD sales data is product category level–and not firm or brand level–I maintain, as identifying assumptions, symmetry across firms (up to individual state) and constant marginal cost with respect to quantity.

4.3 Estimation: Sunk Costs of Innovation

I set the discount factor β at values between .82 and .94.[17] I do not intend to estimate it because its identification is known to be impractical in most cases (c.f., Rust 1987). Likewise, the rate of drop in sunk costs, δ, is difficult to estimate directly from the following procedure, so instead I will assume δ equals the average rate of decline in mc_{new} over time.

The contribution of an old firm i in year t to the likelihood is

$$f^{old}\left(d_{it}|s_t;\phi,\kappa^{inc},\delta\right) = pr^{old}\left(d_{it}=exit\right)^{I(d_{it}=exit)} pr^{old}\left(d_{it}=stay\right)^{I(d_{it}=stay)} \\ pr^{old}\left(d_{it}=adopt\right)^{I(d_{it}=adopt)},$$

where $pr^{old}(\cdot)$ is the probability that an old-only firm takes a particular action d_{it}:

$$\begin{aligned} pr^{old}\left(d_{it}=exit\right) &= \frac{\exp(\phi)}{\exp(\phi)+\exp\left(E_\varepsilon V^{old}_{t+1}(s_{t+1})\right)+\exp\left(E_\varepsilon V^{both}_{t+1}(s_{t+1})-\delta^t\kappa^{inc}\right)}, \\ pr^{old}\left(d_{it}=stay\right) &= \frac{\exp\left(E_\varepsilon V^{old}_{t+1}(s_{t+1})\right)}{\exp(\phi)+\exp\left(E_\varepsilon V^{old}_{t+1}(s_{t+1})\right)+\exp\left(E_\varepsilon V^{both}_{t+1}(s_{t+1})-\delta^t\kappa^{inc}\right)}, \text{ and} \\ pr^{old}\left(d_{it}=adopt\right) &= \frac{\exp\left(E_\varepsilon V^{both}_{t+1}(s_{t+1})-\delta^t\kappa^{inc}\right)}{\exp(\phi)+\exp\left(E_\varepsilon V^{old}_{t+1}(s_{t+1})\right)+\exp\left(E_\varepsilon V^{both}_{t+1}(s_{t+1})-\delta^t\kappa^{inc}\right)}. \end{aligned}$$

Similarly, the contributions of the other three types of firms are

$$\begin{aligned} f^{both}\left(d_{it}|s_t;\phi\right) &= pr^{both}\left(d_{it}=exit\right)^{I(d_{it}=exit)} pr^{both}\left(d_{it}=stay\right)^{I(d_{it}=stay)}, \\ f^{new}\left(d_{it}|s_t;\phi\right) &= pr^{new}\left(d_{it}=exit\right)^{I(d_{it}=exit)} pr^{new}\left(d_{it}=stay\right)^{I(d_{it}=stay)}, \text{ and} \\ f^{pe}\left(d_{it}|s_t;\kappa^{ent},\delta\right) &= pr^{pe}\left(d_{it}=quit\right)^{I(d_{it}=quit)} pr^{pe}\left(d_{it}=adopt\right)^{I(d_{it}=adopt)}, \end{aligned}$$

[17] Values of β outside this range result in either computational errors or unintuitive parameter estimates (e.g., negative ϕ).

where

$$
\begin{aligned}
pr^{both}(d_{it}=exit) &= \frac{\exp(\phi)}{\exp(\phi)+\exp\left(E_\varepsilon V_{t+1}^{both}(s_{t+1})\right)}, \\
pr^{both}(d_{it}=stay) &= \frac{\exp\left(E_\varepsilon V_{t+1}^{both}(s_{t+1})\right)}{\exp(\phi)+\exp\left(E_\varepsilon V_{t+1}^{both}(s_{t+1})\right)}, \\
pr^{new}(d_{it}=exit) &= \frac{\exp(\phi)}{\exp(\phi)+\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})\right)}, \\
pr^{new}(d_{it}=stay) &= \frac{\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})\right)}{\exp(\phi)+\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})\right)}, \\
pr^{pe}(d_{it}=quit) &= \frac{\exp(0)}{\exp(0)+\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})-\delta^t\kappa^{ent}\right)}, \text{ and} \\
pr^{pe}(d_{it}=adopt) &= \frac{\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})-\delta^t\kappa^{ent}\right)}{\exp(0)+\exp\left(E_\varepsilon V_{t+1}^{new}(s_{t+1})-\delta^t\kappa^{ent}\right)}.
\end{aligned}
$$

Year t has $N_t \equiv \left(N_t^{old}, N_t^{both}, N_t^{new}, N_t^{pe}\right)$ active firms in each state, of which $X_t \equiv \left(X_t^{old}, X_t^{both}, X_t^{new}\right)$ decide to exit. Also, $E_t \equiv \left(E_t^{old}, E_t^{pe}\right)$ firms (incumbents and potential entrants) decide to adopt the new technology. The joint likelihood for year t of observing data (N_t, X_t, E_t) is

$$
\begin{aligned}
P(X_t, E_t, N_t) = &\binom{N_t^{old}}{X_t^{old}}\binom{N_t^{old}-X_t^{old}}{E_t^{old}} pr^{old}(d_{it}=exit)^{X_t^{old}} \\
&\times pr^{old}(d_{it}=stay)^{N_t^{old}-X_t^{old}-E_t^{old}}\, pr^{old}(d_{it}=adopt)^{E_t^{old}} \\
&\times \binom{N_t^{both}}{X_t^{both}} pr^{both}(d_{it}=exit)^{X_t^{both}}\, pr^{both}(d_{it}=stay)^{N_t^{both}-X_t^{both}} \\
&\times \binom{N_t^{new}}{X_t^{new}} pr^{new}(d_{it}=exit)^{X_t^{new}}\, pr^{new}(d_{it}=stay)^{N_t^{new}-X_t^{new}} \\
&\times \binom{N_t^{pe}}{E_t^{pe}} pr^{pe}(d_{it}=adopt)^{E_t^{pe}}\, pr^{pe}(d_{it}=quit)^{N_t^{pe}-E_t^{pe}}
\end{aligned} \tag{10}
$$

The overall joint likelihood for $t = 0, 1, 2, ..., T-1$ is

$$P(X, E, N) = \prod_{t=0}^{T-1} P(X_t, E_t, N_t).$$

Thus, the maximum likelihood estimators for the mean sell-off value ϕ and the base sunk costs of technology adoption κ^{inc} and κ^{ent} are

$$\arg \max_{\phi,\kappa^{inc},\kappa^{ent}} \ln \left[P\left(X, E, N\right)\right]. \tag{11}$$

Identification

Intuitively, I rely on a revealed-preference argument to identify the sell-off value and the sunk costs. For each firm i in year t, I compare the benefits and costs of the three dynamic alternatives (exit, stay, and adopt), each of which is associated with the parameters (ϕ, κ^{inc}, and κ^{ent}) and the value of being in a particular state in a given year ($E_t V_{t+1}^{old}\left(s_{t+1}\right)$, $E_t V_{t+1}^{both}\left(s_{t+1}\right)$, and $E_t V_{t+1}^{new}\left(s_{t+1}\right)$). These values of dynamic alternatives are, in turn, based on the model of a dynamic discrete-choice game as well as the period profits earned by "old-only," "both," and "new-only" firms across years and across different industry states (see sections 4.1 and 4.2). Thus, in principle, these dynamic parameters are identified by both time-series and cross-sectional variations.

5 Results

This section reports the estimation results.

5.1 Results: Demand

Table 3 displays demand estimates. I employ two market definitions, broad (1 and 2) and narrow (3 and 4). The former definition aggregates observations across both regions (U.S. and non-U.S.) and user types (computer makers and distributors/end users), in a manner consistent with the industry's context of a single, global market. However, the dataset contains richer variations across regions and user types, which we can exploit for improved precision of estimates. Moreover, the most plausible IVs (Hausman-Nevo IVs) become available under the narrower market definition (i.e., by region/user type). For these reasons, I present results under both market definitions.

The IV estimates in columns (2) and (4) are generally more intuitive and highly statistically significant than the OLS estimates in columns (1) and (3). Specifically, the price coefficient is negative ($\hat{\alpha}_1 < 0$), whereas both smaller size (3.5-inch diameter = new generation) and quality (the log of storage capacity) confer higher benefits ($\hat{\alpha}_2 > 0, \hat{\alpha}_3 > 0$) to the buyers.

In columns (5) through (8), I report results for the nested logit model, which nests HDDs by diameter (generation). The nest parameter estimate ($\hat{\sigma} = .49$) in column (8) sug-

Table 3: Demand Estimates for 5.25- and 3.5-inch HDDs

Model:	Logit				Nested Logit			
Market definition:	Broad		Narrow		Broad		Narrow	
Estimation method:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price ($000)	-1.66^{***}	-2.99^{***}	$-.93^{**}$	-3.28^{***}	.08	4.22^{***}	$-.05$	-1.63^{***}
	(.36)	(.64)	(.38)	(.58)	(.19)	(1.53)	(.10)	(.60)
Nests of Diameters	–	–	–	–	1.01^{***}	2.29^{***}	$.98^{***}$	$.49^{***}$
	(–)	(–)	(–)	(–)	(.05)	(.39)	(.04)	(.15)
Diameter = 3.5-inch	$.84^{**}$	.75	1.75^{***}	$.91^{**}$	1.96^{***}	4.27^{***}	2.24^{***}	1.70^{***}
	(.39)	(.50)	(.27)	(.36)	(.20)	(.76)	(.16)	(.31)
Log Capacity (MB)	.18	$.87^{***}$	.04	1.20^{***}	.06	-1.19^{**}	.08	$.65^{***}$
	(.25)	(.31)	(.22)	(.27)	(.09)	(.53)	(.07)	(.24)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Region/user dummies	–	–	*Yes*	*Yes*	–	–	*Yes*	*Yes*
Adjusted R^2	.43	.29	.50	.27	.85	.00	.80	.67
Number of obs.	176	176	405	405	176	176	405	405
Partial R^2 for Price	–	.32	–	.16	–	.32	–	.16
P-value	–	.00	–	.00	–	.00	–	.00
Partial R^2 for Nest	–	–	–	–	–	.37	–	.25
P-value	–	–	–	–	–	.00	–	.00

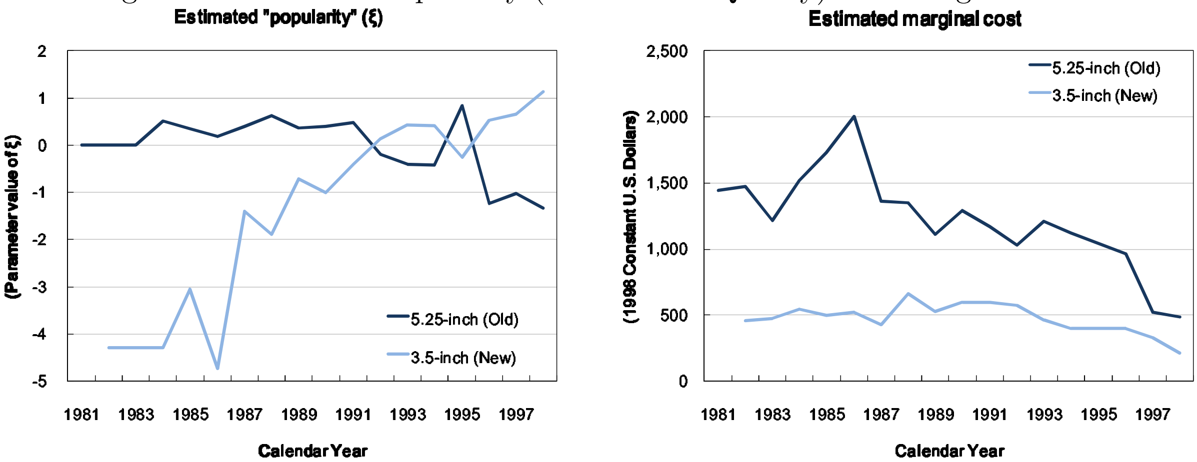
Note: Dependent variable is $ln(ms_j/ms_0)$. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

gests within- and cross-generation substitutions are equally important, implying the presence of cannibalization effects when an incumbent considers the introduction of new-generation products. Results (5), (6), and (7) are difficult to interpret, with positive (or at least not significantly negative) price coefficients. Moreover, the nest parameter estimates are close to or above 1, the theoretical upper bound. I attribute these unintuitive results to the lack of adequate instrumentation. Although column (6) uses some IVs, the broad market definition precludes the use of Hausman-Nevo IVs.

I use column (4), the logit IV estimates under the narrow market definition, as my baseline result for the subsequent analyses. Although the nested logit result (8) is also reasonable, the dynamic model does not incorporate product differentiation within diameters, thus leaving no rationale for preferring (8) over (4). I refrain from using the results based on the broader market definition. Specifically, result (2) is similar to (4) and highly intuitive, but I am concerned about the limited availability of IVs and the reduced variation in data, which sometimes leads to unintuitive results like (6).

All eight estimates incorporate year dummies and also allow for the time-varying unobserved product quality by diameter (ξ_{jt} in equations [8] and [9]; note I suppress time-subscripts in these formulae for notational simplicity). I use equation (9) to recover $\hat{\xi}_{jt}$ as residuals. Figure 7 (left panel) shows the evolution of $\hat{\xi}_{jt}$ for both old and new HDDs. Because $\hat{\xi}_{jt}$ reflect old and new HDDs' relative appeal to the buyers (but unobserved to the econometrician), I interpret and refer to them as "popularity" henceforth. These unobserved popularities of the old and new products switched in 1992, suggesting the 3.5-inch replaced 5.25-inch as the mainstream HDD type.

Figure 7: Estimated Popularity (Unobserved Quality) and Marginal Costs



Note: Results based on the IV estimates of logit demand system.

5.2 Results: Marginal Costs

From the demand estimates and firms' first-order conditions, I infer marginal costs of production (Figure 7, right). The continual drop in the marginal costs reflects two tendencies in the industry. First, HDDs required increasingly fewer parts due to design improvements, probably reflecting to some extent learning by doing. Second, offshore production in Singapore and other South East Asian locations became prevalent, reducing primarily the cost of hiring engineers. Together these developments represent important channels of "process innovation."[18] The new HDDs' marginal cost declines at the average annual rate of 6.12%, which I assume equals the rate of drop in the sunk costs of adoption; that is, $\hat{\delta} = .9388$ because the adoption cost of new technology directly relates to the production of new HDDs.[19]

[18]Although the detailed analysis of such cost reduction is beyond the scope of this paper, the interaction between "process" and "product" innovations will be an interesting subject for future research.

[19]Alternatively, one may assume time-invariant sunk costs (i.e., $\delta = 1$). However, I believe sunk costs dropping in line with production costs is more natural since both costs are concerned with the manufacturing of the same goods. In principle, one can try to estimate δ directly as a part of the dynamic model. In practice, however, such estimates tend to be unreliable, probably due to the same issue that plagues the estimation of β, the discount factor. Because changes in δ or β move almost everything in the model in the same direction, their identification seems impractical.

5.3 Results: Sunk Costs of Innovation

Table 4 shows the maximum likelihood estimates of the mean sell-off value, ϕ, and the base sunk costs of adopting new technology, κ^{inc} and κ^{ent}. Each column represents a set of coefficient estimates given a particular value of the discount factor, β.

Table 4: Estimates of the Dynamic Parameters

(Billion \$)	$\beta = .94$	$\beta = .92$	$\beta = .90$	$\beta = .88$	$\beta = .86$	$\beta = .84$	$\beta = .82$
Sell-off value (ϕ)	12.51	8.87	5.69	**4.00**	2.74	2.04	1.41
Incumbents' sunk cost $\left(\kappa^{inc}\right)$	2.62	2.50	2.38	**1.99**	1.89	1.77	1.72
Entrants' sunk cost $\left(\kappa^{ent}\right)$	8.69	8.25	7.08	**4.60**	2.95	2.06	1.42
Log likelihood	−129.3	−117.1	−113.3	−110.2	−107.3	−104.2	−101.6

Note: Standard errors are not available because of a step function-like shape of likelihood, which is typical of dynamic discrete games and leads to either zero or very large standard errors.

Estimates tend to decrease with β because a lower discount factor implies a lesser value of doing business in the HDD market, hence lower values associated with entry/exit, too. The log likelihood also increases with β, suggesting a slightly better fit (in terms of the choice probabilities, upon which the likelihood is based) for estimates based on lower β. As β approaches .80, however, the sell-off value estimate $\hat{\phi}$ drops close to zero and then turns negative (not reported). The adoption cost estimates $\hat{\kappa}^{inc}$ and $\hat{\kappa}^{ent}$ also turn negative with lower βs. Such results are economically implausible because, taken literally, they would suggest firms are somehow "penalized" upon exit (instead of earning sell-off value) and "rewarded" upon innovation (instead of paying sunk cost).

Consequently, I choose $\beta = .88$ estimates as my baseline result: the choice that best reflects the tradeoff between data fit and economic sensibility. On the one hand, the $\beta = .88$ estimates fit data considerably better than $\beta = .94$, .92, or .90. On the other hand, the coefficient estimates with $\beta = .88$ are sufficiently higher than zero, allowing straightforward interpretations. Furthermore, the simulation of market structure based on $\beta = .88$ performs better than simulations based on lower β in terms of the peak number of firms in "both" and "new-only" states, that is, active players that have adopted new technology, because a lower β leads to lower values of doing business. This lowering of value induces too many exits and too few adoptions to match the number of firms observed in the data. Hence a higher β is desirable in this aspect of data fit (in state evolution, in contrast to the fit in choice probabilities as measured by log likelihood in Table 4). Finally, the existing empirical studies of dynamic oligopolies conventionally used $\beta = .95 \sim .90$, a range that is close to my preferred model.[20]

[20] Collard-Wexler (2010), Schmidt-Dengler (2006), Ryan (2011), and Goettler and Gordon (2011) chose

The baseline ($\beta = .88$) estimates show two important features. One is that the entrants' base sunk cost is higher than the sell-off value upon exit $\left(\hat{\phi} < \hat{\kappa}^{ent}\right)$, which implies "no free lunch;" that is, entering this market for the sole purpose of exiting and running away with sell-off value does not pay off. The other important feature is that the adoption cost is lower for incumbents than for entrants ($\hat{\kappa}^{inc} < \hat{\kappa}^{ent}$); therefore, the seeming "inertia" of incumbents does not stem from their innate cost disadvantage. The explanation lies in other incentives, as I explore in detail with counterfactual analyses in the next section. The result that $\hat{\kappa}^{inc} < \hat{\kappa}^{ent}$ does not necessarily mean incumbents are entirely free from organizational, informational, or other commonly attributed disadvantages. Rather, my estimates simply suggest incumbents enjoy a certain innovation-cost advantage over entrants in net terms. A possible explanation is that incumbents accumulate certain technological or marketing capabilities over the years, which outweigh other potential disadvantages associated with being larger and older. Determining the exact contents of $\hat{\kappa}^{inc}$ and $\hat{\kappa}^{ent}$ is beyond the scope of this paper, but incumbents' (net) cost advantage will have important welfare implications (see section 7).

5.4 Results: Industry State, Policy, and Value

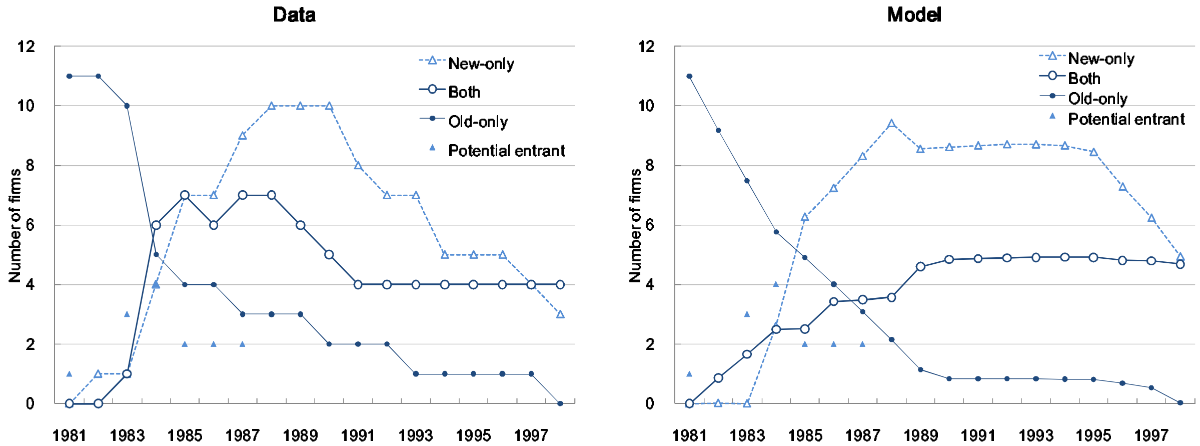
Figure 8 compares the evolutions of the industry state in the data with the estimated model. "Model" (right panel) displays the evolution of the simulated industry state, which is the average equilibrium path based on the estimated choice probabilities (policy functions) with $\beta = .88$.

Overall, the estimated model replicates three key features of the data, albeit in a slightly smoother manner. First, the number of adopting incumbents (firms in "both" state) peaks at a level lower than entrants ("new-only"). Specifically, the peak numbers of "both" and "new-only" are 7 and 10 in the data, compared with approximately 5 and 10 in the model. Second, during the second half of the sample period, the survival rate is higher for adopting incumbents than for entrants, resulting in similar numbers of survivors as of 1998 (i.e., 4 "both" and 3 "new-only" in the data, compared with approximately 5 "both" and 5 "new-only" in the model). Third, the number of non-adopting incumbents ("old-only") declines precipitously during the 1980s and then more slowly during the 1990s before reaching zero in 1998. Thus the estimated model captures the key data features of innovation and market structure dynamics.

The simulation in Figure 8 (right) is based on the solution of the dynamic discrete game,

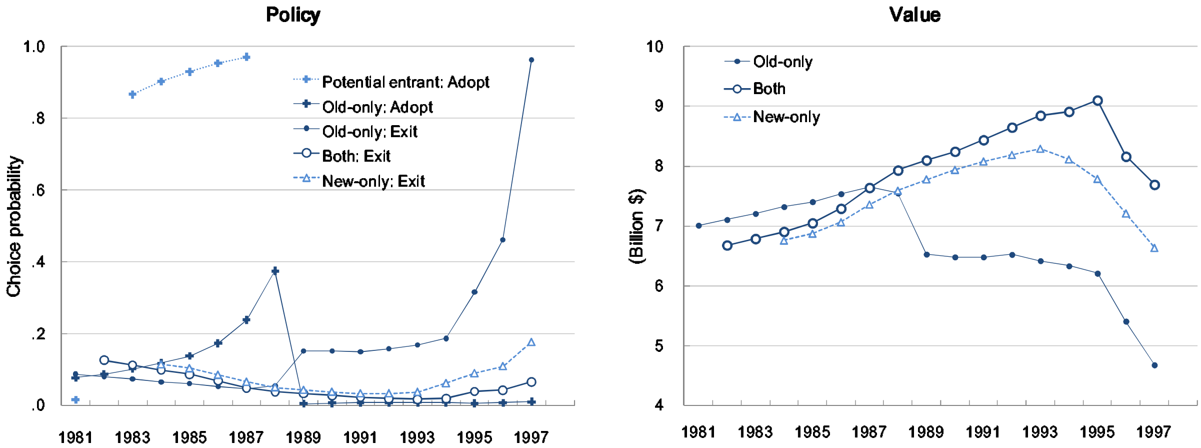
$\beta = .95$, .94, .90, and .90, respectivly, in their studies of the markets of concrete, hospitals, cement, and microprocessors. I believe a lower discount factor would be more adequate for the HDD industry because of its fast pace of technological changes.

Figure 8: Market Structure Dynamics



Note: "Model"(right panel) displays the mean evolution of simulated industry state, based on the estimated choice probabilities (policy functions) with $\beta = .88$.

Figure 9: Estimated Policy and Value Functions



Note: Policy and value functions along the mean equilibrium path, based on $\beta = .88$.

that is, the optimal strategies and payoffs. Figure 9 shows the estimated policy functions (i.e., the optimal choice probabilities) and value functions (i.e., the attractiveness of each alternative). Three features are important. First, incumbents become increasingly more eager to innovate in years approaching 1988, with a peak adoption rate of 37% (Figure 9, left, "Old-only: Adopt"). After 1988, the adoption rate plummets to 1% and recovers only slightly toward 1997, the final year of dynamic decision-making. The estimated equilibrium values reflect this policy trajectory. The value of being an "old-only" firm starts relatively high (Figure 9, right, "Old-only"), but the values of being "both" and "new-only" gradually catch up and surpass that of "old-only" by 1988, as the new-generation HDDs gain in popularity. At this point, innovation becomes most attractive to incumbents: hence the increasing adoption rate toward 1988. However, after 1988, the value of being "old-only" is so low incurring sunk costs and joining the herd of (already numerous) new-HDD producers no longer pays off.

The second important feature is the high adoption rate among entrants. Except for 1981, potential entrants' equilibrium probability of adoption (entry) is consistently above 80% (Figure 9, left, "Potential entrant: Adopt"). The estimated policy matches the data well, with most potential entrants deciding to adopt as well. Third, an increasing number of firms exit toward the end. All classes of firms show this tendency because the value of staying in the industry declines as the game approaches the terminal year, 1998. However, the firms in "both" state, that is, the adopting incumbents, temporarily back this downward trend between 1989 and 1993 because the number of rivals in the new HDD category starts to decrease while its profitability finally begins to take off. In general, the time profile of value function, including whether and how much V_t^{both} trends upward in the middle, depends on the discount factor, with a lower β leading to "bumpier" time-series.

6 "Innovator's Dilemma" Explained

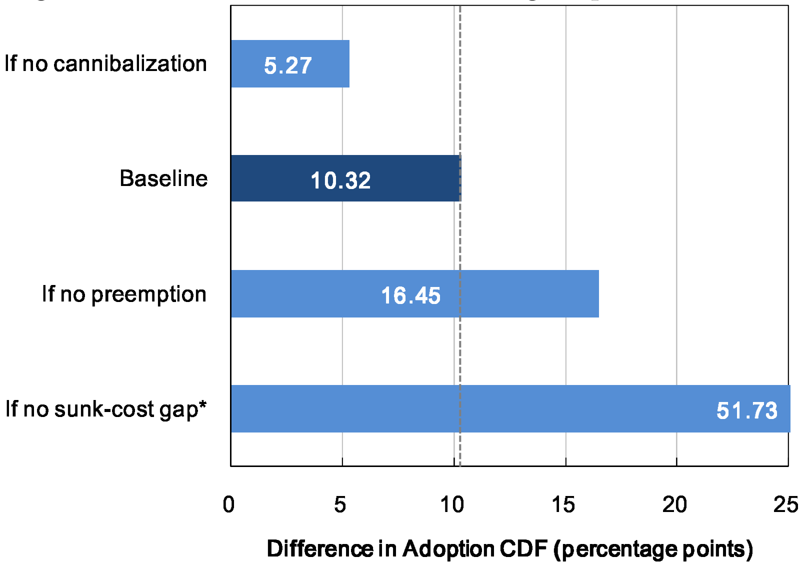
This section answers the first question of the paper, namely, why incumbents are slower than entrants in innovation. I quantify the effects of the three theoretical forces that determine the incumbent-entrant timing gap in technology adoption: cannibalization, sunk-cost gap, and preemption. To measure each effect, I compare the timing gaps in the estimated baseline model with a counterfactual simulation in which that particular incentive mechanism is absent.

Figure 10 summarizes the results of the counterfactual analyses. The incumbent-entrant timing gap is measured by the percentage-point differences between incumbents' and entrants' CDF of adoption timing (c.f., Figure 2), averaged over years. "Baseline" is the estimated model's outcome (10.32 percentage points). The other three values (5.27, 16.45, and 51.73 percentage points) represent the simulated counterfactuals in which I "shut down" particular economic incentives.

The comparison of the counterfactuals against the baseline suggests the following: (1) cannibalization can explain 51% of the timing gap; (2) without preemptive motives (and other dynamic strategic incentives), incumbents would have further delayed innovation by as much as 59%; and (3) contrary to the prior impression of "organizational inertia," incumbents enjoy a cost advantage over entrants (and hence the elimination of this cost advantage would have led to incumbents' much longer delay). These timing-gap outcomes are derived from the simulations shown in Figure 11, which compares the evolutions of the industry state in the baseline model with three counterfactuals.

In the following three subsections, I explain the setup, result, and interpretation of each

Figure 10: Incumbents-Entrant Timing Gap in Innovation



Note: * outside the graph range. Timing gap is measured by the percentage-point difference between incumbents' and entrants' CDF of adoption timing, averaged over years during the first half of the sample period. "Baseline" outcome is based on the estimated model (see previous section), whereas the other three are the counterfactual simulation results, which are explained in detail in this section.

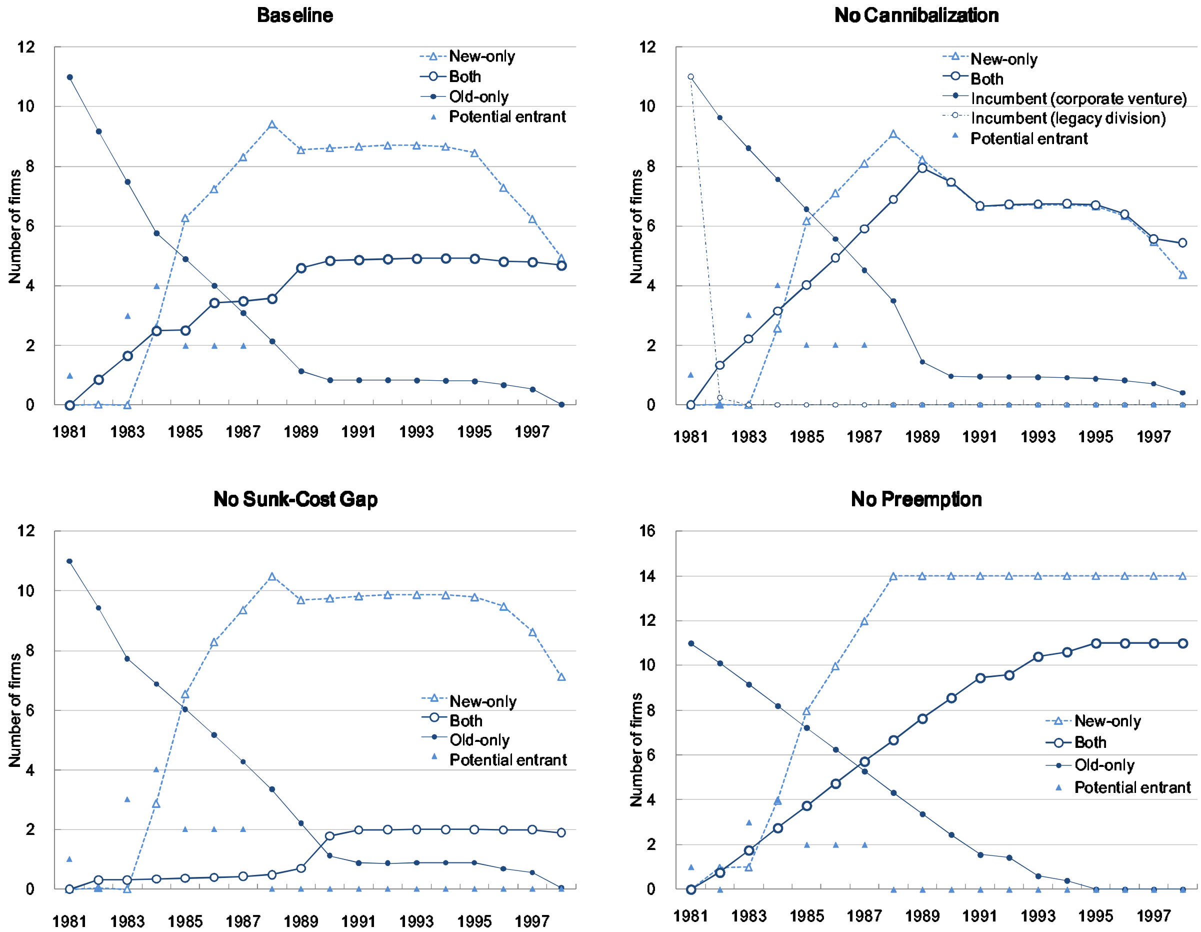
counterfactual.

6.1 Cannibalization (Counterfactual 1)

I eliminate the cannibalization factor from incumbents' adoption behavior by isolating the adoption decision (production of new HDDs) from the profit maximization regarding old HDDs. In other words, I effectively split each incumbent firm into two separate entities: a "legacy" division that takes care of the manufacturing of old HDDs and a "corporate venture" in charge of developing new HDDs. The former division acts as an independent "old-only" firm that decides whether to stay or exit in each year, but without the third alternative to adopt new technology and become "both." The latter division acts like a "potential entrant" with staying power, which can choose to adopt (and become "new-only"), wait, or exit. Thus each incumbent in this no-cannibalization counterfactual is two separate firms dedicated to old and new HDDs in isolation.[21]

[21] An alternative approach to isolate the cannibalization factor would be to directly alter the HDD demand system in such a way that old and new HDDs no longer substitute for each other. Computationally, this alternative approach is easier than the approach I chose, because the latter substantially increases the effective number of firms. A drawback of the alternative approach is that the counterfactual demand system needs to be specified in a rather arbitrary manner. There must be two different markets, of size M_t^{old} and M_t^{new}, when in fact only one market existed (with size M_t), but I see no obvious way to split M_t into M_t^{old} and M_t^{new}, and the outcomes depended heavily on the way I split the market (not reported).

Figure 11: Explaining the Innovator's Dilemma (Counterfactual Series I)



Note: "Baseline" estimated model is explained in section 5. See sections 6.1, 6.2, and 6.3 for the details of the three counterfactuals.

Incumbents (their "corporate venture" divisions, to be precise) are much more eager to adopt new HDDs than in the baseline case. Consequently, an approximately equal numbers of incumbents and entrants produced the new HDDs during the 1990s.

Free of the cannibalization concerns regarding their own old-HDD business, more incumbents (their "corporate venture" divisions) start producing new HDDs earlier. Cannibalization can explain half of the actual timing gap between incumbents and entrants. On a separate note, the sudden exit of "old-only" divisions of incumbents is interesting (Figure 11, top right, "Incumbent (legacy division)"). It reflects the limited value of staying in the old-HDD business with no prospect of starting new HDD production.

6.2 Preemption (Counterfactual 2)

Preemption is a dynamic strategic motive. In an oligopolistic environment, some firms' early adoption would reduce the incremental profits available to late adopters. An incumbent has incentives to preempt other incumbents as well as potential entrants. Thus, the silencing of preemption requires that firms do not perceive the evolution of industry state (the numbers of firms in "old-only," "both," and "new-only" states) as something they can influence by their own actions. In the no-preemption counterfactual, firms take the evolution of industry as exogenous to their dynamic decisions.[22]

In the absence of preemptive motives, incumbents' delay increases substantially, to 16.45 percentage points from 10.32 percentage points in the baseline model. The number of "both" firms (adopting incumbents) grows more slowly.

Each firm ignores its rivals' decisions, so the nature of the dynamic game changes fundamentally from that of strategic entry/exit to a single-agent optimal stopping problem. An incumbent does not need to act aggressively to deter the rivals, so the innovation rate becomes lower and the incumbent-entrant gap wider.

6.3 Sunk Cost Gap (Counterfactual 3)

An important finding from estimating the baseline model is the sunk cost advantage of incumbents relative to entrants, the estimates of which were 1.99 and 4.60, respectively. What if incumbents no longer enjoyed this cost advantage? To eliminate the cost difference, this counterfactual sets the sunk costs at 3.30 for both incumbents and entrants ($\kappa^{inc} = \kappa^{ent} = \bar{\kappa} = 3.30$).[23]

Incumbents' innovation is discouraged. At most, only two "both" firms are active in the market. By contrast, more "new-only" firms thrive even toward the end of the 1990s.

A 66% increase in sunk cost is sufficient to suppress most incumbents' adoption. Since technology adoption is essentially a dynamic discrete choice problem, a material change in the cost of choosing a particular alternative is bound to have large repercussions on the outcome. Another interesting feature is the higher survival rate among entrants. Seven

[22] One might alternatively label this counterfactual as a "no dynamic strategic interaction" or "dynamic monopolistic competition" scenario. I choose to call it a "no-preemption" case to highlight the economic incentives I believe are at the heart of firms' technology adoption decisions.

[23] Alternatively, $\bar{\kappa} = 1.99$ (i.e., entrants enjoy the low cost of incumbents) is an equally plausible setup. However, even in the baseline model, most potential entrants decide to adopt anyway, which limits the upside for entrants' adoption rate. Another possible configuration is $\bar{\kappa} = 4.60$ (i.e., incumbents are as "handicapped" as entrants). This setup results in few incumbents' adoption, only toward the end of the sample period (not reported). Although interesting, this result is too extreme to be compared with the baseline case. Therefore, I chose to show the results for the "mean" counterfactual ($\bar{\kappa} = 3.30$) for more meaningful comparison.

"new-only" firms survive until 1998, whereas only five survive in the baseline case. With few incumbents adopting and directly competing in the new HDD category, entrants can enjoy higher profits and hence improved survival prospects.

7 Policy Experiments

In this section, I evaluate public policies concerning innovation and competition. I conduct counterfactual simulations and compare measures of social welfare. Specifically, I experiment with four policies: (1) broad patent on new HDDs, (2) R&D subsidies to incumbents, (3) ban on non-compete clauses, and (4) ban on international trade. The purpose of these experiments is to inform policy design as well as to deepen our understanding of the interactions between innovation, competition, and welfare.

Table 5 summarizes the welfare analysis. Rows represent different policy simulations, including the benchmark cases. Columns list the components of social welfare: (A) consumer surplus, (B) producer surplus, (C) sell-off value upon exit, and (D) sunk costs of technology adoption. Social welfare is their sum. Given the finite-horizon setup, I display social welfare figures separately for the sample period (1981 through 1998) and for the years since 1999. The latter consists of the terminal values of (A) and (B) but not (C) or (D) because no more exit or adoption/entry occurs after 1998.

Table 5: Comparison of Social Welfare across Policy Experiments

(Billion $)	1981 through 1998						From 1999
	(A) Consumer Surplus	(B) Producer Surplus	(C) Sell-off Value	(D) Adoption Cost	(A+B+C+D) Social Welfare	Change from Baseline	Social Welfare
Benchmarks							
1. Baseline	127.7	9.4	20.0	−39.5	117.6	0%	112.3
• U.S.	102.5	4.5	9.6	−18.0	98.6	0%	84.9
• Non U.S.	25.2	4.9	10.4	−21.6	18.9	0%	27.4
2. Planner	410.7	0.0	0.0	−0.8	409.9	248.7%	485.0
3. Monopolist	60.3	16.6	0.0	−0.8	76.0	−35.3%	30.4
Experiments							
1. Broad Patent							
• Pre-announced	109.6	16.4	6.2	−13.9	118.2	0.5%	99.5
• Surprise in 1988	67.9	15.1	17.0	−39.0	61.0	−48.2%	30.4
2. R&D Subsidy	127.2	9.4	20.7	−45.4*	111.9	−4.8%	104.0
3. Ban NCC	129.6	7.6	18.5	−47.5	108.2	−8.0%	112.5
4. No Trade	107.4	16.8	6.7	−31.1	99.7	−15.2%	95.5
• U.S.	88.5	12.7	0.0	−12.4	88.8	−10.0%	79.4
• Non U.S.	18.9	4.1	6.7	−18.7	11.0	−88.9%	16.2

Note: Each number is the sum of discounted present values as of 1981. * Includes government subsidies.

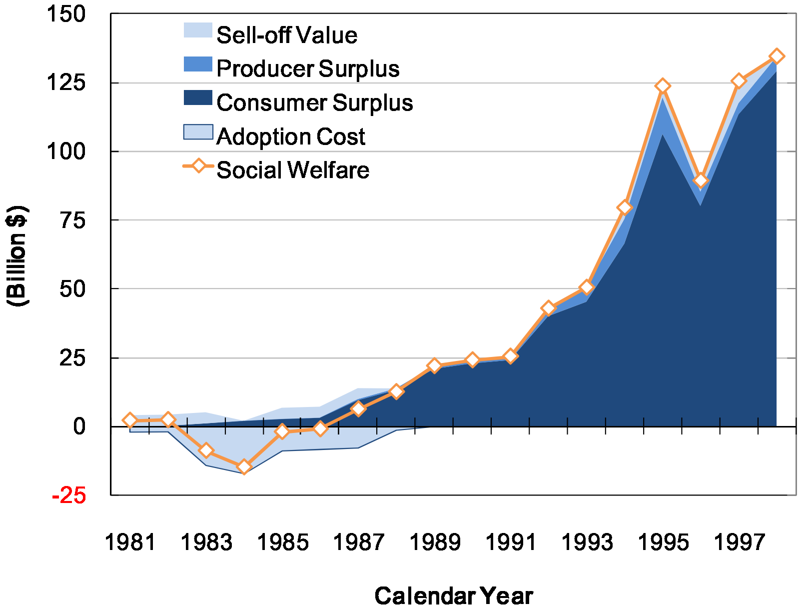
The largest social welfare component is consumer surplus (A). However, the second largest item, adoption costs (D), tends to vary most across different scenarios because the number and timing of technology adoption will drastically alter the total sunk costs. In contrast, consumer surplus stays within a narrower range as long as several firms are supplying old and new HDDs. Therefore, the final welfare outcome (A+B+C+D) mainly reflects the tradeoff between the benefits (A) and costs (D) of innovation.

This tradeoff is clear in Figure 12, which graphs the time profile of social welfare in the baseline case. To illustrate the relative magnitude of surpluses and costs in different years, each welfare component is displayed without time discounting. Three features are noteworthy. First, the size of the consumer surplus grows over time with the growth of market size (M_t). Second, as the number of firms declines during the 1990s, the increased market power leads to higher producer surplus. The sell-off value is also visible because of continual exits. Third, adoption costs are huge and accrue in the early years, so the net social welfare is negative during most of the 1980s, when demand for HDDs is limited. Once the sunk costs are paid, however, all future surpluses count toward a net increase in social welfare. Consequently, the world enjoys a net gain of \$117.6 billion between 1981 and 1998, and \$229.9 billion if we include all years after 1998. If we consider the evolution of the HDD industry an investment project, the social "internal rate of return" would be 33.5%.[24]

To find theoretical benchmarks, I calculate the welfare profiles under the hypothetical scenarios in which a social planner and a monopolist, respectively, make production decisions. In both cases, only one incumbent adopts new technology because that is the cheapest way to produce new HDDs. The planner implements marginal-cost pricing ($p_g = mc_g$), whereas the monopolist charges profit-maximizing prices. Interestingly, both the planner and the monopolist will choose to innovate in the same year, 1986, when the overall demand for HDD just begins to take off. Their optimal innovation timing coincides because the time profiles of their costs are identical, as they both operate a single incumbent firm and consider its optimal adoption year. Their benefits calculations also have similar time profiles based on the overall size of potential demand, although the ways in which the planner and the monopolist evaluate (appropriate) surpluses are different, namely, consumer surplus versus producer surplus.

[24]The internal rate of return (IRR) is the discount rate at which the project's net present value becomes zero. The IRR of 33.5% implies the social return from the entire historical development in the HDD is positive as long as the social discount factor is above .665.

Figure 12: Time Profile of Social Welfare (Baseline)



Note: Numbers are not time discounted. Excludes terminal values (i.e., surpluses accruing after 1998).

7.1 Broad Patent (Experiment 1)

The question of whether broad patents encourage innovation is particularly relevant to the HDD industry, in which Rodime, a Scottish firm that was among the first adopters of the 3.5-inch technology, claimed patent on the whole concept of 3.5-inch HDDs in 1986 (see Table 6). After years of lawsuits between Rodime and its rivals, the U.S. Court of Appeals for the Federal Circuit (CAFC) eventually rejected the claim in 1995 and 1996, but several HDD makers gave up the court battles before the rulings and agreed to pay license fees to Rodime.

Although Rodime's claims were considered outrageous in the industry at the time, and ended in a legal grey zone, studying what the welfare consequences would have been had the patent system and CAFC's rulings been different is worthwhile. I propose two separate experiments, one designed to study the *ex-ante* impact of a pre-announced broad patent regime and the other to study the impact of *ex-post* "surprise" court rulings.

In the first counterfactual, only the first adopter(s) is/are allowed to manufacture new HDDs, and this legal arrangement is pre-announced by the patent authority before 1981, before the game begins. The setup allows for multiple adopters as long as they belong to the first cohort. The motivation for this permissive regime is to reflect the custom of defensive patenting in the computer-related industry, where rival firms tend to hold competing intellectual-property claims and engage in lawsuits and countersuits. Firms typically use

Table 6: Brief History of Rodime's 3.5-inch HDD Patent Affair

Year	Events
1980	Rodime became independent from Burroughs' 5.25-inch HDD plant in Glenrothes, Scotland.
1983	Rodime became the first maker to achieve volume production of 3.5-inch HDDs.
1986	Rodime surprised the industry by obtaining a patent on the concept of a 3.5-inch drive. Rodime sued Miniscribe and Conner Peripheral for patent infringement. IBM sued Rodime, which countersued IBM.
1988	The 3.5-inch patent affair headed for a long tour of the U.S. federal court system. Miniscribe opted out by taking a license from Rodime.
1989	Rodime moved to Singapore for production efficiency, but neared bankruptcy and obtained some financing. Top management was completely overhauled in early 1989.
1991	Patent affair ended when IBM and Conner Peripheral took licenses, as well as Fujitsu and Alps Electric. Several other firms were in negotiation. Rodime pursued joint ventures with Japan's JVC and firms in Taiwan and Korea, but in mid-1991 announced it would file for bankruptcy and cease manufacturing operations. It planned to remain active in pursuing licensing revenues from 3.5-inch HDD patents.
1994	High legal expenses and falling license revenues put financial pressure on Rodime.
1995	In September 1995, a U.S. appeals court ruled some of Rodime's patent claims invalid, a ruling in favor of Quantum. Rodime still argued that other patent claims were valid, in a separate legal action against Seagate.
1996	Appeals court rulings in 1995 and 1996 appear to have weakened Rodime's negotiating position, but it continues to argue that other patent claims are still valid.

Source: *DISK/TREND Reports*, various years.

patents to enhance their bargaining power in negotiating favorable terms in cross-licensing agreements.[25]

In the second counterfactual scenario, Rodime's rivals ignore the company's patent claims until 1988, when the CAFC, a centralized appellate court for patent cases established in 1982, announces its surprise ruling to honor Rodime's patent infringement claims, paving the way for a legal monopoly of the 3.5-inch technology.[26]

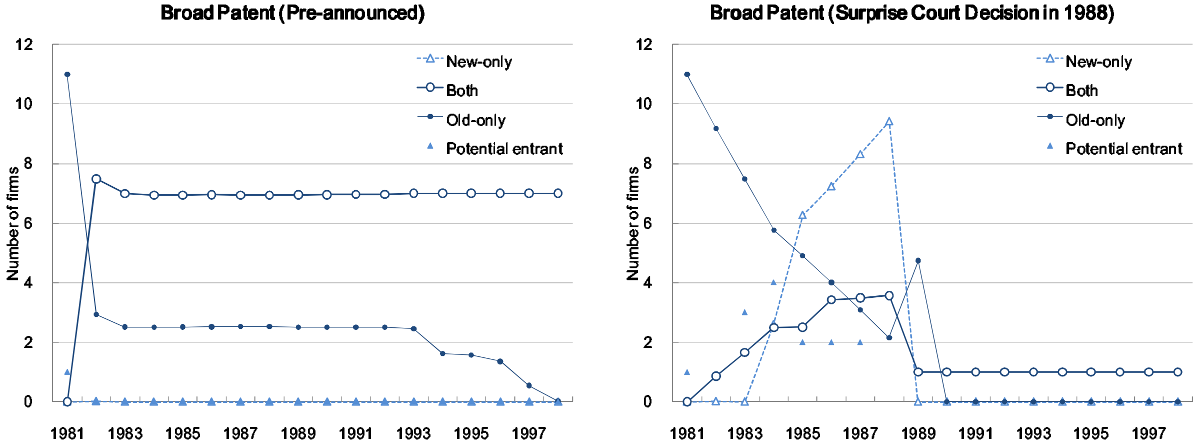
Figure 13 compares the evolutions of the industry state in the two counterfactual simulations. The pre-announced broad patent regime (left panel) induces a relatively simple market structure. Seven of the 11 incumbents decide to adopt new HDDs in 1981, after which further adoption becomes illegal. No entrants can adopt. Social welfare increases by 0.5% between 1981 and 1998, but, ironically, this gain does not come from increased innovation. Rather, social welfare increases because patents prevent innovation by many firms, thereby saving adoption costs.

In the second, "surprise court ruling" experiment (right panel), the industry evolves just as in the baseline case until 1988, the year when the CAFC hypothetically entrenched

[25] Alternatively, one might consider the patent regime in which only and exactly one firm can make 3.5-inch HDDs. I omit this scenario because the outcome is almost equivalent to the benchmark "monopolist" case.

[26] Patent lawsuits usually end with the payment of damages. For simplicity, this experiment assumes that the payments are large enough to make Rodime's rivals indifferent with respect to staying versus exiting.

Figure 13: Policy Experiment 1 (Ex-ante and Ex-post Effects of Broad Patent)



Note: For the details of counterfactuals, see section 7.1

Rodime's legal monopoly. All "new-only" firms immediately go out of business, and all "both" firms except for Rodime itself are forced back to "old-only" status by 1989, a position that is so unattractive the firms all subsequently elect to exit the industry.

Broad patents function as a hard entry barrier. Because adoption cost is an important component of social welfare, limited entry translates into a huge saving in societal cost. Limited competition reduces the 1981–98 consumer surplus by 14.2% ($18.1 billion), but the adoption cost reduction of 64.8% ($25.6 billion) compensates for this loss. Seven adopters seem sufficient to ensure relatively competitive supply and pricing. The innovation timing is front-loaded to 1981, which is a favorable development from the viewpoint of pro-innovation policy.

In stark contrast with the previous experiment, social welfare drops by 48.2% in the ex-post patent scenario because most firms had already paid the sunk costs and started production of 3.5-inch HDDs by 1988, so that there is no cost saving as in the "pre-announced" patent regime. Instead, the only major change is that the industry becomes a monopoly from 1990 and consumers suffer.

In the existing literature, Lerner (1994) found a positive correlation between broader patents and increased innovative activities, whereas Sakakibara and Branstetter (2001) found no measurable relationship.[27] In contrast, the results of my experiments point to the possibility that allowing for broad patents might decrease innovative activities. These diverging results are not necessarily at odds with each other for two reasons. First, even when the number of total innovators decreases in the long run, if the timing is earlier then the number of innovators will be higher in the short run. In other words, a tradeoff seems to be present

[27]Other theoretical and empirical investigations on this topic include Gilbert and Shapiro (1990), Klemperer (1990), Jaffe and Lerner (2004), Chaudhuri, Goldberg, and Jia (2006), and Qian (2007).

between short-run and long-run levels of innovative activities, and patents may change this balance. These changes in the timing and number of innovations embody the ex-ante effect of patents. Second, because patents are legal monopoly rights by definition, if one firm's patent on a particular product/technology is strictly honored and protected, rival firms must be excluded from the same product/technology. This ex-post effect of broad patents is highlighted in the second experiment. In principle, however, we might still think those excluded firms might seek technological opportunities elsewhere and end up conducting innovative activities outside that particular market.

7.2 R&D Subsidy (Experiment 2)

Is subsidizing the adoption of new HDDs socially worthwhile? R&D subsidies are rampant, as arguing against the virtues of innovation is difficult. Whether subsidies are really desirable is another issue, which I explore in this experiment.

I set $\kappa^{inc} = 0$ in this counterfactual, letting the government subsidize 100% of incumbents' innovation cost. This setup does not mean innovations are socially costless; rather, the cost simply accrues to the public sector, which is reflected in Table 5 as adoption cost (D). This R&D subsidy specifically targets incumbents because their costs are lower. More fundamentally, for the government to identify and contact potential entrants is not always feasible.[28]

Subsidies accelerate incumbents' adoption. The peak number of innovating incumbents ("both") reaches eight in 1987, compared with the baseline result of five in 1989. However, the total social welfare is 4.8% lower than in the baseline case because more innovators means higher total adoption costs.

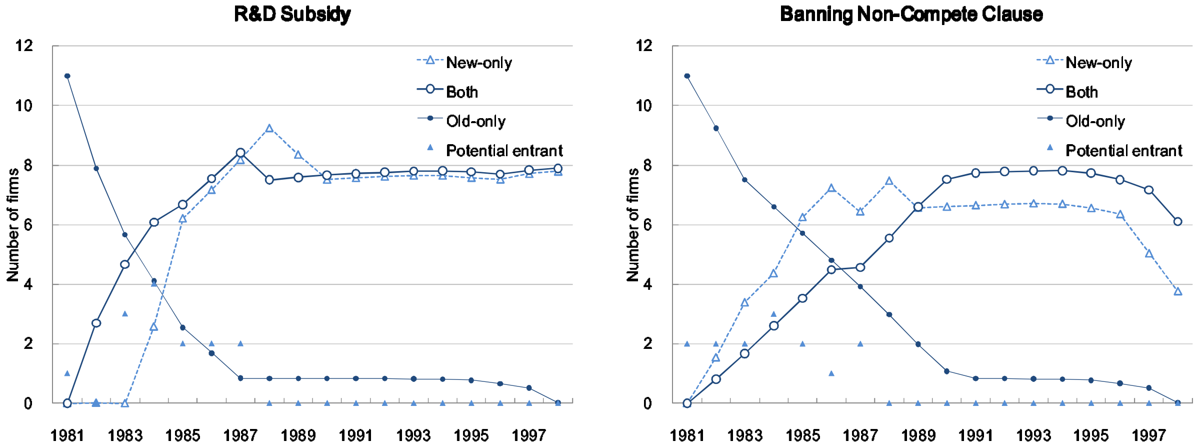
Subsidies successfully encourage more incumbents to adopt, and in earlier years. However, this aggressive adoption does not translate into a significant increase in consumer surplus for two reasons. First, a higher number of exits offsets a higher number of adopters. Second, potential entrants are less likely to enter due to preemption, and even if they do, they are more likely to exit.

This result echoes some of the findings in the existing research. The effect of R&D subsidy has been an active area of innovation studies, where a crucial policy question is whether R&D subsidies increase or decrease innovative activities in general, and private R&D spending in particular.[29] My experiment suggests R&D subsidy would increase the number of adopters,

[28] Raising enough capital to lobby the government is also difficult for potential entrants.

[29] Hall (1993, 1996), Hall and Van Reenen (2000), Irwin and Klenow (1996), Lerner (1998), Branstetter and Sakakibara (1998), Griliches and Regev (1998), Klette and Moen (1999); see also Klette, Moen, and Griliches's (2000) survey. More recent studies include González and Pazó (2008).

Figure 14: Policy Experiments 2 and 3



Note: See sections 7.2 and 7.3 for the details of counterfactuals.

but public R&D spending would substitute for private R&D spending without inducing a complementary increase in private R&D spending, because of the once-and-for-all nature of innovation in the technological context of the HDD industry. Although the nature of R&D efforts varies by industry, this experiment suggests a potential explanation for why studies tend to find small effects of public R&D spending in inducing private R&D.

7.3 Banning Non-compete Clauses (Experiment 3)

As Scherer (1980) and Bresnahan (2003) emphasized as the (then) chief economists of the Federal Trade Commission, entrants are important sources of innovation.[30] Therefore, entry facilitation is a potential channel through which public policy may promote innovation. One possible policy instrument concerns the legality of the private contracts governing the ease of starting new businesses. Specifically, the non-compete clause (NCC, or the covenants not to compete [CNC]) is the type of employment contract that limits the actions of personnel working at an existing firm and considering starting their own businesses (or working for rival firms). Many HDD makers are headquartered in the American state of California, where NCCs are banned. Nevertheless, exceptions to this ban exist, such as the cases involving mergers, and the practice was common during the sample period.[31] Of the 14 potential entrants in my data, five Californian firms are founded by former managers and engineers from existing HDD makers, a typical Silicon Valley phenomenon. Thus a strict ban on NCC may have important welfare implications through innovation and competition.

[30] Managers seem to agree, too. See Grove (1996) for the former Intel CEO's account.

[31] For instance, Finis Conner had to wait for two years before leaving Seagate Technology to found Conner Technology in the late 1990s, because he had been a party to the merger between Seagate Technology and Conner Peripheral in years prior to his departure.

In this counterfactual, the five potential entrants founded by industry veterans appear two years earlier than in the actual data.

The two-year front-loading of the five entrants results in their earlier adoption. This front-loading does not materially alter the trajectory of incumbents. Social welfare decreases by 8% because of increased adoption costs.

As in the case of more aggressive adoption by incumbents (section 7.2), earlier adoption tends to generate limited extra consumer surplus while raising the adoption costs substantially. Consumer surplus does not increase substantially, because the market size (the number of potential buyers) is still small during the early years. Adoption costs increase because they are both initially high and discounted less.

7.4 No International Trade (Experiment 4)

Disputes over intellectual property rights often become international trade disputes in the computer-related industries. For example, Apple sued HTC, a leading manufacturer of the Android-based smart phone in Taiwan, in July 2011 for two patent infringement claims related to touch-screen technologies in iPhones. HTC countersued Apple, but, meanwhile, the U.S. Commerce Department started contemplating banning U.S. imports of HTC's smart phones. A similar dispute between Apple and Sumsung led to a temporary ban on Samsung's Galaxy tablet computer in Germany and Australia. Given the global nature of competition in these high-tech industries, intellectual property and competition policy issues tend to become international trade issues at the same time. Although the international trade of HDDs avoided political interventions during the sample period, other sectors of the computer industry were full of trade disputes around the same time.[32] Because the HDD industry data are relatively free from political complications, they provide a clean laboratory in which to experiment with the welfare impact of trade barriers.

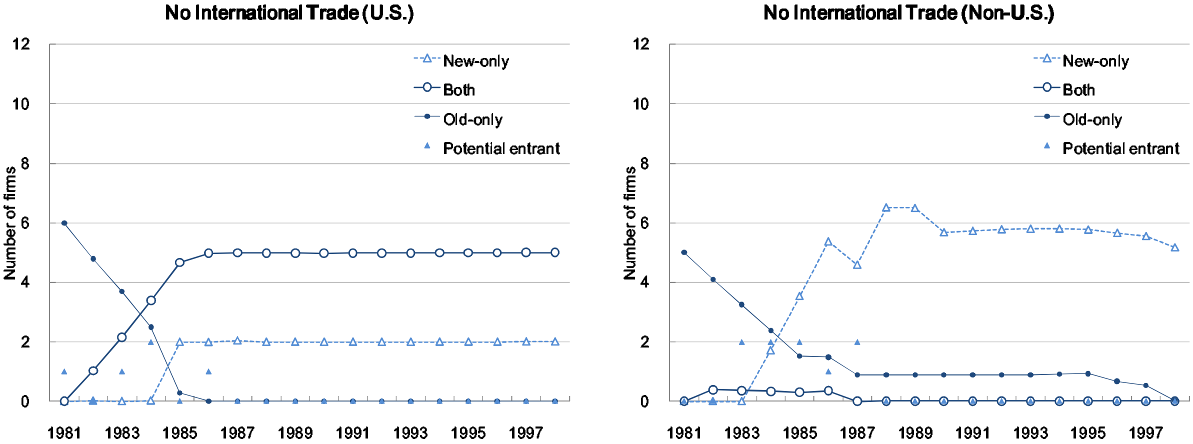
This counterfactual examines an environment in which no HDD trade occurs between the U.S. and the rest of the world. On the demand side, the world market (its pool of potential buyers) is split into the U.S. and non-U.S. On the supply side, American firms can only serve the U.S. market, whereas non-American firms serve the rest of the world. Thus this experiment is one of alternative market sizes and market structures.

In both the United States and elsewhere, consumer surpluses as well as the total adoption costs decrease. The net result is a 15.2% decrease in worldwide social welfare. Interestingly, the effect is asymmetric between the two regions. The U.S. social welfare drops by only 10%

[32] For example, Japan's Ministry of International Trade and Commerce restricted the imports and manufacturing of IBM's computers during the 1960s. The U.S. Commerce Department imposed "anti-dumping" duties on Samsung's memory chips (DRAM) in the early 1990s.

while the rest of the world suffers an 88.9% reduction.

Figure 15: Policy Experiment 4 (No International Trade)



Note: For the details of counterfactuals, see section 7.4.

On the supply side, trade restrictions are anti-competitive in limiting the numbers of effective competitors in both the United States and outside. Moreover, the smaller market size on the demand side implies smaller spoils of innovation for potential adopters, discouraging the production of new HDDs. These two effects lead to more concentrated market structures. The latter effect translates into a lower adoption rate and hence cost savings. Since these cost savings accrue to producers, the effect of trade barriers is positive for the U.S. producers. However, non-U.S. producers' surplus declines because the number of firms originating from outside the United States is disproportionately high compared to the size of the market. Thus, whereas the concentration effect (i.e., a smaller number of firms compete) dominates in the United States, to the advantage of American HDD makers, outside the United States, the market size effect (i.e., fewer buyers of HDDs exist) dominates. In other words, consumers across the globe would suffer from the lack of trade, and so would non-American producers. American firms would be the only parties to benefit from the ban on trade.

8 Conclusion

This paper presents an industry equilibrium model of innovation and entry/exit with dynamic strategic interactions. I estimate the model using an 18-year panel of HDD market data. Contrary to Schumpeter's (1934) earlier conjecture, incumbents actually enjoy an advantage over entrants in terms of innovation sunk costs: a result that echoes his later observation (Schumpeter 1942). This finding implies incumbents are not slower than entrants because of an efficiency handicap.

Then what explains "the innovator's dilemma," or the incumbent-entrant timing gap? The first set of counterfactual simulations quantifies the three theoretical forces that determine incumbents' delayed adoption timing compared to entrants. The results suggest cannibalization between old and new technologies/products can explain at least a half of the dilemma. Because old and new HDDs substitute for each other, the introduction of new HDDs would dampen profits from the old HDDs. Taking this "replacement effect" into consideration, rational incumbents can expect relatively small benefits from innovation compared to new entrants. Thus creative destruction (i.e., the process of transitions from old to new technologies along with firms' turnover) takes place not necessarily due to old firms' lack of creativity, but because of their rational unwillingness to destroy old sources of profits. This finding explains why new entrants, despite their cost disadvantage, sometimes manage to creatively destroy old winners in the industry: the *rational* innovator's dilemma.

Another finding from the first set of simulations (estimating the innovator's dilemma) is that dynamic strategic incentives, such as preemption, are important determinants of innovation and industry evolution. Without strategic interactions, the incumbent-entrant timing gap would have been wider by 59%. Thus certain aspects of industry dynamics call for explicit—although often computationally burdensome—modeling of game-theoretic interactions among firms.

In the second set of simulations, I experiment with various public policies related to innovation and competition. The main finding is that competition is generally pro-innovation, as highlighted in the counterfactual simulation of a "no international trade" scenario. However, the welfare implication of competition is more nuanced. When many firms adopt new technology, the duplication of effort often turns out to be socially wasteful. Three factors explain this outcome. First, the estimated sunk cost of innovation is economically significant. Second, once more than four or five firms compete in the same (new) product category, a further increase in the number of adopters adds little to consumer surplus. Third, although buyers generally do benefit from early production of new goods, the market size is small during the early years. Thus the earlier adoption by many firms would result in negligible gains at sizeable costs. This finding explains why the simulated R&D subsidies lead to more innovation but reduced social welfare, and also why a (pre-announced) broad-based patent, which represents a fairly anti-competitive intellectual property regime, results in increased social welfare.

Although some of these results would be specific to the HDD market, the economic incentives studied here are quite general and could be expected to operate in many oligopolistic markets. Similar trajectories of creative destruction are also widely observed across industries, especially in the computer-related sectors. These considerations lead me to believe this paper's analytical framework, as well as its empirical findings, could be applicable elsewhere: old winners can survive the "gale of creative destruction" only through creative *self*-destruction.

References

[1] Abernathy, William J. 1978. *The Productivity Dilemma.* Johns Hopkins University Press, Baltimore, MD.

[2] ———, and J.M. Utterback. 1978. "Patterns of industrial innovation." *Technology Review*, 41–47.

[3] ———, and Kim B. Clark. 1985. "Innovation: Mapping the Winds of Creative Destruction," *Research Policy*, 14: 3-22.

[4] Ackerberg, Daniel, Benkard, C. Lanier, Berry, Steven, and Ariel Pakes. 2007. "Econometric Tools for Analyzing Market Outcomes." In *Handbook of Econometrics*, Volume 6A. Amsterdam: Elsevier.

[5] Acs, Zoltan J., and David B. Audretsch. 1988. "Innovation in Large and Small Firms: An Empirical Analysis," *American Economic Review*, 78: 678–690.

[6] ———. 1991. "Innovation as a means of entry: An overview." In Geroski, P., Schwalbach, J. (Eds.), *Entry and Market Contestability: An International Comparison.* Basil Blackwell, Oxford.

[7] Adner, Ron, and Peter Zemsky. 2005. "Disruptive Technologies and the Emergence of Competition." *RAND Journal of Economics*, 36(2): 229-254.

[8] Aghion, P., Bloom, N., Blundell, R., Griffith, R., and P. Howitt. 2005. "Competition and Innovation: An inverted U-relationship." *Quarterly Journal of Economics*, 120: 701–28.

[9] Aguirregabiria, V., and P. Mira. 2007. "Sequential estimation of dynamic games." *Econometrica*, 75(1): 1–54.

[10] 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.

[11] Bajari, P., Benkard, C.L., and J. Levin. 2007. "Estimating dynamic models of imperfect competition." *Econometrica*, 75(5): 1331–70.

[12] Berry, Steven T.. 1992. "Estimation of a Model of Entry in the Airline Industry." *Econometrica*, 60(4): 889–917.

[13] Berry, Steven T.. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *RAND Journal of Economics*, 25(2): 242-262.

[14] ———, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 841–90.

[15] Besanko, David, Doraszelski, Ulrich, Kryukov, Yaroslav, and Mark Satterthwaite. 2010. "Learning-by-Doing, Organizational Forgetting, and Industry Dynamics." *Econometrica*, 78(2): 453–508.

[16] Blundell, R., Griffith, R., and J. Van Reenen. 1999. "Market share, market value and innovation in a panel of British manufacturing firms." *Review of Economic Studies*, 66: 529–54.

[17] Bozeman, B., and A.N. Link. 1983. *Investments in Technology: Corporate Strategies and Public Policy Alternatives*. Praeger, New York, NY.

[18] Branstetter, L., Sakakibara, M. 1998. "Japanese research consortia: a microeconometric analysis of industrial policy." *Journal of Industrial Economics*, 46(2): 207–233.

[19] Bresnahan, Timothy F. 1981. "Departures from Marginal-Cost Pricing in the American Automobile Industry." *Journal of Econometrics*, 17: 201–27.

[20] ———. 2003. "Pro-Innovation Competition Policy: Microsoft and Beyond." CPRC Discussion Paper, Competition Policy Research Center, Fair Trade Commission of Japan.

[21] Carroll, Glenn R., and Michael T. Hannan. 2000. *The Demography of Corporations and Industries*. Princeton, NJ: Princeton University Press.

[22] Chaudhuri, Shubhan, P.K. Goldberg, and P. Jia. 2006. "Estimating the Effect of Global Patent Protection in Pharmaceuticals: A Case Study of Quinolones in India." *American Economic Review*, 96: 1477-1514.

[23] Chesbrough, H. 1999. “Arrested development: The experience of European hard disk drive firms in comparison to U.S. and Japanese firms.” *Journal of Evolutional Economics*, 9: 287–330.

[24] Christensen, Clayton M.. 1993. “The Rigid Disk Drive Industry: A History of Commercial and Technological Turbulence.” *Business History Review*, 67: 531-588.

[25] Christensen, Clayton M.. 1997. *The Innovator’s Dilemma*. New York, HarperBusiness.

[26] Cohen, W.M. 2010. “Fifty Years of Empirical Studies of Innovative Activity and Performance.” Chapter 4 of B. Hall and M. Rosenberg eds., *Handbook of the Economics of Innovation*, Volume 1. Amsterdam: Elsevier.

[27] Collard-Wexler, Allan. 2010. “Demand Fluctuations in the Ready-Mix Concrete Industry.” Manuscript, NYU Stern.

[28] Doraszelski, Ulrich, and Ariel Pakes. 2007. “A Framework for Applied Dynamic Analysis in IO.” In M. Armstrong and R. Porter eds., *Handbook of Industrial Organization*, Volume 3. Amsterdam: Elsevier.

[29] Dunne, Timothy, Shawn D. Klimek, Mark J. Roberts, and Daniel Yi Xu. 2009. “Entry, Exit and the Determinants of Market Structure.” Manuscript, New York University.

[30] Ehrnberg, E., and N. Sjöberg, N. 1995. “Technological discontinuities, competition and firm performance.” *Technology Analysis & Strategic Management*, 7: 93–107.

[31] Eizenberg, Alon. 2009. “Upstream Innovation and Product Variety in the U.S. Home PC Market.” Manuscript, The Wharton School, University of Pennsylvania.

[32] Ericson, Richard, and Ariel Pakes. 1995. “Markov-Perfect Industry Dynamics: A Framework for Empirical Work.” *Review of Economic Studies*, 62: 53-82.

[33] Franco, April Mitchell, and Darren Filson. 2006. “Spin-Outs: Knowledge Diffusion through Employee Mobility.” *RAND Journal of Economics*, 37(4): 841–60.

[34] Fudenberg, Drew, and Jean Tirole. 1986. *Dynamic Models of Oligopoly*. London, Routledge.

[35] Galbraith, J.K. 1952. *American Capitalism: The Concept of Countervailing Power*. Houghton Mifflin, Boston, MA.

[36] Gans, J., Hsu, D., and S. Stern. 2002. “When does start-up innovation spur the gale of creative destruction.” *RAND Journal of Economics*, 33: 571–86.

[37] Geroski, P.A. 1989. “Entry, innovation and productivity growth.” *Review of Economics and Statistics*, 71(4): 572–78.

[38] ———. 1991. “Entry and the rate of innovation.” *Economic Innovation and New Technology*, 1: 203–14.

[39] ———. 1994. *Market Structure, Corporate Performance and Innovative Activity.* Clarendon Press, Oxford.

[40] Gilbert, Richard. 2006. “Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?” NBER.

[41] ———, and David Newbery. 1982. “Preemptive Patenting and the Persistence of Monopoly.” *American Economic Review*, 72(2): 514-526.

[42] ———, and Shapiro, C. 1990. “Optimal Patent Length and Breadth.” *RAND Journal of Economics*, 16: 106-112.

[43] Goettler, Ronald, and Brett Gordon. 2011. “Does AMD spur Intel to innovate more?” Manuscript, University of Chicago.

[44] Gort, M., and S. Klepper. 1982. “Time paths in the diffusion of product innovations.” *Economic Journal*, 92: 630–53.

[45] González, Xulia, and Consuelo Pazó. 2008. “Do public subsidies stimulate private R&D spending?” *Research Policy*, 37: 371–89.

[46] Griliches, Z., and Regev, H., 1998. “An econometric evaluation of high-tech policy in Israel.” Paper presented at ATP-conference in Washington, DC, June 1998.

[47] Grove, Andrew S.. 1996. *Only the Paranoid Survive: How to Exploit the Crisis Points that Challenge Every Company and Career*. New York, Currency Doubleday.

[48] Hall, Bronwyn H. 1993. “R&D Tax Policy during the 1980s: Success or Failure?”, *Tax Policy and the Economy*, 7: 1-35.

[49] Hall, Bronwyn H. 1996. “The Private and Social Returns to Research and Development.” In Bruce L.R. Smith and Claude E. Barfield, eds., *Technology, R&D, and the Economy*, Washington, DC: The Brookings Institution and The American Enterprise Institute.

[50] Hall, Bronwyn. 2004. “Innovation and Diffusion.” In *Oxford Handbook of Innovation.* Oxford: Oxford University Press, Chapter 17.

[51] Hall, B.H., van Reenen, J., 1999. “How effective are fiscal incentives for R&D? A review of the evidence.” *Research Policy*, 449–471.

[52] Hamberg, D. 1966. *R&D: Essays on the Economics of Research and Development*. Random House, New York, NY.

[53] Hannan, Timothy H., and John M. McDowell. 1984. “The Determinants of Technology Adoption: The Case of the Banking Firm.” *RAND Journal of Economics*, 15(3): 328-335.

[54] Hausman, Jerry. 1996. “Valuation of New Goods under Perfect and Imperfect Competition.” In T. Bresnahan and R. Gordon, eds., *The Economics of New Goods*, Studies in Income and Wealth, Vol. 58, Chicago: National Bureau of Economic Research.

[55] Henderson, Rebecca M. 1993. “Underinvestment and Incompetence as Responses to Radical Innovation: Evidence from the Photolithographic Alignment Industry.” *RAND Journal of Economics*, 24(2): 248-270.

[56] ———, and Kim B. Clark. 1990. “Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms.” *Administrative Science Quarterly*, 35: 9–30.

[57] Hopenhayn, Hugo A.. 1992. “Exit, Selection, and the Value of Firms.” *Journal of Economic Dynamics and Control*, 16(3-4): 621-653.

[58] Horowitz, I. 1962. “Firm size and research activity.” *Southern Economic Journal*, 28: 298–301.

[59] Hotz, V. Joseph, and Robert A. Miller. 1993. “Conditional Choice Probabilities and the Estimation of Dynamic Models.” *Review of Economic Studies*, 60: 497–529.

[60] Howe, J.D., and D.G. McFetridge. 1976. “The determinants of R&D expenditures.” *Canadian Journal of Economics*, 9: 57–61.

[61] Irwin, D., Klenow, P., 1996. “High-tech R&D subsidies — estimating the effects of SEMATECH.” *Journal of International Economics*, 40: 323–44.

[62] Jaffe, Adam B., and Josh Lerner. 2004. *Innovation and Its Discontents: How Our Broken Patent System Is Endangering Innovation and Progress, and What to Do about It.* Princeton, NJ: Princeton University Press.

[63] Jia, Panle. 2008. “What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Industry.” *Econometrica*, 76(6): 1263–316.

[64] Jovanovic, Boyan. 1982. “Selection and the Evolution of Industry.” *Econometrica*, 50(3): 649-670.

[65] Kalouptsidi, Myrto. 2010. “Time to Build and Shipping Prices.” Manuscript, Yale University.

[66] Karshenas, Massoud, and Paul L. Stoneman. 1993. “Rank, Stock, Order, and Epidemic Effects in the Diffusion of New Process Technologies: An Empirical Model.” *RAND Journal of Economics*, 24(4): 503-528.

[67] King, A.A., and C.L. Tucci. 2002. “Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities.” *Management Science*, 48: 171–86.

[68] Klemperer, P. 1990. “How broad Should the Scope of Patent Protection Be?” *RAND Journal of Economics*, 21:113-130.

[69] Klepper, Steven. 1996. “Entry, Exit, Growth, and Innovation over the Product Life Cycle.” *American Economic Review*, 86(3): 562-583.

[70] ———, and E. Graddy. 1990. “The evolution of new industries and the determinants of market structure.” *RAND Journal of Economics*, 21: 27–44.

[71] ———, and K.L. Simons. 2005. “Industry shakeouts and technological change.” *International Journal of Industrial Organization*, 23: 23–43.

[72] ———, and Peter Thompson. 2006. “Submarkets and the Evolution of Market Structure.” *RAND Journal of Economics*, 37(4): 861-886.

[73] Klette, Tor J., Jarle Moen and Zvi Griliches. 2000. “Do Subsidies to Commercial R&D Reduce Market Failure? Microeconometric Evaluation Studies.” *Research Policy*, 29(4–5): 471–495.

[74] Lerner, Joshua. 1994. “The Importance of Patent Scope: An Empirical Analysis.” *RAND Journal of Economics*, 25: 319–333.

[75] Lerner, Josh. 1997. “An Empirical Exploration of a Technology Race.” *RAND Journal of Economics*, 28(2): 228-247.

[76] Lerner, J. 1998. "The government as venture capitalist: the long-run impact of the SBIR program." Mimeo., Harvard University. Previously published as NBER WP 5753, 1996.

[77] Levin, R.C., Cohen, W.M., and D.C. Mowery. 1985. "R&D appropriability, opportunity, and market structure: New evidence on some Schumpeterian hypotheses." *American Economic Review*, 75: 20–25.

[78] Mansfield, E. 1968. *Industrial Research and Technological Innovation: An Econometric Analysis*. Norton, New York, NY.

[79] Mazzeo, Michael J. 2002. "Product choice and oligopoly market structure." *RAND Journal of Economics*, 33(2): 221–42.

[80] McDonald, Robert, and Daniel Siegel. 1986. "The Value of Waiting to Invest." *Quarterly Journal of Economics*, 101(4): 707-727.

[81] McKendrick, David G., Richard F. Doner, and Stephan Haggard. 2000. *From Silicon Valley to Singapore: Location and Competitive Advantage in the Hard Disk Drive Industry*. Stanford, CA: Stanford University Press.

[82] Mitchell, W. 1989. "Whether and when? Probability and timing of incumbent's entry into emerging industrial subfields." *Administrative Science Quarterly*, 34: 208–34.

[83] Mueller, D.C., and J.E. Tilton. 1969. "Research and development costs as a barrier to entry." *Canadian Journal of Economics*, 2: 570–79.

[84] Mukhopadhyay, A.K. 1985. "Technological progress and change in market concentration in the U.S.: 1963–77." *Southern Economic Journal*, 52: 141–49.

[85] Nelson, Richard R., and Sidney G. Winter. 1978. "Forces generating and limiting concentration under Schumpeterian competition." *Bell Journal of Economics*, 9: 524–48.

[86] ———. 1982. "The Schumpeterian tradeoff revisited." *American Economic Review*, 72: 114–32.

[87] Nevo, Aviv. 2001. "Measuring Market Power in the Ready-to-eat Cereal Industry." *Econometrica*, 69(2): 307–42.

[88] Norets, Andriy. 2009. "Inference in Dynamic Discrete Choice Models with Serially Correlated Unobserved State Variables." *Econometrica*, 77(5), 1665–1682.

[89] Nosko, Chris. 2010. “Competition and Quality Choice in the CPU Market.” Manuscript, Harvard University.

[90] Pakes, Ariel, Michael Ostrovsky, and Steven Berry. 2007. “Simple estimators for the parameters of discrete dynamic games (with entry/exit examples).” *RAND Journal of Economics*, 38(2): 373-399.

[91] Pakes, Ariel, and Paul McGuire. 1994. “Computing Markov-Perfect Nash Equilibria: Numerical Implications of a Dynamic Differentiated Product Model.” *RAND Journal of Economics*, 25(4): 555-589.

[92] Pesendorfer, Martin, and Philipp Schmidt-Dengler. 2008. “Asymptotic Least Squares Estimators for Dynamic Games.” *Review of Economic Studies*, 75: 901–28.

[93] Qian, Yu. 2007. “Do National Patent Laws Stimulate Domestic Innovation in a Global Patenting Environment?: A Cross-Country Analysis of Pharmaceutical Patent Protection, 1978-2002.” *Review of Economics and Statistics*, 89(3): 436-453.

[94] Reinganum, Jennifer F.. 1983. “Uncertain Innovation and the Persistence of Monopoly.” *American Economic Review*, 73(4): 741–748.

[95] Rust, John. 1987. “Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher.” *Econometrica*, 55(5): 999-1033.

[96] Ryan, Stephen P.. 2011. “The Costs of Environmental Regulation in a Concentrated Industry.” *Econometrica*, forthcoming.

[97] Sah, R.J. and J.E. Stiglitz. 1986. “The architecture of economic systems: Hierarchies and polyarchies.” *American Economic Review*, 76: 716–27.

[98] Sakakibara, Mariko and Lee Branstetter. 2001. “Do Stronger Patents Induce More Innovation? Evidence from the 1988 Japanese Patent Law Reforms.” *RAND Journal of Economics*, 32: 77–100.

[99] Scherer, F.M. 1967. “Market structure and the employment of scientists and engineers.” *American Economic Review*, 57: 524–531.

[100] ———. 1980. *Industrial market structure and economic performance*. Rand MacNally, Chicago, IL.

[101] ——— and D. Ross. 1990. *Industrial Market Structure and Economic Performance*. Houghton Mifflin, Boston, MA.

[102] Schmidt-Dengler, Philipp. 2006. "The Timing of New Technology Adoption: The Case of MRI." Manuscript, London School of Economics.

[103] Schumpeter, Joseph A. 1934. *The Theory of Economic Development*. Cambridge, MA: Harvard University Press.

[104] Schumpeter, Joseph A. 1942. *Capitalism, Socialism and Democracy*. New York: Harper.

[105] Scotchmer, Suzanne. 2004. *Innovation and Incentives*. Cambridge, MA: The MIT Press.

[106] Scott, J.T. 1984. "Firm versus industry variability in R&D intensity." In Griliches, Z. (Ed.), *R&D Patents and Productivity*. University of Chicago Press for the NBER, Chicago, IL.

[107] Seim, Katja. 2006. "An Empirical Model of Firm Entry with Endogenous Product-Type Choices." *RAND Journal of Economics*, 37(3), 619-640.

[108] Stoneman, Paul. 2001. "Financial Factors and the Inter Firm Diffusion of New Technology: A Real Options Model." University of Warwick EIFC Working Paper No. 2001-08 (December).

[109] ———, and Giuliana Battisti. 2010. "The Diffusion of New Technology." Chapter 17 of B. Hall and M. Rosenberg eds., *Handbook of the Economics of Innovation*, Volume 1, Amsterdam: Elsevier.

[110] Su, Che-Lin, and Kenneth L. Judd. 2008. "Constrained Optimization Approaches to Estimation of Structural Models." Manuscript, The University of Chicago Booth School of Business.

[111] Sutton, John. 1992. *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*. Cambridge, MA: The MIT Press.

[112] ———. 1998. *Technology and market structure*. MIT Press, Cambridge, MA.

[113] Tripsas, M. 1997. "Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry." *Strategic Management Journal*, 18: 119–42.

[114] Tushman, Michael L., and Philip Anderson. 1986. "Technological Discontinuities and Organizational Environments." *Administrative Science Quarterly*, 31(3): 439-465.

[115] Utterback, J.M. 1979. "The dynamics of product and process innovation in industry." In Hill, C.T., Utterback, J.M. (Eds.), *Technological Innovation for a Dynamic Economy.* Pergamon Press, New York, NY.

[116] Weintraub, Gabriel Y., C. Lanier Benkard, and Benjamin Van Roy. 2008a. "Markov Perfect Industry Dynamics With Many Firms." *Econometrica*, 76(6): 1375-1411.

[117] Weintraub, Gabriel Y., C. Lanier Benkard, Przemyslaw Jeziorski, and Benjamin Van Roy. 2008b. "Nonstationary Oblivious Equilibrium." Manuscript, Columbia University.

[118] Williamson, O.E. 1965. "Innovation and market structure." *Journal of Political Economy*, 73: 67–73.

[119] Xu, Daniel Yi. 2008. "A Structural Empirical Model of R&D, Firm Heterogeneity, and Industry Evolution." Manuscript, New York University.