Innovation Incentives and Competition in the Hard Disk Drive Industry

by

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Abstract

Firms in the hard disk drive industry are continually engaging in R & D and improving the quality of their products. We explore various determinants of the product innovation incentives for firms concerned with both their static and expected future profitability. We estimate the observed innovation outcomes as a function of market condition variables which have significant impact on innovation decisions. In addition, we estimate logit utilities that describe the marginal willingness to pay for quality improvements. One aspect of utility is that the willingness to pay for faster access time to data may be initially low but increases over time. The firms' decisions to introduce faster access time are partly motivated by dynamic considerations.

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1 Introduction

Innovation is an important driver of productivity and economic growth. Considerable theoretical and empirical literature explore the effectiveness of various incentive mechanisms and market conditions in promoting the benefits of innovation. However, conclusions regarding the empirical consequences for technological progress usually depend on industry-specific characteristics, and robust conclusions are few. Using the hard disk drive industry for our case study, this paper studies the dynamics of market structure in a setting where firms are engaged in both a technological race and a patent race. With the hard disk drive (HDD) industry as our reference point, our goal is to better understand how the overall innovation rate depends on market conditions such as changes in market concentration as well as cross-licensing arrangements amongst firms.

The HDD industry provides an interesting setting to look at the interactions between R&D efforts in cost-reduction and quality improvements. For example, while the average capacity of a desktop disk drive increased from 14 Gigabytes in quarter 1 of 2000 to 792 Gigabytes in quarter 4 of 2010, the average price decreased from \$94 to \$46 over the same time period. We plan to investigate the interrelationship between process and product innovations. One possibility is that firms offering the best products may find it more costly than others to achieve the same increment in quality, and so we tend to see more process than product innovations in firms at the quality frontier. Alternatively, there may be complementarities between product and process innovations. Intuitively, since product innovation leads to greater quantities demanded and the returns to process R &D are a direct function of firm size, firms may increase their efforts on process R&D.

Another potentially interesting aspect of the industry is that that there were a few mergers due to firms exits. The total number of firms in the industry winnowed down from 10 at the turn of the century to 3 today. If antitrust authorities are concerned with monopolists having too little innovation incentives, then the acquisitions in the HDD industry may provide variations in market concentration that is useful when examining whether competition in highly concentrated market harms dynamic efficiency. Since the acquisitions also involve the exiting firms transferring their patent portfolios to the acquiring firms, there may also be changes in the post-merger bargaining positions of firms in the licensing market. This source of variation could be useful when estimating more realistic models of the industry that account for cross-licensing arrangements amongst firms.

To understand some of the forces driving innovation, first consider the case where innovations are excludable. If a single innovation is definitely going to be introduced into a market, then the efficiency effect (Gilbert and Newbery, 1982) predicts that the incremental profit to be gained from the innovation is higher for a incumbent monopolist than for an entrant. Whereas the entrant will only earn duopoly profits in competition with the backstop incumbent technology, the incumbent will be able to manage a multi-product monopoly. If a single innovation may be introduced into a market but the timing of that introduction depends on R &D investment, then a potential entrant may outspend an incumbent monopolist in R&D if both are competing to develop the innovation. The entrant values the entire profit to be earned by introducing the innovation sooner, while the incumbent monopolist compares the difference in profit between no innovation (current profits) and successful innovation (incremental profits). When the replacement effect is sufficiently high (e.g., radical innovation), entrant incentives are higher. If we embed the above scenario in a setting in which innovations are continual processes, we can think of the incumbent as an initial innovator and potential entrants as competitors who threaten to introduce a new or improved version of the product. The tension between the replacement effect and the efficiency effect still persists.

Continue to assume that innovations are sequential and so subsequent innovations are build on existing knowledge. Intellectual property rights such as patent protections determine the degree of accessibility of existing technology in subsequent innovations and the ease of imitation amongst firms. Due to the replacement effect, making current period innovation entirely excludable may generate too little incentive to innovate. On the other extreme, making innovations entirely nonexcludable dissipate the all rents from innovation and leads to insufficient incentive to invest in R & D. Intellectual property rights protection may have opposing effects on innovation incentives, raising the profits of current innovators while lowering those of competing incumbents or potential entrants.

The basic structure of the model is as follows. In each period, a logit model determines market shares as a function of the observed drive characteristics and prices. A profit function translates market shares into profit, allowing the marginal cost of production to depend on the production efficiencies of the firms. Firms choose their R& D investment amounts in both demand-enhancing product improvements and cost-reducing process innovations, recognizing how current-period choices may improve the future opportunities for innovations.

Relationship to the Existing Literature

Intellectual Property Rights and Cumulativeness

In a static setting, a monopoly has too little incentive to innovate relative to the social optimum because it cannot fully price discriminate and extract all social surplus. Green and Scotchmer (1995) examine how, in a world with sequential innovations and Coasian bargaining, having some patent protection is optimal. The social value of an early innovation includes the value of follow-on innovations facilitated. However, even if the combined profits from the first innovation and later improvements exceed the total costs, due to competition for later improvements, the first innovator suffers rent dissipation and may have insufficient incentive to invest in the initial innovation. If licensing market operate efficiently, then under Coasian bargaining, ex-ante agreements between the first and second innovators always occur in equilibrium. Patent breadth determines the division of profit between the two innovators and serves to transfer some profit from the second innovator to the first. That is, having patent protection with sufficient breadth helps to elicit efficient rates of investments in the first stage of innovation.

Licensing technology to potential subsequent innovators may fail under asymmetric information, which is the case if the patent holder is not well-informed about a rival's potential future profits. Bessen and Maskin (2009) shows that in a dynamic setting with an infinite sequence of potential cumulative innovations, the patent system may hurt the innovators and reduce social welfare. Imitation may promote innovation if firms differ in their particular expertise that are "complementary". Because having more than one innovator raises the overall probability that a sequential innovation is attained within a given time, the overall rate of innovation may be enhanced by imitation. Although imitation reduces a firm's current profit, it may raise the firm's expected future profits by raising the probability of follow-on innovations. Patents may hurt the firms by impeding follow-on innovations.

Williams (2009) provides empirical evidence consistent with intellectual property rights hindering subsequent R&D. During the final years of DNA sequencing, there was competition between the public Human Genome Project and private firm Celera. Although Celera's temporary licensing rights on its gene sequence lasted 2 year at most, Williams' analysis indicates that Celera's short-term IP lead to significant reductions in subsequent scientific research and product development outcomes. Murray et al. (2008) examine the effects of the removal of IP restrictions for certain types of genetically engineered mice on the diversity of scientific experimentations. They find a significant increase in citations to scientific papers on affected mice relative to scientific papers on unaffected mice.

Product Market Competition and Innovation

Aghion et al (2005) find evidence for an inverted U relationship between competition and citation-weighted patents at the industry level. They develop a theoretic model which helps to explain the non-mononotonic impact of competition on innovation. The rationale accounts for the endogeneity of the industry state. When the market is very competitive, then laggards don't want to become neck-and-neck whereas neck-and-neck firms want to get ahead. As a result, the industry settles into a leader-follower state with little innovation. On the other hand, if the market is very uncompetitive, then laggards would want to catch up but neck-and-neck firms have little incentive to get ahead. The industry then settles into a neck-and-neck state with little innovation. There's more innovation with intermediate competition as there are more incentives for laggards to catch up and neck-and-neck firms to get ahead. Empirically, to estimate the nonlinear relationship between competition and innovation when both are jointly determined by the underlying market conditions, the paper exploits "exogenous" policy instruments that provide variation in the degree of industrywide competition.

One paper which makes the distinction between product innovation and process innovation is Klepper (1996). He develops a model to explain empirical observations of how market structure and the product and process R & D choices of firms evolve as an industry matures. A prominent feature of the evolutionary pattern in many industries with opportunities for both product and process R & D is that there tends to be more process R & D than product R & D over time. To deliver the trade-off between product and process innovations, Klepper's model assumes that product innovations are introduced into a firm's latest products which compete with the its existing "standard" versions. On the other hand, process innovations are only introduced into the standard products. Since the returns to process innovation is a direct function of firm size, as the industry matures and firms grow large, the benefits of process innovation outweigh the returns from product innovation.

Goettler and Gordon (2010) and Macieira (2009) have estimated dynamic oligopoly models to study the effect of competition on technological progress. Goettler and Gordon builds on the dynamic oligopoly framework of Ericson and Pakes to account for durable goods. To estimate the model's parameters, they use a simulated moments estimator that minimizes the distance between actual and simulated moments. Estimation involves solving for the equilibrium for each guess of the model's parameters. One of the findings from the Goettler and Gordon paper is that in the microprocessor industry, the monopolist innovates more than the duopoly since market power enables the monopolist to better extract the rents from innovations. This is consistent with Schumpeter's hypothesis of a positive relationship between market concentration and innovation.

Macieira(2009) uses a variant of Bajari, Benkard, and Levin's two-step method to estimate a model of technology race in the supercomputer industry. He shows that there is an inverse U-shape relationship between innovation rate and the number of competitors for both the leader and laggard firms. Up to a finite number of firms, increased level of competition has a positive effect on technological progress.

Background on the Hard Disk Drive Industry

The hard disk drive industry is one characterized by intense technological competition and steadily declining prices. Throughout the industry's history, drive developers have endeavored to pack more data onto the disk while reducing the drive's physical size and increasing the speed of data access. Other areas of technological advances include improving the overall reliability of the drives and the rate and nature of communication with the computer. Roughly speaking, shrinking the physical size of the drive is considered a radical innovation since it involves not just shrinking the size of the components used but also significant redesign of the ways the components interacted with each other. The introduction of a a smaller drive diameter disrupted the trajectory of incremental capacity improvements in existing drives.

Usage differences among disk drives result in different requirements, designs, and related manufacturing costs. Whereas desktop drives are focused on running client application, enterprise drives must also provide application and storage services to networks. As a result, enterprise drives are subject to more stringent requirements on reliability and the robustness of drive designs. Additionally, since enterprise-class drives must also maintain high performance levels in multi-drive configurations where physical vibrations transmitted through a cabinet occur, enterprise drives have additional features to negate the effects of rotational vibrations. Compared to desktop drives, notebook and certain types of consumer electronics drives are designed to better withstand shocks and vibrations without any danger of data loss. Consumer electronic drives designed specifically for car navigation systems have additional requirements in order to deliver performance in extreme temperatures. In short, hard drives targeted for different applications have different firmwares and hardwares. Technological improvements in one type of disk drives cannot always be seamlessly incorporated into other types of disk drives.

During the time period 2000-2010, new hard drive sub-markets emerged to meet the growing demand of consumer electronics and ultra-light laptops. For example, 1.8" disk drives designed for ultra-thin PC applications totaled less than 45000 at the beginning to 2001, 217000 in Q1 of 2005, and 360000 in Q1 of 2010. The demand for consumer electronics disk drives was minimal at the beginning of the century but grew to 22.39 million by quarter 4 of 2010. With the exception of enterprise disk drives, disk drives with different sizes mostly served distinct markets. For example, the demand for 3.5" CE drives mostly comes from DVR/PVR while 2.5" CE drives were used primarily in game consoles. 2.5" CE drives do not yet have high enough capacity or rpm to compete with 3.5" drives in the DVR/PVR market.

There are entries of firms into new submarkets over the past decade. For example, the players in the 2.5" notebook market were IBM, Fujitsu, Toshiba, and Hitachi GST at the beginning of the century. The later entrants were Samsung, Seagate, and WDC. Similarly, Samsung, Seagate, and WDC entered the 2.5" CE market following Fujitsu, Toshiba, and Hitachi GST. Firms that exited over the last 10 years are Quantum, IBM, Maxtor, and Fujitsu. They were acquired by Maxtor in 2001, Hitachi in 2003, Seagate in 2006, and Toshiba in 2009, respectively. Experts in the industry informed us that exiting firms in the period 2000-2010 were laggards in the technological race. For example, IBM sold its disk drive division to HGST in 2002 because IBM was not cost effective. Prior to selling its disk drive division to Toshiba, Fujitsu's drives suffered from reliability concerns.

Data

The TRENDFOCUS dataset allows us to fragment the disk drive industry into submarkets based on applications. These submarkets are 3.5" Desktop, 3.5" CE, 2.5" CE, $\leq$ 1.8" CE, 2.5" Noteboook, 1.8" Notebook, and Enterprise. The firmware and hardware of drives across submarkets are different to an extent. For example, notebook drives are designed to meet higher shock specifications than desktop drives whereas enterprise drives are the most performance-optimized. On the other hand, IDC data aggregates shipments and prices across submarkets by formfactor. That is, 2.5" CE and 2.5" Notebook drives are grouped under the same category and so are 1.8" CE and Notebook drives.

Quarterly IDC data from 1997 to 2010 provides information on disk drive unit shipments, average prices, and product quality measures at the firm-level. For each submarket, we define a "product" as a disk drive with a particular size, access time, and capacity range. For example, all post-05 desktop drives are 3.5" with access time either 5400 rpm (rotations per minute) or 7200 rpm. Then desktop drives with 7200rpm and capacities in the range 400-499.9GB are considered the same product, distinct from the 5400rpm desktop drives with the same capacity range. For each multi-product firm in a driveclass-formfactor category, IDC reports the shipment units and prices for every product.

IDC data includes additional drive characteristics such as the average number of heads per drive and average number of disks per drives. This information is available by capacity ranges but not further broken down by rpm.

Tables 1, 2, 3, and 4 provide summary statistics for some of the variables that are used in our estimation. Capacity is measured in gigabytes, and prices are in US dollars. For the units-weighted average capacity and market share variables, we treat a firm-quarter as an observation. Maximum capacities, defined per firm-quarter-rpm, is the highest observed capacity for a firm-rpm in all quarters all to the current quarter. The "$\Delta(qual)$" variable is defined as the change in maximum capacity for a firm in two consecutive quarters. The average capacity, maximum capacity, and change in maximum capacity are highly right-skewed.

Table 1: Summary statistics for the Desktop Market

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
capacity	228.888	407.11	1.495	3495	3243
price	93.064	57.667	30.64	425	3242
average capacity	134.629	187.9	2.091	928.469	328
market share	0.171	0.116	0	0.441	328
$\Delta(average\ capacity)$	11.655	22.529	-16.002	169.751	319
maximum capacity	1379.398	1300.556	1.495	3495	625
$log(maximum\ capacity)$	5.924	2.023	0.402	8.159	625
$\Delta(qual)$	166.891	393.259	0	1398.5	621
$log(\Delta(qual))$	0.092	0.189	0	2.64	621

To help motivate our later discussion about the firms' strategic decisions to improve product performances, Table 5 provides some summary statistics of the quarterly change in maximum capacities. For each market, an observation is a firm-quarter. We use TRENDFOCUS data from 2005 to 2010 and pool $\Delta(capacity)$ into two groups based on the whether the firm's capacity from the previous period is greater than or less than the median capacity from the last quarter. There is substantial heterogeneity in capacity improvements. On average, there's greater improvements for firms with higher capacities from the last period.

Table 2: Summary statistics for the Mobile 2.5inch Market

Variable	Mean	Std. Dev.	Min.	Max.	N
capacity	137.374	171.751	1	1745	2624
price	91.549	65.943	28	570	2624
average capacity	98.646	109.595	1.495	452.011	280
market share	0.2	0.114	0.001	0.563	280
$\Delta(average\ capacity)$	8.313	12.491	-16.922	75.742	271
maximum capacity	439.904	455.697	1	1745	570
$log(maximum\ capacity)$	4.943	1.924	0	7.465	570
$\Delta(qual)$	31.494	74.95	0	300	563
$log(\Delta(qual))$	0.072	0.141	0	0.785	563

Table 3: Summary statistics for the Enterprise Market

Variable	Mean	Std. Dev.	Min.	Max.	N
capacity	96.701	133.604	1.495	849.5	1746
price	301.525	268.777	69	2200	1745
average capacity	74.357	82.723	3.645	374.693	251
market share	0.223	0.185	0.001	0.674	251
$\Delta(average\ capacity)$	5.477	14.27	-23.888	190.175	242
maximum capacity	290.082	264.433	3.495	849.5	512
$log(maximum\ capacity)$	4.722	1.606	1.251	6.745	512
$\Delta(qual)$	22.543	53.929	0	202	506
$log(\Delta(qual))$	0.072	0.165	0	1.576	506

Table 4: Summary statistics for the Mobile 1.8 inch Market

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
capacity	84.438	63.338	2.495	269.5	466
price	76.871	36.112	31.43	325	466
average capacity	59.81	45.048	2.495	184.924	86
market share	0.488	0.373	0	1	86
$\Delta(average\ capacity)$	3.058	13.136	-31.389	66.599	82
maximum capacity	165.856	78.208	34.95	269.5	138
$log(maximum\ capacity)$	4.898	0.606	3.355	5.597	138
$\Delta(qual)$	1.897	7.936	0	65	137
$log(\Delta(qual))$	0.02	0.079	0	0.648	137

Table 5: Quarterly Changes in Maximum Capacity

	Desktop			ENTERPRISE		
Capacity	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
< Median	84.000	99.244	254.742	63.000	9.524	38.997
> Median	28.000	124.304	306.099	10.000	52.500	112.083
	Consumer Electronics 3.5			Consumer Electronics 2.5		
Capacity	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
< Median	67.000	55.164	199.425	86.000	32.099	120.908
> Median	30.000	110.700	231.029	23.000	40.652	82.741
	Mobile 2.5			Mobile 1.8		
Capacity	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
< Median	95.000	39.595	150.974	36.000	5.694	19.241
> Median	38.000	75.803	146.116	11.000	18.636	23.032
	Consumer Electronics 1.8					
Capacity	Obs	Mean	Std. Dev.			
< Median	60.000	4.742	16.835			
> Median	14.000	6.107	15.224			

2 Conceptual Framework

To help clarify the forces driving innovation in the hard disk drive industry, we first discuss the strategic effects for firms maximizing static profit and then consider the effects of competition for forward-looking firms. We also explore the potential linkage between product and process innovations.

2.1 Investment Decisions Leading to Increasing Dominance

We discuss market conditions under which leading firms with lower costs or higher qualities invest more than lagging firms. Consider the following example of price competition with differentiated goods. We use this example where firms are maximizing static profit to illustrate some of the insights from Athey and Schmutzler (2001).

Suppose that firms with marginal costs $\{c_i\}_i$ sell differentiated goods with quality $\{\alpha_i\}_i$. The firms face inverse demand functions $p_i = \alpha_i - \beta q_i - \gamma \sum_{j \neq i} q_j$ and engage in price competition. Given the firms' initial states $\{\alpha_i, c_i\}_i$, we explore their incentives to further increase α_i or decrease c_i.

Assume that $\beta > \gamma$ so that the firm's demand is more responsive to own price than opponents' prices. For the two-player game one can verify that the equilibrium prices and quantities are $p_i^* - c_i = \frac{(2\beta^2-\gamma^2)(\alpha_i-c_i)-\beta\gamma(\alpha_j-c_j)}{4\beta^2-\gamma^2}$ and $q_i = \frac{\beta(2\beta^2-\gamma^2)(\alpha_i-c_i)-\beta^2\gamma(\alpha_j-c_j)}{(4\beta^2-\gamma^2)(\beta^2-\gamma^2)}$.

Let x_i denote the input choice variable c_i or α_i. Since both $p_i^* - c_i$ and q_i are linear in x_i, we have that $\pi^i_{x_i,x_i} = 2\frac{\partial(p_i^*-c_i)}{\partial x_i}\frac{\partial q_i}{\partial x_i}$ and $\pi^i_{x_i,x_j} = \frac{\partial(p_i^*-c_i)}{\partial x_i}\frac{\partial q_i}{\partial x_j} + \frac{\partial(p_i^*-c_i)}{\partial x_j}\frac{\partial q_i}{\partial x_i}$.

For $\beta \geq \gamma$, the second-order partials for firm i's profit function are $\frac{\partial(p_i^*-c_i)}{\partial \alpha_i} \geq 0$, $\frac{\partial(p_i^*-c_i)}{\partial \alpha_j} \leq 0$, $\frac{\partial q_i}{\partial \alpha_i} \geq 0$, $\frac{\partial q_i}{\partial \alpha_j} \leq 0$. This implies that $\pi^i_{\alpha_i,\alpha_j} \leq 0$ and $\pi^i_{\alpha_i,\alpha_i} \geq 0$. Likewise, one can verify that $\pi^i_{c_i,c_j} \leq 0$ and $\pi^i_{\alpha_i,\alpha_i} \geq 0$. In other words, cost reduction or quality improvements from opponents hurt one's demand and market shares. The negative effects of improvements in the opponents' state variables on i's profits are greater the higher the firm's quality α_i or the lower the cost c_i .

Given the firm's state $\theta_i^{t-1} = c_i^{t-1}$ or α_i^{t-1}, suppose that there's no uncertainty and that the firm chooses cost-reducing or demanding enhancing actions a_i^t so that the firm's current period profit $\pi^i(a_i^t, \theta_i^{t-1}) = \pi^i(a^t + \theta^{t-1})$. It follows from the above conditions on the firm's second-order partials that $a_i^t(\theta_i^{t-1}, \theta_j^{t-1})$ is increasing in θ_i^{t-1} and decreasing in θ_j^{t-1}. Moreover, as $\pi^i(\theta_i, \theta_j) = \pi^j(\theta_j, \theta_i)$ and that firms with the same initial conditions have the same profit functions, $\theta_i^{t-1} > \theta_j^{t-1}$ implies that $a_i^t > a_j^t$.

To see that that how the initial leadership that firm i has over j leads to further market dominance, observe that some immediate consequences of the above conditions on second-order partials are that $\pi^i_{a_i,a_j} \leq 0, \pi^i_{a_i,\theta_j} \leq 0$, and $\pi^i_{a_i,\theta_i} \geq 0$. These conditions imply that the direct effects of increasing firm i's state variable θ_i^{t-1} and decreasing firm j's θ_j^{t-1} is to increase the marginal returns to firm i's own investment and decrease the marginal returns to firm j's investment. Moreover, $\pi^i_{a_i,a_j} \le 0$ implies that the actions of the two players are strategic substitutes, and so the interaction between a_i and a_j reinforces the direct effects of increasing θ_i^{t-1} or decreasing θ_j^{t-1}.

A more formal argument uses Topkis' result to establish comparative statics. Define a new game wherer player i's payoff $\tilde{\pi}^i(\tilde{a},\tilde{\theta}) = \pi^i(\tilde{a}_i, -\tilde{a}_j; \tilde{\theta}_i, -\tilde{\theta}_j)$. We compare the equilibrium choices of player i given two parameter vectors $(\theta_H, -\theta_L)$ and $(\theta_L, -\theta_H)$, where the initial conditions of the two players are switched. Since $(\theta_H, -\theta_L) \ge (\theta_L, -\theta_H)$ and π^i has increasing differences in $(a_i, -a_j)$, a result by Topkis implies that player i's equlibrium choices under the two different scenarios must satisfy $\tilde{a}_i{}^*(\theta_H, -\theta_L) \ge \tilde{a}_j{}^*(\theta_L, -\theta_H)$. Reverting back to the original game, we have that $a_i^*(\theta_H, \theta_L) \ge a_j^*(\theta_L, \theta_H) = \tilde{a}_i{}^*(\theta_L, -\theta_H)$.

With more than two firms, if the second-order partial conditions on the profit function hold for any pair of firms, Athey and Schmutzler showed that each player j's action is increasing in its own state θ_j and decreasing in θ_{-j} if a mild "exchangeability" condition on the firm's profit functions is satisfied.

For our example of Bertrand competition with differentiated goods, define $K_1 = (2\beta + \gamma(N-3))(2\beta + \gamma(2N-3))$ and $K_2 = (2\beta+\gamma(N-3))(2\beta+\gamma(2N-3))\,(\beta(\beta+\gamma(N-2)) - \gamma^2(N-1))$. We can show that

$$
\begin{aligned}
p_i^* - c_i = {} & \frac{(\beta+\gamma(N-2))\,(2\beta+\gamma(N-3)) + \gamma(\beta-\gamma)}{K_1}\alpha_i - \frac{2\beta^2 + 3\beta\gamma(N-2) + \gamma^2(N^2-5N+5)}{K_1}c_i \\
& - \frac{\gamma\,(\beta+\gamma(N-2))}{K_1}\sum_{k\neq i}(\alpha_k - c_k),
\end{aligned}
$$

$$
q_i = \frac{(\beta+\gamma(N-2))\,(2\beta^2 + 3\beta\gamma(N-2) + \gamma^2(N^2-5N+5))}{K}(\alpha_i - c_i) - \frac{\gamma(\beta+\gamma(N-2))^2}{K}\sum_{k\neq i}(\alpha_k - c_k).
$$

We can verify the second-order conditions $\pi^i_{a_i,a_j} \le 0, \pi^i_{a_i,\theta_j} \le 0$, and $\pi^i_{a_i,\theta_i} \ge 0$. Profit functions are exchangeable in the sense that if we transpose the initial conditions for firms i and j, then $\pi^i(\ldots,\theta_i,\ldots,\theta_j,\ldots) = \pi^j(\ldots,\tilde{\theta}_i,\ldots,\tilde{\theta}_j,\ldots)$, where $\tilde{\theta}_i = \theta_j$ and $\tilde{\theta}_j = \theta_i$. In particular, for our example firms with the same initial conditions have the same profit functions and only care about the aggregates over the other firms. Intuitively, when comparing the profits of players i and j with $\theta_i \ge \theta_j$, we can hold the actions of the remaining players at their equilibrium. Since the profit functions of the remaining players are unaffected by the identities of the players with initial profits θ_i or θ_j, the equilibrium choices argument for the two-player game still applies while fixing the actions of the remaining firms.

We sum up some of the conditions supporting weakly increasing market dominance in a deterministic incremental investment framework. The main requirements are that

- increases in the opponent's state variables decrease the incremental returns to firm's i investment
- increases in firm i's own state variables increase the incremental returns to own investment
- and that the players' profit functions satisfy an exchangeabitility condition.

Athey and Schmutzler (2001) showed that these conditions are satisfied in many circumstances where investments precede product market competition. Moreover, the exchangeability condition is usually satisfied when all differences among firms are summarized in the state variables.

2.2 Dynamic R &D Competition

The above static example of product market competition delivers the prediction that the leader innovates more and the laggard less as the differences between their state variables grow. However, there may be strategic effects for far-sighted firms that negate the predictions from the static setting.

We adapt the following framework from Segal and Whinston (2007). Both the incumbent and potential entrant conduct R&D. To keep the model simple, we do not account for the technological gap between the incumbent and the potential entrant. In a richer model, their equilibrium investment decisions should depend on their relative technological positions.

The incumbent and entrant choose effort levels ϕ_I and ϕ_E with costs $c(\phi_I)$ and $c(\phi_E)$ respectively, where ϕ_I and ϕ_E are their respective probabilities of successful innovations. The incumbent earns monopoly profit π_m if the entrant is unsuccessful. If the entrant succeeds at innovating but the incumbent does not, then they earn profits π_E and π_I in the current period, and the entrant displaces the current incumbent in the next period. We let $r_I(\phi_E)$ denote the probability that an incumbent who innovates maintains its incumbency so that $r_I(\phi_E)$ accounts for the cases of both successful and unsuccessful innovations by the entrant. Similarly, $r_E(\phi_I)$ denotes the probability that an entrant replaces the incumbent conditional on the entrant's successful innovation.

The incumbent and potential entrant choose effort levels to maximize their expected discounted profits

$$\begin{aligned} V_I = \quad & (1-\phi_E)(\pi_m+\delta V_I)+\phi_I\left(r_I(\phi_E)-(1-\phi_E)\right)(\pi_m+\delta V_I) \\ & +\left((1-\phi_I)\phi_E+\phi_I(1-r_I(\phi_E))\right)(\phi_I+\delta V_E)-c_I(\phi_I) \end{aligned}$$

and

$$\begin{aligned} V_E &= (1-\phi_E)\delta V_E+\phi_E(1-r_E(\phi_I))\delta V_E+\phi_E r_E(\phi_I)(\phi_E+\delta V_I) \\ &= \delta V_E+\phi_E r_E(\phi_I)(\pi_E+\delta V_I-\delta V_E)-c_I(\phi_E) \end{aligned}$$

The incumbent choose innovation probability ϕ_I to maximize

$$max_{\tau_I}\tau_I\left(r_I(\phi_E)-(1-\phi_E)\right)\left(\pi_m-\pi_I+\delta(V_I-V_E)\right)-c_I(\tau_I),$$

where $r_I(\phi_E)-(1-\phi_E)$ is the probability that the innovating incumbent retains its incumbency even though the entrant innovates successfully. The incumbent and entrant's innovation benefits are $w_I=(\pi_m-\pi_I+\delta(V_I-V_E))$ and $w_E=\pi_E+\delta(V_I-V_E)$ respectively. Substituting for V_I and V_E in w_I and w_E gives
$w_I=\frac{1}{1-\delta+\delta\{\phi_E(1-\phi_I)+\phi_I(1-r_I)\}+\delta\phi_E r_E}\{\pi_m-(1-\delta)\pi_I+\delta\phi_E r_E(\pi_m-\pi_E-\pi_I)+\delta(c_E-c_I)\}$
and
$w_E=\frac{1}{1-\delta+\delta\{\phi_E(1-\phi_I)+\phi_I(1-r_I)\}+\delta\phi_E r_E}\{\delta\pi_m+(1-\delta)\pi_E-\delta\left((1-\phi_I)\phi_E+\phi_I(1-r_I)\right)(\pi_m-\pi_E-\pi_I)+\delta(c_E-c_I)\}$.

Segal and Whinston show that it can be useful to think of the equilibrium R&D effort level (ϕ_I^*,ϕ_E^*) as the intersection of the "innovation supply" and "innovation benefit" curves. The incumbent's choice of ϕ_I is determined by the intersection of innovation supply curve $\Phi_I(w)=\text{argmax}_\tau\{\tau[r_I(\phi_E^*)-(1-\phi_E^*)]w-c_I(\tau)\}$ and the innovation benefit curve $W_I(\phi_I;\phi_E^*)=\frac{1}{1-\delta+\delta\{\phi_E^*(1-\phi_I)+\phi_I(1-r_I)\}+\delta\phi_E^* r_E}\{\pi_m-(1-\delta)\pi_I+\delta\phi_E^* r_E(\pi_m-\pi_E-\pi_I)+\delta(c_E-c_I)\}$. Similarly, the entrant's equilibrium (ϕ_E^*,w_E^*) is the intersection of $\Phi_E(w)=\text{argmax}_\tau r_E(\phi_I)w-c_E(\tau)$ and $W_E(\phi_E;\phi_I^*)=\frac{1}{1-\delta+\delta\{\phi_E(1-\phi_I^*)+\phi_I^*(1-r_I)\}+\delta\phi_E r_E}\{\delta\pi_m+(1-\delta)\pi_E-\delta\left((1-\phi_I^*)\phi_E+\phi_I^*(1-r_I)\right)(\pi_m-\pi_E-\pi_I)+\delta(c_E-c_I)\}$.

Changes in the degree of product market competition may affect the firm's innovation incentives directly by changing the incremental returns to investing while holding the opponent's actions fixed. For example, suppose π_m is independent of the competition intensity but greater product market competition reduces π_I and π_m. Then fixing the entrant's innovation probability, the incumbent's innovation prize w_I is increasing as π_I and π_E decrease. Intuitively, because competition reduces profits and $\pi_m\geq\pi_I+\pi_E$, the "efficiency effect" suggests that the incumbent may have greater incentive to remain the incumbent as product market competition increases.

The overall effect of product market competition on innovation intensities also depend on indirect effects that opponent's R&D intensity may have on a firm's innovation prize.

Fixing ϕ_I, product market competition which reduces π_E and π_I lowers the entrant's innovation benefit curve $W_E(\phi_E;\phi_I)$. Reasoning intuitively, an entrant earns π_E after successful innovation even if the incumbent innovates successfully. When the probability for the incumbent displacing the entrant remains unchanged, greater product market competition reduces the entrant's returns from innovation. However, lowering ϕ_E lowers the incumbent's probability of being displaced. Decreasing ϕ_E may then lead to a decrease in incumbent's response ϕ_I, which has an ambiguous effect on $W_E(\phi_E;\phi_I)$. After accounting for the indirect effects of product market competition through the interactions of ϕ_E and ϕ_i, the conclusions are ambiguous.

The above "winner-take-all" example illustrates that the incumbent may have incentive to conduct R&D in order to maintain its leadership position. We can think of increasing product market competition as decreasing the technological gap between the leader/incumbent and entrant/laggard. The incumbent's incentive to avoid displacement may in fact increase as product market competition increases.

2.3 Process vs. Product Innovations

So far we have discussed how investment incentives of firms depend on their relative technology distances assuming that firms only innovate in one dimension. Next we consider firms having opportunities for both cost reduction and quality improvements and the possible effects of one kind of investment decision on the returns to investment from the other kind. We draw on the framework from Athey and Schumutzler (1995). Suppose for now the costs of engaging in product and process innovations are independent. Product innovation i_D (D=design) and process innovation i_T (T=technology) are binary choice variables with independent adjustment costs $A_D(i_D)$ and $A_T(i_T)$. The firm makes decisions regarding Q, i_T, and i_D in order to maximize its profit function

$$[P(Q, i_D) - C(Q, i_T)]Q - A_D(i_D) - A_T(i_T).$$

The costs of engaging in product and process innovations are independent, but their decisions interact through the choice of Q. To see when product innovation and process innovation are complementary, observe that the marginal effects of i_D and i_T on the returns to Q are $[P(Q, i_D = 1) - P(Q, i_D = 0)] + Q\frac{\partial}{\partial Q}[P(Q, i_D = 1) - P(Q, i_D = 0)]$
and

$$[C(Q, i_T = 0) - C(Q, i_T = 1)] + Q\frac{\partial}{\partial Q}[C(Q, i_T = 0) - C(Q, i_T = 1)].$$

If the process innovation lowers not only the total cost of production but also the marginal cost of production $\frac{\partial}{\partial Q}[C(Q, i_T = 0) - C(Q, i_T = 1)] > 0$, then quantities produced and the choice of process innovation are complementary. In order for product innovation to increase marginal revenue, we need that the quality improvement shifts the demand curve outward by enough ($[P(Q, i_D = 1) - P(Q, i_D = 0)]$) to offset the potential negative effect from $\frac{\partial}{\partial Q}[P(Q, i_D = 1) - P(Q, i_D = 0)]$. Roughly, we need that the demand curve after the quality improvement remains sufficiently flat. If otherwise, the firm may have an incentive to restrict output in return for higher prices. We need the enhancement to demand from the quality improvement to be large enough in order to outweigh the firm's possible incentive to lower output and increase price.

When both process and product innovations increase marginal revenue, the profit function is supermodular in (i_D, i_T, Q), and so product and process innovation are mutually reinforcing.

Next we consider an extension of the Athey and Schmutzler framework. To achieve the same decrease in the average cost of production, higher levels of process R&D expenditures may be required for higher levels of product R&D. For example, modify the firm's profit function to be

$$[P(Q, i_D) - C(Q, i_T, i_D)]Q - A_D(i_D) - A_T(i_T).$$

Suppose that i_D and i_T are continuous choice variables that interact directly through the cost term $C(Q, i_T, i_D)$. If the marginal decrease in C from implementing process innovation is more difficult for higher levels of product innovation, then $\frac{-\partial C(Q, i_T, i_D)}{\partial i_T \partial i_D} < 0$. The effect on production cost counteracts the indirect complementarity between i_T and i_D through Q discussed before.

We plan to determine empirically if there is really any tradeoff between product and process innovations. On one hand, if improvements to the production process may be less transferreable after product innovation, firms with higher levels of product innovation may have less incentives to engage in process innovations. On the other hand, if product innovation enhances demand and the returns to process innovation are a direct function of market shares, then there is an opposing force encouraging firms with greater levels of product innovation to engage in process innovation. Finally, each firm's choices of product and process innovation intensities will also depend on the underlying market conditions such as the level of product market competition.

3 Model

The state space is composed of (i) some transformation of the vector summarizing qualities and "production experiences" for all multi-product firms in the market
(ii) a set of iid private information shocks that affect each firm's payoff from making investment and exit decisions for the next period.

Static Profits

Suppose that consumers choose one of the drives offered in the market or the "outside good". We might think of the outside good as consisting of using old hard drives purchased in previous periods rather than upgrading to a new drive.

Consumer i chooses drive j with characteristics $x'_j = [log(\text{capacity}_j)\ \text{rpm}_j]$ or $x'_j = [log(\text{capacity}_j)\ \text{rpm}_j\ \text{size}_j]$ that gives the highest utility

$$U_{ij} = x'_j\beta - \alpha p_j + \xi_j + \epsilon_{ij}. \tag{1}$$

Define $\omega_j = x'_j\beta$ and let E^f_m denote the production "experience" of firm f in market m at the beginning of the period. "Experience" could be attained through learning-by-doing or through costly efforts to improve the production process. For the vector of quality measures $\Omega^f_m = (\omega_1, \ldots, \omega_j)$, the static profit function of firm f in market m is

$$\pi_f(\Omega_m, E_m^f) = \sum_{j \in \mathcal{F}_f} [p_j(\omega_j) - mc_j(E_m^f)]\mathbf{M}s_j((\omega_j, p_j); \Omega_m) - C_f, \qquad (2)$$

where C_f summarizes R&D costs with investment outcomes realized at the beginning of the next period. The marginal cost of product j, mc_j, is decreasing in the firm's overall level of experience E_m^f but possibly increasing in ω_j. For example, in the most extreme case, cost reduction achieved through process innovation could be rendered obsolete by subsequent radical product innovations.

The static profit of firm f over all markets is $\sum_m \pi_f(\Omega_m, E_m^f)$.

Hypotheses about Disk Drive Production: Learning by Doing vs. Process Innovation?

Learning-by-doing: Firms improve production efficiency over time as cumulative output rises. Like the semi-conductor industry, learning by doing partly takes the form of ever-increasing "yields," that is, ever-increasing percentages of usable hard drives. Learning curves can lead to a dynamic incentive to set the price below the level of static marginal cost, especially upon the introduction of a new product. Industries in which learning curves are steep may tend to become highly concentrated over time.

Let experience be a function of the firm's past experience and current production. Dividing a firm's products in each submarket into groups based on capacity bins and rpm's, we let E_i denote the production experience of group i. Adapting the functional form for marginal cost from Irwin and Klenow's paper Learning-by-Doing Spillovers in the Semiconductor Industry to hard drive production, assume that current marginal cost is related to experience E_i through

$$c_i = \nu_i E_i^{\theta} e^{u_i}. \qquad (3)$$

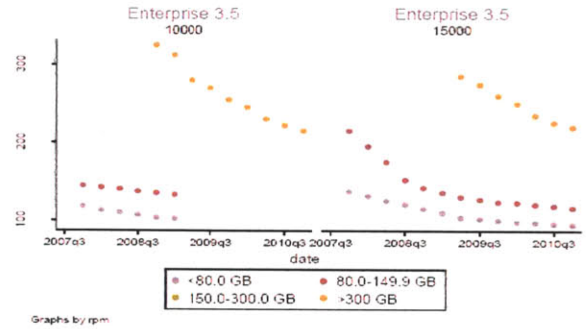
Possible functional forms for $u_{i,t}$ include
$u_{i,t} = \mu + \alpha \cdot t + \rho u_{i,t-1} + \epsilon_{i,t}$, with $\mid \rho \mid < 1$
or $u_{i,t} = \mu + \rho u_{i,t-1} + \epsilon_{i,t}$.

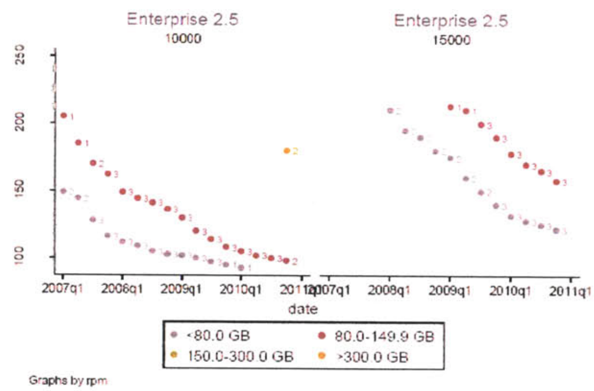
The parameters θ measures learning, error u_i includes productivity shock that may be observable to the firm but unobservable to the econometrician, ν_i is firm fixed effect, and ρ measures the persistence of the productivity shocks.

The time trend incorporates trends in inputs prices of capital and raw materials that are used in manufacturing disk drives. We expect α to be negative since experts in the HDD industry says that the cost of components have been decreasing over time.

One possible choice for E_i is $E_i = Q_i + \Psi Q_{i-1}$, where Q_i is cumulative output of group i from past periods and Q_{i-1} is cumulative output of products in the capacity bin below Q_i or cumulative output of products in the same capacity range but lower rpm. We may want to account for output in other submarkets in E_i since production experiences are transferrable across submarkets. A third source of technological transfer is from competing firms as firms learn not just from their cumulative production but also from other firm's cumulative production.

The plots below show quarterly average enterprise prices (in US \$) by rpm and size/formfactor. The first entrant may charge higher prices due to the fact that they have few rival firms, but prices for all the product are essentially flat once the product reaches maturity.



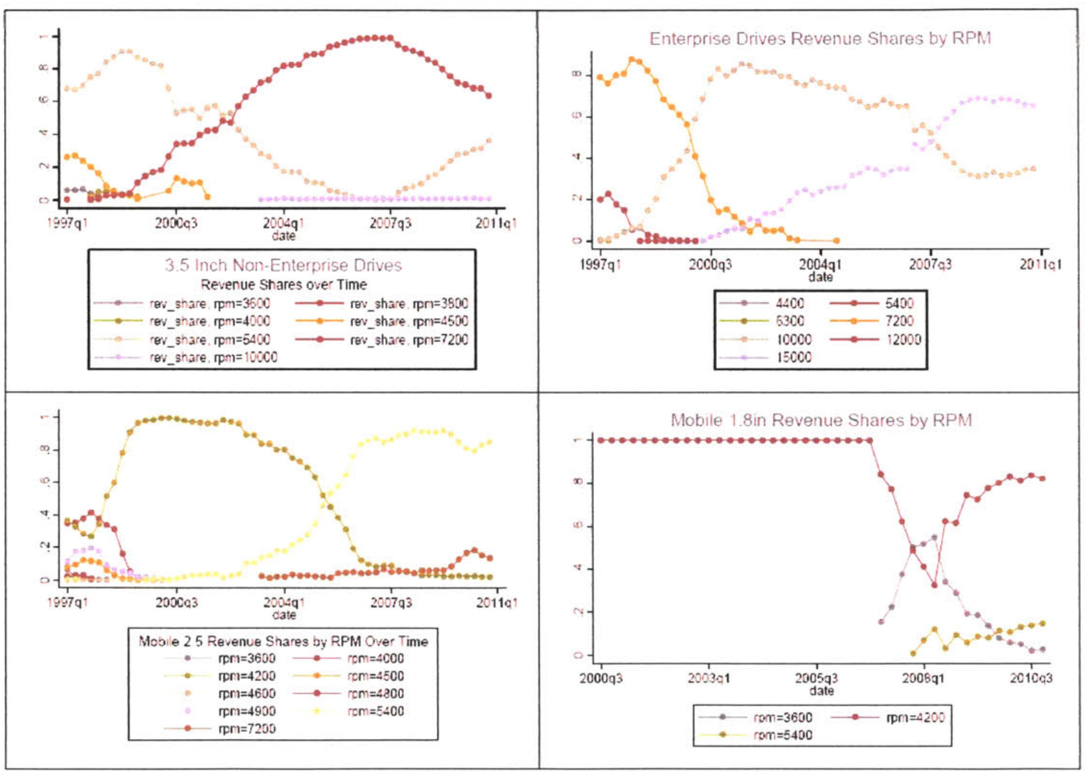


Process Innovation In learning-by-doing models, firms tend to price below the level of static marginal cost, especially during the post-entry period while the firms work down their learning curves. HDD expert Gary Davis suggests that although there is learning-by-doing in the industry, pricing below static costs never occurred. Rather, process innovation is a major determinant of the marginal cost of production. Process innovation takes the form of both better production techniques leading to lower reject rates and decreases in the unit cost of each usable disk drive. In the absence of learning-by-doing effects so that per-period prices are chosen only to maximize static profit, marginal costs are recovered from the first-order conditions for the firms' static profit-maximization pricing decisions.

R & D Expenditure Function

One possibility is to use the overall quality measure $\omega_j = x_j'\beta$ and assume that R&D cost is increasing in ω_j. More realistically, the adjustment costs for capacity increase and rpm increase could be very different, even if the resulting change in ω_j is the same. In reality, it more more expensive to upgrade capacity at higher rpms. For example, one way to increase the areal density of a drive is by increasing the tracks per inch. Since track follow is more difficult to higher rpm, it is more difficult to increase capacity for higher rpms.

RPMs do not transition in a continuous way like capacities. For example, at the beginning of the century, all Samsung 3.5" desktop drives were at 5400rpm. Eventually, 7200rpm were introduced into selective models. Beginning in 2009, all Samsung desktop drives are at 7200rpm. In the enterprise class, rpms transitioned from 7200 and 10,000 rpm to 10,000 and 15,000 rpm today. However, the IDC analyst informs us that there are in fact more rpms than in observed in the data. RPM transitions can be approximated by discrete decisions, and we think of there as being a discrete grid for rpms with uneven distances between grid points.



For now just assume that R&D cost is only a function of ω_j. Fixing market m, let $\overline{\omega}_{m(t-1)}$ denote the product with maximum quality in period $t-1$ and $\overline{\omega}_{mt}$ denote the product with maximum quality in period t. There are R & D adjustment costs $A_D(\overline{\omega}_{mt} - \overline{\omega}_{m(t-1)})$ ("D"=design) and $A_T(E_{mt} - E_{m(t-1)})$ ("T"=production technology) given increment in frontier quality $\overline{\omega}_{mt} - \overline{\omega}_{m(t-1)}$ and production efficiency $E_{mt} - E_{m(t-1)}$.

R & D decisions are chosen to maximize the firm's expected value

$$max_{\left(E_{mt}-E_{m(t-1)}\geq 0,\overline{\omega}_{mt}-\overline{\omega}_{jm(t-1)}\geq 0\right)}\sum_{t=1}^{\infty}\beta^{t-1}\mathbf{E}\{\sum_{m}\pi_f(\Omega_m,E^f_m)-A_D(\overline{\omega}_{mt}-\overline{\omega}_{m(t-1)})-A_T(E_{mt}-E_{m(t-1)})\} \tag{4}$$

Alternative specifications of the investment cost functions A_D and A_T may capture the extent to which knowledge capital is transferrable across markets. The R & D cost A_D may be a function of the composite term $\overline{\omega}_{mt}-\overline{\omega}_{m(t-1)}-\alpha_D\sum_{\widetilde{m}}\left(\overline{\omega}_{\widetilde{m}t}-\overline{\omega}_{\widetilde{m}(t-1)}\right)$, where the sum is taken over other markets $\{\widetilde{m}\}$ in which the firm is a competitor. The parameter α_D measures the extent of R & D spillover across markets. If the firm's technology improvement in market m only gets the spill-over benefits from market $\widetilde{m}$ if $\overline{\omega}_{\widetilde{m}(t-1)}\geq\overline{\omega}_{m(t-1)}$,
we can change the "spillover pool" to be those outside markets $\{\widetilde{m}\}$ with performance measures $\overline{\omega}_{\widetilde{m}(t-1)}\geq\overline{\omega}_{m(t-1)}$.
Likewise, we can specify the process innovation cost as

$$A_T(E_{mt}-E_{m(t-1)};\{E_{\widetilde{m}t}-E_{\widetilde{m}(t-1)}\}_{\widetilde{m}})=A_T\left((E_{mt}-E_{m(t-1)})-\alpha_T\left(\sum_{\widetilde{m}}E_{\widetilde{m}t}-E_{\widetilde{m}(t-1)}\right)\right). \tag{5}$$

As before, α_T captures spill-overs across markets, and we can think of $\alpha_T\left(\sum_{\widetilde{m}}E_{\widetilde{m}t}-E_{\widetilde{m}(t-1)}\right)$ as production expertise common across markets.

Alternatively, we can think of the firm as first making rpm decisions and then choosing optimal capacities conditional on rpm. This is partly motivated by the observation that firms typically introduce the highest capacities at a lower rpm before incorporating the capacity increase in a drive with higher rpm. In each period, the firm faces the discrete decision: incurring the R&D cost of introducing a product at a higher rpm but enjoying higher profits in the future periods from introducing a new product at a higher rpm sooner vs. delaying the introduction of a higher rpm. The foregone opportunity cost for the firm from not introducing a higher rpm sooner includes potential future profits from having high-performance products with higher capacities at the higher rpm.

Then for each market m, rpm r, and quarter t, we define the quality measure $\overline{\omega}_{rmt}$ to be the maximum capacity over all drives with rpm r in market m. If implementing process innovations reduce the unit production costs, then firm maximizes its expected discounted profit given by

$$\max_{\left(mc^f_{mt}-mc^f_{m(t-1)}\geq 0,\overline{\omega}^f_{mt}-\overline{\omega}^f_{m(t-1)}\geq 0\right)}\sum_{t=1}^{\infty}\beta^{t-1}\quad\mathbf{E}\{\sum_{m}\pi_f(\Omega_{mt},mc^f_{mt})-\sum_{\text{rpm r, market m}}A_D(\overline{\omega}^f_{rmt}-\overline{\omega}^f_{rm(t-1)})-$$
$$\sum_{\text{rpm r, market m}}A_T(mc^f_{rmt}-mc^f_{rm(t-1)})\}. \tag{6}$$

Assuming the existence of a pure-strategy Bertrand-Nash price equilibrium, the vector of marginal costs in market m, mc_m, is recovered from the first-order conditions

$$p_m - mc_m = \Phi^{-1} s(p_m; \Omega_m) \tag{7}$$

where $s(\cdot), p$, and mc_m are the vectors of market shares, prices, and marginal cost, respectively, and Φ is the matrix with element Φ_{jk} equal to $-\frac{\partial s_k}{\partial p_j}$ if drives j and k are produced by the same firm, 0 otherwise.

Complementary Choice Variables: If R&D costs for improving production efficiency does not depend on improvement in drive performances, the choices for process innovation and product innovation may be mutually reinforcing (see section 2.3). We would then observe that decreases in marginal costs are positively correlated with advancements in a firm's own technological frontier.

State Space

Assume all payoff-relevant features of firms can be encoded into a state vector. The technology advantages of each firm in a market are summarized by the quality measure of the firm's product with the highest performance and the corresponding marginal cost of production. As the technology measure, $\omega_f = x'_f\beta$ ($x'_f =$ [ln(capacity) rpm]), grows without bound, we can scale the ω_f by dividing ω_f in each period by the $max_{\{firmj\}}\omega_j$. Changes in the marginal costs of production, $mc_f(\omega_f)$, reflect improved operational efficiency and higher production yields.

We need an additional state variable to help determine the overall profit of a firm. Nevo and Rossi (An approach for extending dynamic models to settings with multiproduct firms, 2008) show that when the demand comes from the logit utility, the firm's profit depends on the quality levels and marginal costs through an "adjusted inclusive value"(AIV). The AIV equals $log[\sum_{j\in\mathcal{F}_f} exp(x'_j\beta - \alpha mc_j)]$, where α is the price coefficient from the utility function. This sufficient statistic for firm profit is similar to the inclusive value, but it's adjusted to account for different marginal costs of production. Since the AIV state variable grows without bound, we may need to transform it into a relative state variable in a way so that utility flows are insensitive to the the transformations.

Evolution of the State Space

We consider both improvement in product performance and production efficiency to be governed by first-order Markov processes with transition probabilities depending on inferred R&D expenditures.

We can think of the actual change in productivity $E_t - E_{t-1}$ as the sum of the expected change in productivity and a random shock ε_t. That is, ε_t includes the realization of the uncertainties inherent in the R&D process. Similarly for technological improvement $\omega_t - \omega_{t-1}$. That is, given the firm's own technology state and expectation on industry technology evolution, the firm chooses to invest in a "target" level of technology improvement. The realized measure of innovative activities, $\omega_t - \omega_{t-1}$ or $E_t - E_{t-1}$, differs from the firm's planned level of improvement due to risks and uncertainties in the innovation process.

Consider the following base case specification. Suppose that changes in production efficiency is captured by changes in the marginal costs of production, $MC_{t-1} - MC_t$. Improvement in the performance measure (Prf) of drives is denoted by $\Delta(Prf)$, which $Prf_t - Prf_{t-1}$ if $Prf_t - Prf_{t-1} > 0$ and zero otherwise. One description for the changes $MC_{t-1} - MC_t$ and $\Delta(Prf)$ is

$$\begin{aligned} MC_{t-1} - MC_t &= \alpha_1(\Delta(Prf)) + s_t^{(MC)}\beta_1 + \epsilon_{1t}, \\ \Delta(Prf) &= \alpha_2(MC_{t-1} - MC_t) + s_t^{(Prf)}\beta_2 + \epsilon_{2t} \end{aligned} \tag{8}$$

where ϵ_{1t} and ϵ_{2t} are idd shocks. For vectors $s_t^{(MC)}$ and $s_t^{(Prf)}$ summarizing the firm's own and rivals technological positions in period t, $s_t^{(MC)}\beta_1$ and $s_t^{(Prf)}\beta_2$ measure the firm's optimal or target choices given the current period's own and industry states.

Timing

- t.1:Incumbent firms observe s_t, the vector summarizing the experience and performance of frontier product for all incumbents in each submarket. Firms decide on product prices, and realize profits from product market competition.
- t.2: Each firm f observe random shocks to their R &D cost functions and choose target innovation levels e_t^f and $\mathbf{E}[mc_{ft-1} - mc_{ft}]$. They incur the investment costs A_D and A_T from equation 4.
- t.3: Remaining incumbents decide whether or not to exit the industry while potential entrants observe random entry cost and make entry choices into a submarket(s).
- t.4: Observed states s_{t+1} for the next period are realized.

- t.3: Exit decisions: We are not sure how to think of the determinants of a firm's sell-off values or the process an exiting firm is matched with a remaining incumbent.

  If we think of the continuing incumbents bidding to acquire an exiting firm, then the bidder's value of not acquiring a firm seems to depend on which other firm has acquired the exiting firm. One cannot really think of this as a second-price auction where the incremental value a bidder has for a sell-off firm only depends on the bidder itself.
- t.4: We would like the development costs associated with the start-up technology position of an entrant's first product to be determined by the same cost function specifications for R&D efforts $A_T(\cdot)$ and $A_D(\cdot)$. However, we're not sure how to make this feasible. For example, the firm's target technology position at time 0 depends on the the non-existent quality measure $\bar{\omega}$ of the firm's frontier product at time -1. Given the logit model, only a price of $-\infty$ would generate $exp(\bar{\omega}) = 0$ purchase. An option would be to assume that the firm's start-up technology position is randomly drawn from some distribution.

Equilibrium Concept

The equilibrium concept we plan to employ is symmetric Markov perfect Nash equilibrium, where firms' actions in each period are a function only of pay-off relevant state variables. Firms maximize their expected discounted value of profits given in equation 6 conditional on their expectations of the evolution of present and potential future competitors.

4 Estimation

We plan to estimate the model using a two-step approach. Consumer demand and the transition processes of the state variables are estimated in the first stage. In the second stage, the set of dynamic parameters in the investment cost functions $A_D(\cdot)$ and $A_T(\cdot)$ and potential entry and exit cost parameters are estimated. The spill-over parameters θ_D and θ_T embedded in the investment cost functions are estimated in the second step as well. In typical BBL-type (Bajari-Benkard-Levin) estimation procedures, the second step involves using forward simulation to calculate future firm payoffs and then finding the parameters which make the observed policies optimal.

4.1 Consumer Demand

We consider the market demand for each of the four different types of drives: desktop 3.5 inch, mobile 2.5 inch, mobile 1.8 inch, and enterprise. A market is defined as the global market for a type of drives for each quarter from 1997 to 2010. Suppose that the consumers in each market have identical tastes and own one disk drive at a time. A consumer derives utility from product j with observable characteristics x_{jt} and unobservable quality ξ_{jt}. The utility of consumer i from the purchase is given by

$$u_{ijt} = x_{jt}\beta_t - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{9}$$

where the tastes β_t may be time-dependent.

Consumer's utility from the no-purchase option is

$$u_{0t} = \nu_{0t} + \epsilon_{0t}. \tag{10}$$

For consumers who purchased hard drives in the previous quarters, the "outside options" include using old drives and not upgrading to new ones. Another outside alternative for all potential disk drive buyers is a solid-state drive (SSD). Compared to mechanical disk drives, SSDs are data storage devices that offer faster speed performance in term of input/output operations per seconds. SSDs are also more reliable and can better withstand shocks and vibrations with data integrity. Since the cost per GB of capacity for solid state drives has been decreasing over time, the mean quality of the consumer's outside option, ν_{0t}, has been increasing over time.

When the consumers' idiosyncratic taste shocks ϵ_{jt} are IID Type I extreme values, the choice probabilities implied by the demand model give

$$ln(s_{jt}) - ln(s_{0t}) = x_{jt}\beta_t - \alpha p_{jt} - \nu_{0t} + \xi_{jt}, \tag{11}$$

where s_{jt} and s_{0t} are the observed shares of product j and the outside option at time t. We include a time trend variable in the demand estimation to explain changes in ν_{0t} and a constant in the quality vector x_{jt} to control for the mean of ξ_{jt}.

We estimate the above equation using instrumental variable regression with moment conditions $\mathbb{E}[Z'_{jt}\xi_{jt}] = \mathbb{E}[Z'_{jt}(ln(s_{jt}) - ln(s_{0t}) - (x_{jt}\beta_t - \alpha p_{jt} - \nu_{0t}))] = 0$. The vector of exogenous variables Z_{jt} include price instruments. Our instruments consist of the average number of disks and heads inside hard drives with the same capacity and by the same firm as jt and average prices in the other markets at time t. Disks and heads are the most costly components inside a drive, and they do not impact utility beyond their effects on capacity and/or rpm. For example, one way to increase the capacity of a disk drive is by stacking by more disks inside a drive. There also needs to be one head per coated side of a disk. We use the average price in the outside market as an additional instrument since there may be cost shocks common across markets or if improvements in the manufacturing process are transferrable across markets, cost pass-through in both markets result in correlated prices.

The demand estimates are displayed in tables 6 and 7. The time trend variable diff_date is defined as the number of quarters from the first quarter in the data sample. Capacity is a continuous product attribute. We use rpm dummies to control for other unmeasured attributes associated with drives at a given rpm. Preferences for different rpms may vary over time, as summarized by the rpm time trend variables "trend_rpm". The demand parameters presented in table 6 are estimated separately for each market. Table 7 reports demand estimated on data pooled across all markets. Firm fixed-effects or firm-market fixed-effects are included in the utility specifications but not reported.

The outside share for each market is chosen to be the total units sold over the past three years with either capacity or rpm weakly less than the minimum capacity or rpm in the current quarter. Disk drives are durable goods with warranty periods that are typically three years. We assume that people who own disk drives from the past 3 years are potential buyers. They are included in the "outside share" since we assume that these consumers would have updated to better drives if the prices of drives from the current period are low enough. We re-estimated our demand specifications using other ad-hoc definitions of the outside share. The signs and relative magnitudes of the coefficients are unchanged across different definitions of the outside share.

Table 6: Estimated Parameters of Logit Demand

	Desktop		Enterprise		Mobile 2.5		Mobile 1.8	
price	-0.0279***	(0.00244)	-0.00732***	(0.000738)	-0.0371***	(0.00521)	-0.0658***	(0.0169)
log(capacity)	0.811***	(0.112)	1.031***	(0.126)	1.274***	(0.177)	1.612**	(0.563)
$\mathbb{1}_{\text{rpm}=3600}$							-7.840***	(2.179)
$\mathbb{1}_{\text{rpm}=4000}$					-2.499***	(0.195)		
$\mathbb{1}_{\text{rpm}=4200}$					2.011***	(0.332)		
$\mathbb{1}_{\text{rpm}=4900}$					3.370**	(1.262)		
$\mathbb{1}_{\text{rpm}=5400}$	-0.586*	(0.265)			-0.218	(0.375)	-10.49***	(2.037)
$\mathbb{1}_{\text{rpm}=7200}$	-0.764**	(0.263)			0.0694	(0.549)		
$\mathbb{1}_{\text{rpm}=10000}$	0.0203	(0.403)	1.045***	(0.179)				
$\mathbb{1}_{\text{rpm}=12000}$			-2.005***	(0.255)				
$\mathbb{1}_{\text{rpm}=15000}$			-0.672**	(0.232)				
$\text{trend}_{\text{rpm}=3600}$							-0.510***	(0.0635)
$\text{trend}_{\text{rpm}=4200}$							-0.339***	(0.0711)
$\text{trend}_{\text{rpm}=5400}$					0.101***	(0.0126)	-0.358**	(0.121)
$\text{trend}_{\text{rpm}=7200}$	0.0492***	(0.00583)			0.0691*	(0.0274)		
$\text{trend}_{\text{rpm}=10000}$			0.111**	(0.0408)				
$\text{trend}_{\text{rpm}=15000}$			0.180***	(0.0415)				
$\mathbb{1}_{\text{size}=2.5}$			-1.909***	(0.322)				
$\text{trend}_{\text{size}=2.5}$			0.106***	(0.0169)				
diff_date	-0.0615***	(0.0125)	-0.247***	(0.0437)	-0.175***	(0.0206)		
constant'	-8.232***	(0.327)	-6.901***	(0.272)	-7.180***	(0.455)	1.693	(1.048)
N	2663		1400		2309		432	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Specification includes firm dummies.

Desktop Market

The difference in utility between 5400 and 7200 rpm drives in quarter 1 of 2000, or the difference between the coefficients of $\mathbb{I}_{5400}$ and $\mathbb{I}_{7200}$, is statistically significant. However, the positive time trend for the 7200 rpm suggests that the extra value consumers have for 7200 rpm over 5400 rpm increases over time. The increasing utility for the 7200 rpm can be partly accounted for by the reduced power consumption required for the higher rpm. Increased power consumption is an unobserved quality attribute associated with a higher rpm. Over the successive product generations, the motors and silicon chips inside the 7200 rpm drives operate more efficiently. This trend is reflected in the 7200 rpm time trend.

The coefficient on the 10000 rpm dummy is insignificantly different from zero. Given the positive time trend for 7200 rpm, the estimates seem to suggest that utility from 7200 rpm eventually surpasses that for 10000 rpm. This is counterintuitive but may be accounted for by the following. The pure logit functional form is restrictive since it assumes homogeneous consumer tastes. In reality, compared to the majority of desktop consumers, a small fraction of buyers are game enthusiasts with high valuation for fast data transfer rates but relatively lower price sensitivity. The 10000 rpm coefficient accounts for the purchasing decision of the small fraction of game enthusiasts. The majority of desktop buyers do not have as high a marginal willingness to pay for the extra rpm and are more likely to choose between 5400 and 7200 rpm. Given the lower demand but higher costs involved in manufacturing drives with 10,000 rpm, it is not surprising that Western Digitals is the only firm selling 10,000 rpm while all competitors in the desktop drive market offer 7200rpm drives.

Enterprise Market

The logit demand specification for the enterprise market includes time trends for the 2.5 inch formfactor ($\text{trend}_{\text{size}=2.5}$), 10000 rpm ($\text{trend}_{\text{rpm}=10000}$), and 15000 rpm ($\text{trend}_{\text{rpm}=15000}$). The 15000 rpm was unveiled in quarter 2 of 2000 (t_0^{15000}), and the first quarter for the 2.5 inch formfactor was quarter 2 of 2004 ($t_0^{2.5}$). The estimates shown in column 2 of table 6 are derived from the utility function

$$\begin{aligned} u_{ijt} &= \beta_1 log(capacity_{jt}) + (\beta_{21} + \beta_{22}(t - t_0^{2.5}))\mathbb{I}_{\text{formfactor}=2.5\text{inch}} + \sum_{rpms} \beta_{r1}\mathbb{I}_{\text{rpm}=r} \qquad (12) \\ &+ \sum_{rpms=\{10000,15000\}} \beta_{r2}(t - t_0^{15000})\mathbb{I}_{\text{rpm}=r} + \sum_{firms} \beta_f \mathbb{I}_{firmf} + \beta_4 \text{diff\_date} - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt}, \end{aligned}$$

where j indexes product and t indexes time period. The dummies $\mathbb{I}_{\text{rpm}=r}$ control for rpm, and the $\mathbb{I}'_{firmf}$s are firm-fixed effects.

Comparing the price coefficient for enterprise demand to those for the other markets suggests that the enterprise consumers are less price-sensitive. This is not implausible since enterprise drives typically provide application and storage services to networks and are mostly bought by organizations or institutions. Compare to the individual purchasers and homeowners of other types of drives, the income effect may tend to be less substantial for enterprise drives. Another possibility is that demand is less sensitive to price changes since the purchasers do not directly pay for the enterprise drives.

Despite being the highest rpm, the coefficient of the 15,000 rpm dummy is significantly negative. Compared to the benchmark group of 7200 enterprise drives, the utility from a 15,000 rpm drive appears lower in quarter 2 of 2000, the quarter when 15,000 rpm drives were launched. However, the coefficient on $\text{trend}_{\text{rpm}=15000}$, the linear time trend for the 15,000 rpm, is positively significant. One interpretation is that the utility associated with consuming the highest rpm drive may be increasing in the quarters after its introduction. When a new generation of drives with a higher rpm is first brought to market, it is prone to manufacturing defects. There has been multiple cases of product recalls for new technology drives due to mistakes in the manufacturing process. An alternative "behavior" explanation is that there is inertia in the buyers' purchasing decisions. The adoption of a higher rpm takes time, and the probability of choosing a higher rpm increasing in the quarters post-introduction as the new technology diffuses.

The same story may apply to explain the growing market shares of 2.5 inch drives. The smaller formfactor was brought to the market in quarter 2 of 2004. Although the coefficient on 2.5in dummy is negative and significant, the positive time trend suggests that the valuation for the smaller size is increasing over time.

The coefficient on the 12,000 rpm indicator variable is negative and significant. The 12,000 rpm was a first attempt to introduce enterprise drives with access time faster than 10,000. However, 12000 rpm were taken off the market before quarter 2 of 2000. The disks inside both the 10,000 and 12,000 rpm drives were 84 mm in diameter. High rpms lead to more disk flutter and more frequent track misregistration (performance errors in drives). As in the case of the 15,000 rpm drives which were introduced after the 12,000 rpm drives, one way to compensate for the higher rpm and maintain performance quality is to decrease the physical size of the disks. However, since the disks inside both 10,000 and 12,000 rpm drives were 84mm in diameters, the rpm gain of the 12,000 drives did not compensate for the higher error rates.

Mobile 2.5 in Drives

The logit specification for the mobile 2.5 in market include the linear time trend variables $\text{trend}_{\text{rpm}=5400}$ and $\text{trend}_{\text{rpm}=7200}$, both taken to be quarters elapsed since their respective quarters of first observations. The total effect of 5400 rpm on utility is measured by $coeff(\mathbb{I}_{5400}) + coeff(\text{trend}_{\text{rpm}=5400}) *$ (quarters since quarter 1 of 2000) for 5400 rpm , and $coeff(\mathbb{I}_{5400}) + coeff(\text{trend}_{\text{rpm}=5400}) *$ (quarters since quarter 2 of 2003) for 7200 rpm drives. The positive coefficients on either rpm suggest that although the fixed effects of either rpm may be initially low compared to the 4200 rpm, the utility rises over time.

The estimated coefficient on the 4200 rpm dummy is larger than the coefficient on the 5400 or 7200 rpm dummy. However, the positive coefficients of trend_{5400} and trend_{7200} indicate that the differences in utilities between 4200 rpm and the two higher rpms decline in the quarters after the higher rpms are first launched. These observations accord with the technology diffusion story from the section on enterprise demand.

The estimated coefficients of trend_{5400} and trend_{7200} also suggest that 5400 rpm is gaining market shares faster than 7200 rpm. One intuitive explanation is that 7200 rpm drives are targeted for high-performance mobile users and that the 7200rpm drives face the stiffest competition from SSD drives with faster data access rates. In other words, the pure logit demand is an approximation of consumer demand where the consumers' preferences for capacities and rpms may actually be heterogeneous. To help fix ideas, suppose there are two types of consumers, one type having high valuations for the performance characteristics of drives and another type caring less than performance but more about price.Imagine that demand for the 7200rp is driven by the first type and that the second type accounts for most the the 5400 rpm shares. The marginal utility derived from the outside option is higher for the first type that cares more about quality improvements in SSD drives. On the other hand, the utility from the outside option may be changing very little for the second type over the quarters. Recall that the time trend variable diff_date controls for changes in the outside share. When estimating the logit utility, the difference in utility derived from the outside share is reflected in the difference between $\text{diff\_date}+\text{trend}_{\text{rpm}=5400}$ and $\text{diff\_date}+\text{trend}_{\text{rpm}=7200}$, or $\text{trend}_{\text{rpm}=5400}$ and $\text{trend}_{\text{rpm}=7200}$.

Mobile 1.8inch

Using IDC's classfication of mobile 1.8inch drive, the demand is fueled by two separate markets, the market for consumer electronic (CE) applications and the market for slim, ultra-lightweight laptops. Examples of CE 1.8inch applications are camcorders, ipods, and portable media players such as MP3. Almost all CE drives are at either 3600 or 4200 rpm, with only $\approx 1\%$ of units shipped in quarter 4 of 2010 coming from 5400 rpm drives. One of the major drawbacks of using 5400 rpm drives for CE applications is the high power consumption. Notebook drives, on the other hand, are exclusively 4200 or 5400 rpm. Our prices and shipment information for 1.8inch drives are not broken down by the distinct applications.

The omitted dummy in table 6 is $\mathbb{I}_{\text{rpm}=4200}$, and the coefficient on $\mathbb{I}_{3600}$ is significantly negative as expected. One potential explanation for the negative coefficient on $\mathbb{I}_{5400}$ is the technology diffusion story discussed in the enterprise section. Since 5400 rpm was first unveiled in the laptop market, the negative coefficient on I_{5400} represents the initial differences in utility between the 5400 rpm and 4200 rpm in the laptop market.

The variables $trend_{3600}$, $trend_{4200}$, and $trend_{5400}$ are defined the quarters elapsed since a rpm is first observed in the dataset. These variables account for how the utility derived from the different rpms change over time. The negative time trends for all rpms partly reflect that the mean utility of solid state drives, which is captured in the outside alternative, is increasing over time. Compared to disk drives, solid state drives offer faster access time, lower power consumption, and better shock resistance. These features are especially valued in the portable laptop sector. As a result, solid state drives have become increasingly popular substitutes to mechanical hard disk drives.

The coefficient of $trend_{4200}$ is greater than that of $trend_{3600}$ and $trend_{5400}$. For both the second and third specifications, Wald tests show that the coefficient on the 4200 rpm time trend is very significantly different from the 3600 rpm time trend. However, $trend_{5400}$ is not significantly different from $trend_{4200}$ or $trend_{3600}$ at the 20% level. Differences in the $trend_{rpm}$'s might partly be explained by how market share changes in the two separate submarkets. Recall that 1.8inch 3600 and 5400 rpm drives are actually not substitutes. The 3600 rpm drives are targeted for CE applications, while the demand for 5400 rpm drives is driven by the notebook submarket, which posted faster growth than the CE submarket. 4200 rpm, on the other hand, meets demand in both the CE and notebook sectors.

Table 7 presents re-estimations of the demand parameters using data pooled across all markets. The marginal utility of capacity is constant across markets, but price is allowed to vary between enterprise and non-enterprise drives. RPM fixed effects and time trends are also different across markets. Compared to the enterprise and mobile 2.5inch markets, desktop drives face less competition from solid state drives. Hence we allow the time trend coefficient on diff_date to be different for desktop drives.

Column one reports the preliminary OLS regression of the logit demand. Column two instruments for price in the the non-enterprise markets using the average number of disks and averaged number of heads as instruments. Although the price and log(capacity) coefficients increase when non-enterprise price is instrumented, the signs and relative magnitudes of the coefficients are the same across columns one and two. In column three, the instrumented variables are the prices in enterprise and non-enterprise markets. With average heads and disks counts as instruments, the coefficients on non-enterprise price and log(capacity) become non-intuitive. We may need to find better instruments in the future.

4.2 Estimating the R & D Policy Functions

We assume that each firm makes decisions based only on its own state and the overall industry states. However, in typical application of Ericson-Pakes type models, policy functions are estimated for the firms' Markov Perfect Equilibrium behavior. In particular, investment decisions of firms are based not only on their own state variables but also the states of opponents that capture their competitive advantages. When the firms' strategies are symmetric, the state vector for each firm's strategy includes the vector that represents the distribution across firms with each possible value of the firm state variable. However, as a first step, we assume that a a firm's decisions only based on its own characteristics and statistics summarizing the overall level of competition in the industry.

To investigate the determinants of a firm's innovation decisions, we regress indicators of each firm's innovation intensity on market condition variables measuring the firm's relative

Table 7: Estimates of Logit Demand for Pooled Data

Market		OLS	IV (1)	IV (2)
Non-Enterprise	Price	-0.0227***	-0.0359***	0.0433*
		(0.000)	(0.000)	(0.014)
Enterprise	Price	-0.00590***	-0.00776***	-0.0137***
		(0.000)	(0.000)	(0.000)
	log(capacity)	0.708***	1.138***	-0.917*
		(0.000)	(0.000)	(0.050)
Enterprise	$\mathbb{I}_{size=2.5}$	-2.041***	-1.842***	-3.983***
		(0.000)	(0.000)	(0.000)
Enterprise	$trend_{size=2.5}$	0.0992***	0.106***	0.128***
		(0.000)	(0.000)	(0.000)
Enterprise	$\mathbb{I}_{rpm=12000}$	-1.805***	-1.534***	-2.978***
		(0.000)	(0.000)	(0.000)
Enterprise	$\mathbb{I}_{rpm=10000}$	1.422***	1.394***	2.843***
		(0.000)	(0.000)	(0.000)
Enterprise	$\mathbb{I}_{rpm=15000}$	-0.241	-0.297	0.462
		(0.256)	(0.179)	(0.324)
Enterprise	$trend_{rpm=10000}$	0.0234*	0.0220*	-0.0863**
		(0.012)	(0.025)	(0.001)
Enterprise	$trend_{rpm=15000}$	0.0850***	0.0922***	-0.0328
		(0.000)	(0.000)	(0.271)
Desktop	$\mathbb{I}_{rpm=5400}$	-0.683**	-0.436	-1.923***
		(0.010)	(0.105)	(0.000)
Desktop	$\mathbb{I}_{rpm=7200}$	-0.917***	-0.589*	-2.770***
		(0.000)	(0.028)	(0.000)
Desktop	$\mathbb{I}_{rpm=10000}$	-0.395	0.799	-5.968***
		(0.267)	(0.054)	(0.000)
Desktop	$trend_{rpm=7200}$	0.0500***	0.0503***	0.0565***
		(0.000)	(0.000)	(0.000)
	p-values in parentheses =* $p<0.05$	** $p<0.01$	*** $p<0.001$	

Table 8: Estimates of Logit Demand for Pooled Data

Market		OLS	IV (1)	IV (2)
Mobile 2.5	$\mathbb{1}_{rpm=4000}$	-1.877***	-2.350***	-0.0895
		(0.000)	(0.000)	(0.862)
Mobile 2.5	$\mathbb{1}_{rpm=4200}$	2.654***	2.235***	3.835***
		(0.000)	(0.000)	(0.000)
Mobile 2.5	$\mathbb{1}_{rpm=4900}$	2.005*	3.393**	-5.834**
		(0.013)	(0.002)	(0.010)
Mobile 2.5	$\mathbb{1}_{rpm=5400}$	-0.108	-0.0745	-1.264*
		(0.746)	(0.835)	(0.028)
Mobile 2.5	$\mathbb{1}_{rpm=7200}$	-0.0324	0.238	-2.496**
		(0.947)	(0.649)	(0.003)
Mobile 2.5	$\text{trend}_{rpm=5400}$	0.127***	0.106***	0.226***
		(0.000)	(0.000)	(0.000)
Mobile 2.5	$\text{trend}_{rpm=7200}$	0.116***	0.0765**	0.312***
		(0.000)	(0.001)	(0.000)
Mobile 1.8	$\mathbb{1}_{rpm=3600}$	-3.828***	-5.537***	3.794
		(0.000)	(0.000)	(0.083)
Mobile 1.8	$\mathbb{1}_{rpm=5400}$	-7.487***	-8.976***	-1.274
		(0.000)	(0.000)	(0.500)
Mobile 1.8	$\text{trend}_{rpm=3600}$	-0.423***	-0.456***	-0.280***
		(0.000)	(0.000)	(0.000)
Mobile 1.8	$\text{trend}_{rpm=4200}$	-0.191***	-0.245***	0.0518
		(0.000)	(0.000)	(0.452)
Mobile 1.8	$\text{trend}_{rpm=5400}$	-0.139*	-0.211**	0.204
		(0.041)	(0.005)	(0.057)
Enterprise/Mobile 2.5	diff_date	-0.122***	-0.168***	0.0784
		(0.000)	(0.000)	(0.160)
Desktop	diff_date	-0.0486***	-0.0962***	0.144**
		(0.000)	(0.000)	(0.008)
	constant	-8.192***	-8.682***	-6.985***
		(0.000)	(0.000)	(0.000)
	N	6804	6804	6804
	p-values in parentheses			
	=* p<0.05	** p<0.01	*** p<0.001	

position and the intensity of competition in the market. We assume that the realized product improvements are the results of the firm's investment in innovation and that investment decisions for time t are made after observing the time t-1 market condition variables. Our choices for the determinants of innovation incentives are partly motivated by the theoretical model from Aghion et al (2005).

The outcome of a multi-product firm's innovation efforts is the improvement in the performance measures of the firm's best hard drives. Observations are per firm-market-qrtr-rpm in the regressions below. For the preliminary regression in table 9, the dependent variable $max(capacity)_t$, is the firm's maximum capacity for a given rpm at time t. Our choices for the RHS predictor variables in the baseline regression are $qual_{-1}$, $neck_{-1}$, Hrf_{-1}, and $Hrf \cdot qual_{-1}$. The explanatory variable $qual_{-1}$ is the normalized capacity from the last period, or $\frac{capacity_j}{\max_{firm i} capacity_i} \in [0,1]$ for firm j. The degree of neck-and-neckness for firm j is $\text{neck} \cdot 1 = \sum_i (\frac{capacity_j}{\max_{firm k} capacity_k} - \frac{capacity_i}{\max_{firm k} capacity_k})^2 \in [0, N-1]$, where N is the number of firms. In other words, $neck_{-1}$ measures how close firm j is to its neighbors in the quality space by comparing its normalized maximum capacity to the normalized maximum capacities of its competitors with the same rpm. Large value of $neck_{-1}$ implies a small degree of neck-to-neckness. Hrf is the usually market concentration index and a measure for the degree of product market competition. The covariate $Hrf_1 * qual_1$, which measures the differential response of firms to product market competition.

Table 9: Arellano-Bond Estimator for Decision to Introduce Improved Capacities

	(1)	
	maximum capacity	
maximum capacity$_{-1}$	0.992***	(0.000)
$qual_{-1}$	-638.7***	(0.000)
$neck_{-1}$	-53.78*	(0.027)
Hrf_{-1}	-614.1**	(0.003)
$Hrf \cdot qual_{-1}$	551.5*	(0.012)
constant	640.2***	(0.000)
N	866	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Rather than defining $max(capacity)_t$ to be the maximum capacity at time t, we define $max(capacity)_t$ to the maximum capacity of a firm's best drive in all time periods up to t in our subsequent discussions. One measure of innovation outcome for the firm is $\Delta_{capacity} = max(capacity)_t - max(capacity)_{t-1}$. The difference in the capacity frontier for the firm between two consecutive periods is an appropriate proxy of the quarterly innovation level for the firm if we assume that the knowledge stock of firms do not depreciate over time.

If $max(capacity)_{t-1}$ is attained in some period prior to $t-1$ but not offered in $t-1$, we assume that the firm still retains the technological know-how required to produce drives with capacity $max(capacity)_{t-1}$ in period t-1. The dependent variable is $max(capacity)_t$ for the levels regression. For the regression using first-diffs, dependent variable is $\Delta_{\text{capacity}} = max(capacity)_t - max(capacity)_{t-1}$. It is truncated below by zero for the tobit specification. To keep the notation less burdensome from now on, "*capacity*" refers to "$max(capacity)$". Tobit Specification for first-diffs:

Table 10: Tobit Innovation Decisions in First Differences

	(1)	
	$\Delta(capacity)$	
model		
$qual_{-1}$	-953.9***	(0.000)
$neck_{-1}$	-116.6*	(0.031)
Hrf_{-1}	-1386.2**	(0.003)
$Hrf \cdot qual_{-1}$	1244.2*	(0.016)
constant	518.5*	(0.013)
σ		
constant	459.5***	(0.000)
N	957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Next we consider the Tobit specification $\max^*_{capacity} = X_1\beta + \nu$. The observed $max_{capacity}$ is defined by

$$max_{capacity} = \begin{cases} max^*_{capacity} & \text{if } max^*_{capacity} > max_{capacity,-1} \\ max_{capacity,-1} & \text{otherwise} \end{cases}$$

The above specification is estimated by maximizing the log-likelihood $lnL =$

$$\sum_i \{d_i \left(-ln(\sigma) + ln\phi\left(\frac{\max_{capacity} - X_1\beta}{\sigma}\right)\right) + (1-d_i)ln\left(1 - \Phi\left(\frac{X_1\beta - max_{capacity,-1}}{\sigma}\right)\right)\}.$$

The two Tobit regressions in table 11 use the usual market concentration measure to proxy for the degree of competition. Rather than using the sum of the squared market shares, the two Tobit regressions in table 12 use "con", the concentration of quality shares, defined as the sum of the squared $\frac{qual^i_{-1}}{\sum_{firm\ j}(qual^j_{-1})}$. Here $qual^i_{-1}$ is the lagged value for firm i's normalized quality measure, and the denominator is the total lagged quality measures over all firms.

Since the dependent variable proxies for quality improvement outcome, "con" maybe a better measure of competition. Roughly speaking, "con" captures differentiation among firms due to differences in a quality attribute whereas differences in market shares reflect differences in both production costs and qualities.

Table 11: Tobit Innovation Decisions in Levels

	(1)		(2)	
	capcty		capacity	
eq1				
$neck_{-1}$	-118.9*	(0.025)	-117.1*	(0.026)
$qual_{-1}$	-1002.5***	(0.000)	-964.9***	(0.000)
Hrf_{-1}	-1362.6**	(0.003)	-1307.8**	(0.004)
$Hrf \cdot qual_{-1}$	1278.8*	(0.012)	1062.0*	(0.042)
$capacity_{-1}$	1.086***	(0.000)	1.086***	(0.000)
$share_{-1}$			189.5	(0.113)
constant	511.6*	(0.012)	474.0*	(0.020)
σ_1				
constant	449.5***	(0.000)	448.4***	(0.000)
N	957		957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficients on lagged neck suggest that firms that are less differentiated from its competitors have incentives to engage in R&D investments aimed at "escaping competition". Intuitively, as in Aghion et al (2005), innovation incentives depend on the difference between preinnovation and postinnovation rents and closeness to one's neighbor in the product space leads to erosions of preinnovation rents. The coefficient on qual indicates that it is more difficult for frontier firms with higher qual to extend the frontier than it is for laggards to imitate.

Holding fix a firm's qual and ignoring the potential countervailing effects of $neck_{-1}$ and $qual_{-1}$, the net effect of product market competition is given by $Hrf_{-1} + Hrf \cdot qual + -1$. For the left-hand side regressions measuring product innnovation incentives, since $coeff\,(Hrf_{-1}) + coeff\,(Hrf \cdot qual_{-1}) < 0$ and the difference from zero is highly statistically significant, all firms innovate more as product market competition increases or Hrf decreases. However, fixing the degree of product market competition, the positive coefficient on $Hrf \cdot qual_{-1}$ indicates that leaders have greater incentive to innovate than laggards. The differential in incentives increases as the degree of product market competition decreases or as the market shares of the frontier firm increase.

Table 12: Tobit Innovation Decisions in Levels

	(1)		(2)	
	capacity		capacity	
eq1				
$neck_{-1}$	-127.2*	(0.017)	-128.6*	(0.015)
$qual_{-1}$	-1198.4***	(0.000)	-1222.4***	(0.000)
con_{-1}	-2236.5***	(0.001)	-2316.4***	(0.000)
$con \cdot qual_{-1}$	2201.9**	(0.001)	2045.5**	(0.003)
$capacity_{-1}$	1.089***	(0.000)	1.089***	(0.000)
$share_{-1}$			247.2*	(0.044)
constant	678.7**	(0.002)	690.6**	(0.002)
σ_1				
constant	450.2***	(0.000)	448.6***	(0.000)
N	957		957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The observations are consistent with some of the predictions from the Athey and Schmutzler (2001) framework for firms maximizing static profits. Recall from the discussion in section 2.1, the firm's own incremental returns to investing is increasing in one's own state and decreasing in in any opponent's initial state. The players' actions are strategic substitutes where the negative impact of a competitor's improvement on a firm's own profit is weakly greater for higher levels of own investment . Individually, the first two factors encourage leaders to innovate more than laggards. Taken together with the third factor, the three factors strengthen the incentives of leaders to innovate more than laggards.

The observation that laggards innovate more as product market competition increases can also be fit into the framework from section 2.1. Suppose we fix $qual_L$ for a laggard. Roughly, increased product market competition is correlated with decreasing the techonological lead the leaders hold over $qual_L$. The relative state of the laggards is improved. This is consistent with the laggard innovating more if we assume the $qual_L$'s opponents are myopic or discount the future sufficiently.

Accounting for the dynamic incentives of firms complicate the discussion. As discussed in "Conceptual framework" section 2.2, there is possible incentive for the leaders to innovate more as product market competition increases in order to prevent displacement by lagging competitors. Leading firms offering higher capacities have incentives to invest in even greater capacities in order to maintain or to further increase their markups an market shares. Using Hrf or con to proxy for product market competition delivers the same predictions for the

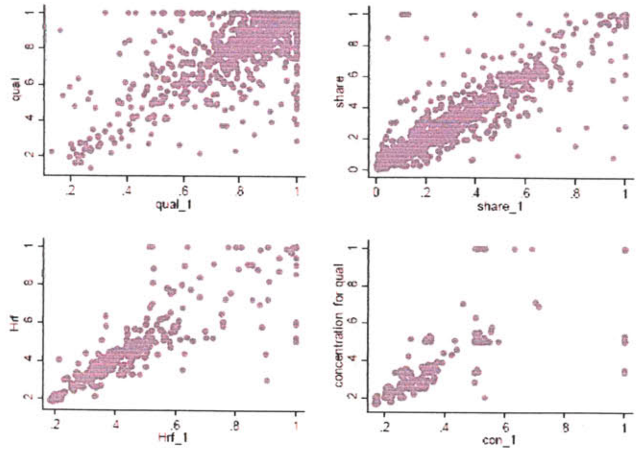


Figure 1: Market Condition Variables Plotted Against Lagged Values

small fraction of firms at the frontier. Since $coeff(con_{-1}) + coeff(con \cdot qual_{-1}) < 0$ for firms with $qual_{-1}$ closest to 1 and the difference from zero is highly statistically significant, the frontier firms innovate less as product market competition decreases. Using the regressors Hrf and $Hrf \cdot qual_{-1}$ also suggests that those frontier firms will innovate more as competition intensifies.

The positive coefficient on $Hrf \cdot qual_{-1}$ and $con \cdot qual_{-1}$ are also consistent with our discussion of the potential complementarities between product and process innovations in section 2.3. Quality improvements and cost reductions may be complementary through their complementarities with the quantity produced. Holding fix process innovations which we do not directly observe at this point, if product innovation shifts the demand curve outward enough, we should also observe that product innovation and market shares are positively related. This is consistent with the positive coefficient on $Hrf \cdot qual_{-1}$. Although a correlation of 0.38 is not strong, qual and market share are positively correlated in our data. Morever, market shares and quals are also highly correlated with their own lagged values. Firms with larger $share_{t-1}$ expect to have larger $share_t$. Hence holding Hrf fixed, the potential complementarity between market shares and product innnovations is another force encouraging firms with higher values of qual to innovate more.

We include lagged share $share_{-1}$ to explicitly control for complementarities between market shares and product innovation as discussed in section 2.3. Firms offering higher qual tend to have larger market shares in more concentrated market. For the regression estimates shown column (2) of table 11, $share_{-1}$ is not significant at the 5% level. However, $share_{-1}$ is statistically significant at the 5% level in coulmn (2) of table 12. Note that firms offering higher qual tend to have larger market shares as the market concentration increases. For our sample of 957 observations, the correlation between $con \cdot qual$ and share is 0.749, and the the correlation between $Hrf \cdot qual$ and share is 0.734.

Measuring innovation and the market condition variables using average capacities in place of maximum capacities delivers similar predictions. For the specifications in table 13, the dependent variable is a firm's units-weighted average capacity for a fixed rpm and the independent variables $neck_{-1}$ and $qual_{-1}$ are calculated using average capacities. Note that higher values of $capacity - capacity_{-1}$ could be the result of lower cost or higher quality. A firm that does not introduce hard drives at higher capacities may still have positive values of $capacity - capacity_{-1}$ by investing in cost reduction and offering lower prices for its high-end products than its competitors. Compared to the specifications above, the coefficient estimates below are less statistically significant, suggesting using average capacities does not measure product innovation incentives as well. Agreeing with the specifications above, the positive coefficient on Hrf_{-1} indicates that firms with low values of $qual_{-1}$ innovate more as the market concentration decreases, and firms with higher qual's have greater incentives to innovate for the same Hrf_{-1}. As $Hrf \cdot qual_{-1} + Hrf_{-1} > 0$ for the firms with the largest values of qual, the coefficient estimates suggest that firms with the largest values of qual increase their average capacities as Hrf increases. Since changes in average capacities reflect the overall effects of product and process innovations, the firms with the largest market shares could be engaging in more cost-reduction or quality improvement as the market concentration increases.

Table 13: Tobit Estimates for Innovation Decisions

	(1) capacity		(2) capacity	
eq1				
$neck_{-1}$	-10.96	(0.170)	-10.39	(0.193)
$qual_{-1}$	-71.81*	(0.016)	-66.83*	(0.026)
Hrf_{-1}	-93.84	(0.089)	-88.10	(0.112)
$Hrf \cdot qual_{-1}$	99.32	(0.102)	80.61	(0.198)
$capacity_{-1}$	1.123***	(0.000)	1.124***	(0.000)
$share_{-1}$			14.37	(0.195)
constant	50.17	(0.057)	45.47	(0.088)
σ_1				
constant	60.31***	(0.000)	60.38***	(0.000)
N	957		957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Recall that R & D for a fixed RPM in a given market may both benefit from and contribute to R & D for other RPMs and other markets. We add to the base case specification by considering how investment decision for a given RPM or market responds to market conditions for other RPMs or other markets. At this stage, we have not recovered the structural parameters α_T and α_D describing the degree of technology transfers across markets or rpms in equations 5 and 6. However, we can still investigate, in a reduced-form way, the impact of other markets or RPMs on the optimal investment behavior of firms in equilibrium.

Relating Investment Decisions Across Markets

Since HDD manufacturers operate in multiple markets with technological spillovers across markets, it is reasonable to suspect that firms account for the benefits of R&D efforts in outside markets when making investment decisions in each market.

Define $\Delta_{capacity}$ to be a firm's change in maximum capacities between two periods. A firm's investment decisions $(\Delta^i_{capacity}, \Delta^j_{capacity})$ in a pair of technologically similar markets (i, j) can be described by

$$\begin{aligned} \Delta^i_{capacity} &= \gamma_1 \Delta^j_{capacity} + X_i\beta_1 + \epsilon_i \\ \Delta^j_{capacity} &= \gamma_2 \Delta^i_{capacity} + X_j\beta_2 + \epsilon_j \end{aligned} \tag{13}$$

where γ_1 and γ_2 measure the extent of spill-over benefits across markets.
The firm's joint decisions imply that

$$\begin{aligned} \Delta_i &= X_i\beta_1 + X_j(\beta_2 \frac{\gamma_1}{(1-\gamma_1\gamma_2)}) + \nu_i \\ \Delta_j &= X_j\beta_2 + X_i(\beta_1 \frac{\gamma_2}{1-\gamma_1\gamma_2}) + \nu_j \end{aligned} \tag{14}$$

If either γ_1 or $\gamma_2 \neq 0$, then the errors $\nu_i = \gamma_1\epsilon_j + \epsilon_i$ and $\nu_j = \gamma_2\epsilon_i + \epsilon_j$ are correlated.

We consider the matched market pairs (Desktop 3.5, CE 3.5), (Mobile 2.5, CE 2.5), and (MOBILE 1.8, CE 1.8) for drives with the same rpm. Below we display the estimates for $\Delta_{capacity} = X_1\beta + X_{2,-1}\alpha + \nu$. X_1 is a vector of lagged market condition variables, and $X_{2,-1}$ is $\{\mathbb{I}_{\text{market 2}} * \text{lagged market conditions in market 2}\}$ where $\mathbb{I}_{\text{market 2}}$ is a dummy for offering the same rpm hard drive in a matched market.

Table 15 displays the estimates for the tobit specification $\max^*_{capacity} = X_1\beta + X2_1\alpha + \nu$, where the observed $max_{capacity}$ is defined by

$$max_{capacity} = \begin{cases} max^*_{capacity} & \text{if } max^*_{capacity} > max_{capacity,-1} \\ max_{capacity,-1} & \text{otherwise} \end{cases}$$

Table 14: Capacity Improvement Decisions Across Markets

	(1)	
	$\Delta(capacity)$	
model		
$qual_{-1}$	-902.7***	(0.000)
$neck_{-1}$	-119.6*	(0.027)
Hrf_{-1}	-1111.1*	(0.015)
$Hrf \cdot qual_{-1}$	1032.0*	(0.044)
$qual_{2,-1}$	268.4**	(0.003)
$neck_{2,-1}$	-43.79	(0.566)
$Hrf_{2,-1}$	637.4*	(0.019)
$Hrf \cdot qual_{2,-1}$	-1039.4**	(0.003)
constant	374.0	(0.071)
σ		
constant	450.7***	(0.000)
N	957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Tobit Estimates for Capacity Investment Decisions Across Markets

	(1)		(2)	
	capacity		capacity	
eq1				
$neck_{-1}$	-118.9*	(0.025)	-120.9*	(0.024)
$qual_{-1}$	-1002.5***	(0.000)	-932.3***	(0.000)
Hrf_{-1}	-1362.6**	(0.003)	-1113.4*	(0.014)
$Hrf \cdot qual_{-1}$	1278.8*	(0.012)	1063.0*	(0.036)
$capacity_{-1}$	1.086***	(0.000)	1.051***	(0.000)
$neck_{2,-1}$			-43.44	(0.566)
$qual_{2,-1}$			247.3**	(0.007)
$Hrf_{2,-1}$			598.1*	(0.027)
$Hrf \cdot qual_{2,-1}$			-979.3**	(0.005)
constant	511.6*	(0.012)	381.0	(0.063)
σ_1				
constant	449.5***	(0.000)	445.6***	(0.000)
N	957		957	
lrtest χ^2			11.56	
lrtest df			4	
lrtest p			0.0209	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimating the above via ML, a Wald $\chi^2(4)$ test for the joint significance of the $X_{2,-1}$ coefficients gives the test statistics 11.11 with a p-value of 0.0253. The coefficient estimates are recorded in column (2) of table 15. If positive spillovers across markets is a significant determinant of investment decisions in individual markets, one expects that the coefficients of the $X_{2,-1}$ variables will have the same sign as the X_1 variables. However, the coefficients of *qual*, *Hrf*, and *Hrf * qual* for the outside market are individually significant but have the opposite signs from their X_1 counterparts. One possibility is that if it is costly to incorporate capacity improvements in all markets, firms will allocate their R & D expenditure to the market where the highest returns are expected. All else equal, the probability of observing a given increase of $\Delta_{capacity}$ is lower for a firm with $\mathbb{I}_{\text{market } 2}$ if the firm is incentivized to innovate in the other market as well.

Next restrict our sample to observations where the firm participates in both markets from the matched market pair (Desktop 3.5, CE 3.5), (Mobile 2.5, CE 2.5), or (MOBILE 1.8, CE 1.8). As displayed in column (2) of table 16, the coefficients of $X_{2,-1}$ are no longer significant.

An alternative specification which captures spillovers across markets is the bivariate tobit

$$\begin{aligned}
\Delta(capacity)_i &= X_j\beta_2\frac{\gamma_1}{(1-\gamma_1\gamma_2)} + X_i\beta_1\frac{1}{1-\gamma_1\gamma_2} + \nu_i = X_i\theta_1 + X_j\theta_2 + \nu_i \\
\Delta(capacity)_j &= X_j\beta_2\frac{1}{1-\gamma_1\gamma_2} + X_i\beta_1\frac{\gamma_2}{(1-\gamma_1\gamma_2)} + \nu_j = X_j\tilde{\theta}_2 + X_i\tilde{\theta}_1 + \nu_j \qquad (15)
\end{aligned}$$

with ν_i and ν_j being correlated.

The above specification follows from

$$\begin{aligned}
\Delta(capacity)_i &= \gamma_1\Delta(capacity)_j + X_i\beta_1 + \epsilon_i \\
\Delta(capacity)_j &= \gamma_2\Delta(capacity)_i + X_j\beta_2 + \epsilon_j. \qquad (16)
\end{aligned}$$

The change in maximum capacity, $\Delta(capacity)$, is bounded below by 0. Denote $d_i = \mathbb{I}_{\Delta(capacity)_i>0}$ and $d_j = \mathbb{I}_{\Delta(capacity)_j>0}$.

The likelihood for the bivariate tobit is the product of the following terms:

$$\left[\phi\left(\frac{\Delta(capacity)_j - \left(X_i\tilde{\theta}_1 + X_j\tilde{\theta}_2\right)}{\sigma_j}\right)\cdot\phi\left(\frac{\Delta(capacity)_i - [(X_i\theta_1+X_j\theta_2) + \frac{\rho\sigma_i}{\sigma_j}\left(\Delta(capacity)_j - \left(X_i\tilde{\theta}_1+X_j\tilde{\theta}_2\right)\right)]}{\sigma_i(1-\rho^2)^{1/2}}\right)\right]^{d_i=1,d_j=1}$$

$$\left[\phi\left(\frac{\Delta(capacity)_i - (X_j\theta_2 + X_i\theta_1)}{\sigma_i}\right)\cdot\Phi\left(\frac{-[(X_i\tilde{\theta}_1+X_j\tilde{\theta}_2) + \frac{\rho\sigma_j}{\sigma_i}(\Delta(capacity)_i - (X_j\theta_2+X_i\theta_1))]}{\sigma_j(1-\rho^2)^{1/2}}\right)\right]^{d_i=1,d_j=0}$$

$$\left[\phi\left(\frac{\Delta(capacity)_j - \left(X_i\tilde{\theta}_1 + X_j\tilde{\theta}_2\right)}{\sigma_j}\right)\cdot\Phi\left(\frac{-[(X_j\theta_2+X_i\theta_1) + \frac{\rho\sigma_i}{\sigma_j}\left(\Delta(capacity)_j - \left(X_i\tilde{\theta}_1+X_j\tilde{\theta}_2\right)\right)]}{\sigma_i(1-\rho^2)^{1/2}}\right)\right]^{d_i=0,d_j=1}$$

$$\left[binormalcdf\left(\frac{-(X_i\theta_1+X_j\theta_2)}{\sigma_j}, \frac{-\left(X_j\tilde{\theta}_2+X_i\tilde{\theta}_1\right)}{\sigma_i}, \rho\right)\right]^{d_i=0,d_j=0}$$

Table 16: Tobit Estimates for Capacity Investment Decisions Across Markets

	(1)		(2)	
	capacity		capacity	
eq1				
$neck_{-1}$	6.976	(0.932)	5.218	(0.950)
$qual_{-1}$	-1487.0***	(0.000)	-1347.7***	(0.000)
Hrf_{-1}	-2091.9**	(0.005)	-1628.6*	(0.034)
$Hrf \cdot qual_{-1}$	2124.5**	(0.010)	1694.3*	(0.044)
$capacity_{-1}$	1.071***	(0.000)	1.061***	(0.000)
$neck_{2,-1}$			-32.55	(0.711)
$qual_{2,-1}$			311.2	(0.385)
$Hrf_{2,-1}$			737.5	(0.328)
$Hrf \cdot qual_{2,-1}$			-1149.0	(0.173)
constant	855.4**	(0.005)	544.8	(0.211)
σ_1				
constant	503.4***	(0.000)	501.9***	(0.000)
N	551		551	
lrtest χ^2			5.414	
lrtest df			4	
lrtest p			0.247	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the regression output table 17 , equation 1 is $\Delta(capacity)_i = X_i\theta_1 + X_j\theta_2 + \nu_i$ where the vector of var_{11}'s corresponds to X_i and the vector of $var2_{11}$s denotes X_j. Similarly for equation 2, the var_{12}'s are own lagged market condition variables and the $var2_{12}$'s describe the outside market.

For the market pairs Desktop 3.5, CE 3.5, Mobile 2.5, CE 2.5, and Mobile 1.8, CE 1.8, equation 1 is estimated for the Desktop and Mobile markets in which consumers have greater willingness to pay for capacity improvements than they do in the CE submarkets. Model 2 imposes no restrictions on the coefficients across equations. Model 3 is the specification

$$\begin{aligned} \Delta(capacity)_i &= X_i\theta_1 + X_j\tilde{\theta}_2 \cdot \alpha_D + \nu_i \\ \Delta(capacity)_j &= X_j\tilde{\theta}_2 + X_i\theta_1 \cdot \alpha_R + \nu_j. \end{aligned} \tag{17}$$

Note that although the parameter estimate for neither α_D nor α_R is statistically significant, the estimated α_D is larger than α_R. This is expected since the observations for equation 1 are from markets with greater demand for higher capacities. Capacities in Desktop 3.5, Mobile 2.5, and Mobile 1.8 drives tend to be higher than those in CE 3.5, CE 2.5, and CE 1.8 respectively.

A $\chi^2(9)$ Wald test for the joint significance of $var2_{11}$, $var2_{12}$, and rho from model 2 gives a p-value of 0.299. A $\chi^2(3)$ Wald test that alphaR, alphaD, and rho are zero for the restricted model returns a p-value of 0.325 for the test statistic 3.468. For the joint specification, one does not have sufficient evidence that a firm's product innovation decision in each market depends on the value of innovations in another market.

Determinants of Investment Decisions Across RPMs

Since drives at different rpms may be imperfect substitutes for consumers, the firms may be concerned that upgrading the capacities of drives at one rpm would cannabilize the market share of the other rpm drives. When the difference in capacities between products at different rpms is smaller, the drives may become closer competitors. Firms are concerned about the erosion of their price-cost margins. For example, recall the benchmark model of vertical product differentiation where the market is covered. Firms 1 and 2 producing goods of qualities s_1 and s_2 with $s_2 > s_1$. Firms face demand from consumers with tastes distributed uniform $[\underline{\theta}, \overline{\theta}]$. When the consumers' preferences are described by $\theta s - p$ and $\overline{\theta} \geq 2\underline{\theta}$, the two firms' profits under price competition are given by $\pi^1(s_1, s_2) = (\overline{\theta} - 2\underline{\theta})^2(s_2 - s_1)/9$ and $\pi^2(s_1, s_2) = (2\overline{\theta} - \underline{\theta})^2(s_2 - s_1)/9$. Rather than having 2 firms, think of a single firm offering two drives at different rpms. For the moment disregard quality differences due to differences in rpm. The quality differential $s_2 - s_1$ represents differences in capacities between the drives at the two different rpms. Since the profit earned by both drives are higher when the capacity difference is greater, holding fix the higher capacity, the firm does not have an incentive to update the lower capacity. Doing so just triggers rougher price competition. The situation described is too stark partly because disk drive firms engage in technological

Table 17: Bivariate Tobit Estimates for Innovation Decisions Across Markets

	(1)	(2)	(3)
	$\Delta(capacity)$	$\Delta(capacity)$	$\Delta(capacity)$
eq1			
$qual_{11}$	-1368.8*	-956.8	-1012.3
	(0.013)	(0.093)	(0.082)
$neck_{11}$	138.4	48.39	113.5
	(0.353)	(0.749)	(0.436)
Hrf_{11}	-2556.1	-869.6	-1838.8
	(0.066)	(0.579)	(0.214)
$Hrf \cdot qual_{11}$	1991.4	318.3	1065.4
	(0.198)	(0.852)	(0.518)
$qual2_{11}$		870.5	
		(0.157)	
$neck2_{11}$		-94.18	
		(0.490)	
$Hrf2_{11}$		1858.9	
		(0.118)	
$Hrf \cdot quaL2_{11}$		-2708.7	
		(0.058)	
constant	914.0	-8.295	798.2
	(0.057)	(0.991)	(0.112)
eq2			
$qual_{12}$	-1091.8*	-1067.1	-643.6
	(0.043)	(0.052)	(0.306)
$neck_{12}$	-26.91	18.47	-24.01
	(0.805)	(0.872)	(0.824)
Hrf_{12}	-937.9	-638.7	-68.53
	(0.360)	(0.547)	(0.951)
$Hrf \cdot qual_{12}$	849.0	814.8	-133.5
	(0.468)	(0.501)	(0.919)
$qual2_{12}$		203.1	
		(0.732)	
$neck2_{12}$		64.28	
		(0.649)	
$Hrf2_{12}$		-386.4	
		(0.820)	
$Hrf \cdot qual2_{12}$		-258.0	
		(0.886)	
constant	496.4	343.9	185.0
	(0.275)	(0.628)	(0.730)
σ_1			
constant	558.6***	548.3***	561.0***
	(0.000)	(0.000)	(0.000)
σ_2			
constant	474.8***	470.1***	477.0***
	(0.000)	(0.000)	(0.000)
atan_rho			
constant	-0.308	-0.339	-0.375
	(0.208)	(0.193)	(0.157)
α_R			
constant			0.254
			(0.286)
α_D			
constant			0.385
			(0.336)
N	264	264	264

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

races and the market is covered by more than one firm. Still, for a multiproduct firm offering drives at different rpms, price competition from the higher capacity rpm may dampen the firm's incentive to introduce capacity improvements to its lower capacity rpm drive.

Competition from firms offering a different rpm may also impact a firm's incentives to improve the capacity of its own drives. For example, suppose a firm's drives with rpm i are at a much higher capacity than those offered by other firms with rpms i and j. The firm may be enjoying a large markup associated with it capacity differentation. If market conditions for rpm j are conducive to quality upgrades for firms offering rpm j, then the firm with rpm i may be motivated to innovate in order to maintain its lead over the other firms.

First suppose that a firm offers exactly two rpms, "i" and "j". The investment decisions across rpms can be described by the two equations below. In the specification below, rpm "i" has higher maximum capacity than that for "j". The X_i and X_j vectors are the firm's lagged market conditions variables for drives with rpms i and j. The coefficient on maximum capacities for the "outside rpm" , γ_1 and γ_2, measure the net effects of technological spillovers and potential cannbalization across rpms. For the lower capacity rpm, "j", the positive effect of technological transfers across rpms may counteract the potential business-stealing effect described previously. The vector $\tilde{X}_j$ consists of the explanatory variables $qual_j$, Hrf_j, and $Hrf * qual_j$. The variable $qual_j$ controls for potential informational leakage across firms. A firm offering rpm i may glean some of the technological know-how from frontier firms with rpm j. On the other hand, Hrf_j and $Hrf * qual_j$ measure the impact of competition from firms offering rpm j on a firm's incentives to improve the capacity of its own drives with rpm i. We omit $neck_j$ from $\tilde{X}_j$. Recall that smaller values of $neck_j$, or closeness of a firm's rpm j frontier to its competitors, induce innovation incentive by reducing the preinnovation rents for rpm j drives. Hence $neck_j$ should only affect the firm's decision-making regarding rpm i through its effects on capacity j.

In the specification below, X_i and X_j are the lagged market conditions which summarize the firm's own state variables for drives with rpms i and j. Define $X_i = [capacity_{i,-1}\ qual_{i,-1}\ neck_{i,-1}\ Hrf_{i,-1}\ Hrf * qual_{i,-1}]$ and similarly for X_j. We think of the firm's decision-making as being

$$
\begin{aligned}
capacity_i &= capacity_j \gamma_1 + X_i \beta_1^1 + [qual_{j,-1}\ Hrf_{j,-1}\ Hrf * qual_{j,-1}]\beta_2^1 + \epsilon_i \\
capacity_j &= capacity_i \gamma_2 + [qual_{i,-1}\ Hrf_{i,-1}\ Hrf * qual_{i,-1}]\beta_1^2 + X_j \beta_2^2 + \epsilon_j \qquad (18)
\end{aligned}
$$

Use $\tilde{X}_i$ to denote the vector $[qual_{i,-1}\ Hrf_{i,-1}\ Hrf * qual_{i,-1}]$. Let $\tilde{\beta}_1^1$ be the coefficients of $qual_{i,-1}, Hrf_{i,-1}$, and $Hrf * qual_{i,-1}$, taken to be the same as their respective coefficients from β_1^1. The reduced form equations are:

$$\begin{aligned}
capacity_i &= \tilde{X}_i\left(\tilde{\beta}_1^1 + \left(\frac{\gamma_1\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_1^1 + \frac{\gamma_1}{1-\gamma_1\gamma_2}\beta_1^2\right)\right) + [capacity_{i,-1}\ neck_{i,-1}]\left(\tilde{\beta}_1^1 + \frac{\gamma_1\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_1^1\right) \\
&+\tilde{X}_j\left(\frac{1}{1-\gamma_1\gamma_2}\beta_2^1 + \frac{\gamma_1}{1-\gamma_1\gamma_2}\tilde{\beta}_2^2\right) + [capacity_{j,-1}\ neck_{j,-1}]\left(\frac{\gamma_1}{1-\gamma_1\gamma_2}\tilde{\beta}_2^2\right) + \nu_i \\
capacity_j &= \tilde{X}_j\left(\tilde{\beta}_2^2 + \left(\frac{\gamma_1\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_2^2 + \frac{\gamma_2}{1-\gamma_1\gamma_2}\beta_2^1\right)\right) + [capacity_{j,-1}\ neck_{j,-1}]\left(\tilde{\beta}_2^2 + \frac{\gamma_1\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_2^2\right) \\
&+\tilde{X}_i\left(\frac{\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_1^1 + \frac{1}{1-\gamma_1\gamma_2}\beta_1^2\right) + [capacity_{i,-1}\ neck_{i,-1}]\left(\frac{\gamma_2}{1-\gamma_1\gamma_2}\tilde{\beta}_1^1\right) + \nu_j \qquad (19)
\end{aligned}$$

with

$$\begin{aligned}
\nu_i &= \frac{1}{1-\gamma_1\gamma_2}\epsilon_i + \frac{\gamma_1}{1-\gamma_1\gamma_2}\epsilon_j \\
\nu_j &= \frac{\gamma_2}{1-\gamma_1\gamma_2}\epsilon_i + \frac{1}{1-\gamma_1\gamma_2}\epsilon_j.
\end{aligned}$$

Assume that $\beta_1^1 = \beta_2^2$ and that they are the same across all firms. In our data set, we observe many firms, especially those serving the 2.5 inch Mobile submarket, offering drives with 3 different rpms in the same quarter. We consider the following tobit specification, modified from the reduced form equations described above. The subscript "j" now stands for the "outside capacity", taken to be the firm's average maximum capacity for its other rpms. The RHS firm and market characteristics variables are also taken to be the units-weighted averages over the other rpms.

$$\begin{aligned}
capacity_i \quad &= X_i\beta + X_i\cdot\left(\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}\geq\text{outside capacity}\}}\right)\theta_1 \\
&+X_j\cdot\left(\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}\geq\text{outside capacity}\}}\right)\theta_2 \\
&+X_i\cdot\left(\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}<\text{outside capacity}\}}\right)\theta_3 \\
&+X_j\cdot\left(\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}<\text{outside capacity}\}}\right)\theta_4 + \epsilon_i \qquad (20)
\end{aligned}$$

The correlation matrix in table 4.2 is for the restricted sample of firms that offer at least two rpms in a participating submarket. "2" denotes the "outside" rpm or averages over outside rpms in the same submarket. The low correlations between $qual_{-1}$ and $qual_{2,-1}$ and $neck_{-1}$ and $neck_{2,-1}$ do not suggest that a firm's technological positions are similar across rpms.

Estimating specification 20 via maximal likelihood, none of the interaction terms are individually significant. A test for the joint significance of $\theta_1, \theta_2, \theta_3$, and θ_4 gives a p-value of 0.574 from the $\chi^2(19)$ statistics.

Below we consider an alternative ad-hoc specification. Here *capacity* and *capacity*$_{-1}$ are observed values of maximum recorded capacities for the same rpm over two consecutive time

	qual_1	$neck_{-1}$	Hrf_{-1}	Hrf_qual_1	$qual_{2,-1}$	$neck_{2,-1}$	$Hrf_{2,-1}$	$Hrf \cdot qual_{2,-1}$
$qual_{-1}$	1							
$neck_{-1}$	-0.3831	1						
Hrf_{-1}	0.0973	-0.1818	1					
$Hrf \cdot qual_{-1}$	0.5327	-0.3308	0.8766	1				
$qual_{2,-1}$	0.0297	-0.0519	-0.0787	-0.0474	1			
$neck_{2,-1}$	-0.0355	0.0566	0.0521	0.0202	-0.3839	1		
$Hrf_{2,-1}$	-0.0931	0.0985	0.2515	0.1612	0.0328	-0.127	1	
$Hrf \cdot qual_{2,-1}$	-0.0629	0.0533	0.1828	0.1206	0.5114	-0.2962	0.8561	1

periods. Again, the "outside capacity" ("2") is taken to be the firm's average maximum capacity for its other rpms.

$$\begin{aligned} capacity &= capacity_{-1} + X_1\beta_1 \\ &\quad + X_2 \cdot \left(\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}\geq\text{outside capacity}\}}\beta_2 + \mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}<\text{outside capacity}\}}\beta_3\right) \\ &\quad + \epsilon \end{aligned} \tag{21}$$

Roughly speaking, when capacity > outside capacity, product differentiation motives and technological spill-over motives may both lead to the prediction that the coefficients on X_2 and X_1 should have the same sign. When capacity < outside capacity, the net effect on the coefficient of X_2 is unclear due to the two opposing effects.

The dependent variable is a firm's maximum capacity in a submarket for a given rpm. The control variables $X_2 \cdot (\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}\geq\text{outside capacity}\}})$ are $qual_{2,-1}$, $neck_{2,-1}$, $Hrf_{2,-1}$, and $Hrf \cdot qual_{2,-1}$. Controls $X_2 \cdot (\mathbb{I}_{\{\text{multiple rpms}\}}\mathbb{I}_{\{\text{capacity}<\text{outside capacity}\}})$ are $qual_{3,-1}$, $neck_{3,-1}$, $Hrf_{3,-1}$, and $Hrf \cdot qual_{3,-1}$. For firms offering more than 2 rpms, the market characteristics vector X_2 is taken to be the units-weighted average over the other rpms.

The coefficient estimates reported in column 1 of table 18 do not seem to provide support for product differentiation motives. However, note that the coefficient on $qual_{3,-1}$ $(\mathbb{I}_{\{\text{multiple rpms}\}}$ $\mathbb{I}_{\{\text{capacity}<\text{outside capacity}\}})$ in column 2 of table 18 is statistically significant. A possible interpretation supporting spillover effects is as follows. Recall that "qual" is defined as the technology rank for a given rpm in a market and that for firms with non-zero values of $qual_3$, the maximum capacity in the "inside market" is smaller than the maximum capacity in the "outside market". To fix ideas, suppose firms a and b with $qual_3^b > qual_3^a$ have the same value of $qual_{-1}$ in the "inside market" but different non-zero values of $qual_3$'s. The significantly negative coefficient of $qual_3$ suggests that the firm a with more similar maximum capacities in the inside and outside market is more likely to improve the capacities of its drives in the inside market. This might result if it is more likely to spread The development costs for denser drives across multiple rpms when drives at different rpms are more similar in capacity. Since the cost of innovation is lower for each drive, it becomes more profitable for the firm to innovate across the rpms.

Table 18: Estimates of Multi-Product Firm's Innovation Decisions Across RPMs

	(1)		(2)	
	capacity		capacity	
eq1				
$capacity_{-1}$	1.057***	(0.000)	1.053***	(0.000)
$neck_{-1}$	-169.5**	(0.002)	-169.2**	(0.002)
$qual_{-1}$	-1050.9***	(0.000)	-1038.7***	(0.000)
Hrf_{-1}	-1216.6**	(0.007)	-1278.2**	(0.004)
$Hrf \cdot qual_{-1}$	1182.4*	(0.018)	1210.4*	(0.015)
$neck_{2,-1}$	123.7	(0.334)		
$qual_{2,-1}$	153.2	(0.222)		
$Hrf_{2,-1}$	-31.57	(0.913)		
$Hrf \cdot qual_{2,-1}$	-382.3	(0.346)		
$neck_{3,-1}$	150.5	(0.286)		
$qual_{3,-1}$	-181.4	(0.197)	-265.1***	(0.000)
$Hrf_{3,-1}$	-268.6	(0.627)		
$Hrf \cdot qual_{3,-1}$	-79.26	(0.909)		
constant	604.3**	(0.003)	615.5**	(0.002)
σ_1				
constant	440.2***	(0.000)	442.4***	(0.000)
N	957		957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Next we measure drive performances using average rather than maximum capacities. Table 19 reports the estimates from the tobit specification using average capacities in place of max capacities. The signs on $qual_2$ and $qual_3$ are now both significant at the 10% level. Their signs are both consistent with the above story about the presence of spillover effects.

RPM Transition Decisions

We now consider possible factors affecting a firm's decision to initiate or terminate a product line with a given rpm. For the probit estimates displayed in table 20, "entry" is equal to 1 in

Table 19: Estimates of Quality Improvement Decisions

	(1)	
	average capacity	
eq1		
$capacity_{-1}$	1.120***	(0.000)
$neck_{-1}$	-11.51	(0.157)
$qual_{-1}$	-73.75*	(0.013)
Hrf_{-1}	-88.96	(0.107)
$Hrf \cdot qual_{-1}$	92.76	(0.127)
$qual_{2,-1}$	14.35*	(0.015)
$qual_{3,-1}$	-10.53	(0.074)
constant	51.66*	(0.049)
σ_1		
constant	59.99***	(0.000)
N	957	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the first quarter when a firm commercially introduces disk drives at a higher rpm. "Exit" is 1 for the quarter when a firm remains in a market but stops offering drives at a lower rpm. There are 21 entries and 18 exits in the post-05 data from TRENDFOCUS.

The "$X_{2,-1}$" explanatory variables describe market conditions for the firm's other rpm(s) in the previous quarter, and the "X_{-1}" explanatory variables are for the same rpm in the previous quarter. If we think of upgrading to a higher rpm as being an example of an "innovation", then the estimated coefficients of the "$X_{2,-1}$" variables could be given the same interpretations as before. Except for the statistically insignificant coefficient on the degree of neck-and-neckness from the previous quarter, the other "$X_{2,-1}$" variables in probit regression for entries have the expected signs. The "X_{-1}" covariates, on the other hand, do not seem to be statistically significant determinants of exit decisions. While it may be appropriate to think of both rpm upgrades and capacity improvements as measures of R & D outcomes for firms engaged in technology races, exit decisions may be less affected by innovation incentives. Decisions to maintain older product lines may be motivated by other reasons such as price discrimination. For example, firms such as Seagate and Samsung have continued to offer 5400 rpm drives at a lower price for several quarters post-05 despite offering 7200 rpms throughout the post-05 time period. The 5400 rpm drives tend to have lower capacities than 7200 rpms drives but are popular with the most price-sensitive consumers.

Table 20: Probit Estimates for RPM Transition Decisions

	(1)		(2)	
	entry		exit	
$qual_{2,-1}$	-2.287***	(0.000)		
$neck_{2,-1}$	0.00759	(0.983)		
$Hrf_{2,-1}$	-4.238**	(0.002)		
$Hrf \cdot qual_{2,-1}$	4.674**	(0.003)		
$qual_{-1}$			-1.240	(0.367)
$neck_{-1}$			-1.141	(0.097)
Hrf_{-1}			1.659	(0.404)
$Hrf \cdot qual_{-1}$			-0.207	(0.927)
constant	0.216	(0.662)	-1.583	(0.178)
N	486		811	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Estimating R & D Expenditure

One approach to estimating the R & D cost functions and recovering the parameters governing spillover effects is by using the optimality conditions for the equilibrium behavior of firms. One finds a set of structural parameters in the process and product R&D cost functions that best matches the observed production and investment outcomes of the firms. For example, in BBL, assuming that the firms' decisions are optimal given their beliefs, the estimate parameters from the second stage are those which minimizes violations of the optimality conditions.

An alternative approach which does not require using the equilibrium behavior of the firms is to estimate the parameters in the R&D cost function that best matches reported R&D expenditures from Compustat. The sample moment condition is constructed using only firms mostly specializing in the disk drive business. Recall from section 4.2, given the observed capacity improvements and industry states, we recover each firm's "targeted" innovation levels. To help fix ideas, suppose that firm f serving markets $\{m\}_m$ offers only one rpm in each market. Its innovation policies are $i_f = \{i_{f1}, i_{f2}, \ldots, i_{fm}, \ldots\}$ for $i_{fm} = X_{fm}\hat{\beta}$, where X_{fm} is the vector of market condition covariates and $\hat{\beta}$ the estimated coefficients from the tobit specification displayed in table 4.2.

Given productivity shocks $\{\epsilon_{fm}\}_m$ and $\{\varepsilon_{fm}\}_m$, assume the cost of product innovation of firm f in market m is $C_{fm}(i_f; \{\epsilon_{fm}, \varepsilon_{fm}\}_m) = (\beta_1 + \beta_2 qual_{fm} + \epsilon_{fm})i_{fm} - \theta \sum_{\tilde{m} \neq m}(\beta_1 + \beta_2 qual_{f\tilde{m}} + \epsilon_{f\tilde{m}})i_{f\tilde{m}} + \varepsilon_{fm}$. Here "$qual_{fm}$", measuring firm f's distance from market m's frontier, is defined earlier in section 4.2. One expects firm f's product R&D cost in market m to be increasing in the target innovation level i_{fm}. In addition, since β_2 captures the technological tranfers among firm, we expect β_2 to be negative since the firms that lag behind can more easily improve upgrade the capacities of their drives. The parameter θ should be positive to account for technological spillovers across markets. The firm's total R&D cost is the sum of product R&D costs expressed above and process R&D cost $A_T(mc_{fm(t-1)} - mc_{fmt})$ over all markets m.

In order to use the R & D cost data from Compustat, we are limited to the firms Seagate, WDC, and Maxtor (acquired by Seagate in 2006). The remaining firms are conglomerates with multiple business lines. A potential concern is that the estimated cost function parameters will have large variances because we have few relevant observations and because we need to account for the extra variance that comes from the simulation errors $\{\epsilon_{fm}\}_{f,m}$.

5 Conclusion

We take the first steps in estimating a dynamic model of competition in the hard disk drive industry which will hopefully provide insights into what drives product and process innovation choices. We plan to examine the interaction between product and process R & D decisions in a framework that allows for the multi-product nature of firms, knowledge spillovers across a firm's own product line and spill-over from the R & D of rival firms.

After having estimated the model parameters, we plan to simulate the effects of a merger on the competition and innovation in the industry. Disk drive experts inform us that prior to 2011, disk drive manufacturers exited the industry because they were laggards in the technology race or because they could not match the continuing firms in terms of productive efficiency. However, the merger between Hitachi and Western Digital in 2011 is the first case of a deviation from the historic pattern of exits and acquisitions. In terms of total unit shipments, WD and HGST are the largest and third largest hard drive manufacturers. Also, both were profitable at the time of the merger. One of our goals for future research is to perform counterfactual simulation of the Western Digital-Hitachi merger. The net effect of mergers on the overall rate of technological progress depends on a variety of factors with potentially offsetting effects on innovation incentives. Moreover, our reduced-form estimates suggest that, depending on the relative technological positions, firms respond differently to changes in market conditions such as market concentration and crowdedness in the product space. Holding other factors constant, firms closer to the quality frontier tends to exert more R & D effort in product innovation than those farther away from the frontier. In order to properly evaluate the effects of mergers on technological change, we will also need to account for cost-reduction incentives and potential complementarities between process and production innovations. Assuming Bertrand price competition, the estimated demand in this paper will allow us to recover the marginal costs of production and measure how process innovation incentives respond to changes in market conditions.

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