Exploration and Exploitation in the Presence of Network Externalities

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This paper examines the conditions under which exploration of a new, incompatible technology is conducive to firm growth in the presence of network externalities. In particular, this study is motivated by the divergent evolutions of the PC and the workstation markets in response to a new technology: reduced instruction set computing (RISC). In the PC market, Intel has developed new microprocessors by maintaining compatibility with the established architecture, whereas it was radically replaced by RISC in the workstation market. History indicates that unlike the PC market, the workstation market consisted of a large number of power users, who are less sensitive to compatibility than ordinary users. Our numerical analysis indicates that the exploration of a new, incompatible technology is more likely to increase the chance of firm growth when there are a substantial number of power users or when a new technology is introduced before an established technology takes off.
(*Network Externalities; Exploration and Exploitation; Innovation; Technology*)

1. Introduction

Strategic choice at the time of technological change has been a focus of interest at the intersections of diverse fields such as technology management, organizational learning, and industrial organization economics. When a new technology offers uncertain opportunities, a firm can choose to exploit an existing technology to ensure its immediate survival. Alternatively, it can opt to explore the new technology, which may provide better opportunities in the long run (Levinthal and March 1981, Nelson and Winter 1982). Exploration of this sort, however, requires scare resources that could be better used for enhancing the firm's market position through the refinement of the existing technology. Thus, a strategic dilemma arises from the tension between the exploration of new opportunities and the exploitation of old opportunities, which has been considered as a fundamental problem for adaptive systems (Holland 1975, 1992, March 1991).

This study addresses such a dilemma in the presence of network externalities. The emergence of a superior but incompatible technology often exacerbates the dilemma for incumbents, because the adoption of it can increase the chance of enhancing the performance of their products, but the incompatibility sharply reduces customer benefits due to network effects (Shapiro and Varian 1999). Intel faced this sort of dilemma in the early 1990s, when the reduced instruction set computing (RISC) architecture challenged the complex instruction set computing (CISC) technology, which was the architecture for

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Intel's prior microprocessors such as the 286 and 386. If Intel had adopted RISC, the firm might have dramatically improved performance of its next generation microprocessors. But they would not have offered a great deal of benefits to customers who had many kinds of software applications or files compatible with the prior microprocessors. Grove (1996, p. 105) articulated Intel's dilemma at the time:

> The issue concerned the heart of our company, the microprocessor business... [The issue] demanded a decision immediately, and the decision was crucial. On the one hand, if the RISC trend represented a strategic inflection point and we didn't take appropriate action, our life as a microprocessor leader would be short. On the other hand, the 386's fantastic momentum seemed sure to extend into the 486 and perhaps even to future generations of microprocessors [based on the CISC architecture]. Should we abandon a good thing, which for now at least was a sure thing, and lower ourselves back down into a competitive battle with the other RISC architectures, a battle in which we had no particular advantage?

The theoretical literature presents two contrasting managerial prescriptions to cope with this dilemma. Studies of technology management and organizational learning have emphasized the exploration of new technological possibilities by pointing out the potential downfall of firms in the absence of exploration. The exploitation of an existing technology is often portrayed as a myopic choice, which may eventually cause firms to suffer from technological exhaustion. On the other hand, research on network externalities has stressed the difficulty of gaining a footing by a new technology under network effects. The commonly accepted view has been that each customer receives greater benefits—the larger is the installed base of the selected technology. Thus, when an existing technology has built up a large installed base, customers tend to turn away from a new, incompatible technology. Apparently, this suggests that firms are more likely to prosper by exploiting the existing technology.

In the eyes of laymen, the above two streams of research offer seemingly inconsistent managerial prescriptions. Indeed, the history of the computer industry illustrates the complexity of prescriptions. Throughout the 1990s, the workstation market and the PC market followed divergent evolutionary paths in response to the new RISC technology. In the workstation market, RISC replaced CISC (Khazam and Mowery 1996). Sun prospered by effectively shifting its technology base from CISC to RISC, while Digital Equipment quickly lost its market share by delaying the adoption of RISC (Utterback 1994). In contrast, Intel, in the PC market, has continued to prosper by making its new products compatible with the CISC architecture (Botticelli et al. 1998). Apparently, ensuring network benefits turned out to be more important than enhancing performance in the PC market. A question is: Under what circumstances should incumbents explore a new, incompatible technology?

We address this question by modeling the situation of two competing technologies in the presence of network externalities. Although the differences between our model and prior work on this issue will be fully discussed in the next section, the main distinctions arise in two primary aspects. First, we evaluate the viability of exploring alternative possibilities by modeling the evolution of the whole system. The methodological stance here is close in spirit to Nelson and Winter (1977, 1982), Lant and Mezias (1990, 1992), Mezias and Glynn (1993), and Mezias and Eisner (1997). A benefit of this approach is that one need not assume that buyers and sellers know the future consequences of their choices. Thus far, standard economic analysis with this assumption has not been able to address how new, incompatible technologies are successfully introduced under uncertainty (Katz and Shapiro 1994). We believe our approach can fill this gap. Second, we classify two types of customers: *power users* and *light users*. Power users are defined to be much less sensitive to compatibility than light users. Prior work on network externalities assumed that all the users are equally sensitive to compatibility, ignoring the role of power users in the market's transition to a new technology.

The incorporation of the two factors permits us to resolve the seeming inconsistency described above. We find that the exploitation strategy is more likely to increase the chance of firm growth when a majority of customers are not power users, or when demand for an old technology has been escalated. But when there are a substantial number of power users or when a new technology emerges before such an escalation of demand, the exploration strategy is more likely to be effective. We believe that sorting out conditions in this way can give new insights to managers who face a strategic dilemma between exploration and exploitation.

The organization of this paper is as follows. The second section reviews the literature germane to the central issue. The third section introduces a formal model. The fourth section shows the results of computer simulations. Then, we discuss the main findings and their implications.

2. Literature Review

This section reviews the relevant literature by focusing on exploration and exploitation.

2.1. Learning Myopia Argument vs. Lock-in Argument

As previously mentioned, the literature consists of two seemingly contrasting views concerning our central question: the learning myopia and lock-in arguments.

First, we turn to the learning myopia argument. In the face of radical technological change, the potential downfall of established companies has attracted a great deal of attention in research on technology management (Anderson and Tushman 1990, Henderson and Clark 1990, Christensen 1993, Tripsas 1997) and organizational learning (e.g., Levinthal and March 1981, Levitt and March 1988, Lant and Mezias 1990, 1992, Cohen and Levinthal 1989, Mezias and Glynn 1993, Mezias and Eisner 1997). These streams of research acknowledge that there are gains with respect to experience in a technology. Once a firm accumulates sufficient experience with one technology, it is natural for the firm to be trapped in this technology or to be blinded to alternative opportunities—this phenomenon is labeled "competency trap" by Levitt and March (1988) or "learning myopia" by Levinthal and March (1993).

The literature, however, warns that too much exploitation of the existing technology may lead the firm to be locked out of opportunities in the long run. For example, March (1991, p. 73) noted: "Since long-run intelligence depends on sustaining a reasonable level of exploration, these tendencies to increase exploitation and reduce exploration make adaptive processes potentially self-destructive." This is particularly true when an incremental gain in performance declines with the use of the existing technology. Indeed, research on learning curve (e.g., Argote et al. 1990, Argote and Epple 1990, Epple et al. 1991) has established that such diminishing performance gain over time is prevalent. With this assumption, Lee and Ryu (2002) numerically demonstrated that an undue focus on exploitation eventually leads to technological exhaustion in the market where firms compete for developing new products. The upshot is that firms exploiting the established technology to the exclusion of exploring a new technology are expected to underperform in the long run.

On the other hand, the lock-in argument has focused on the difficulty of gaining a footing by a new, incompatible technology. When a given product is subject to network externalities, its value increases with the number of customers using similar ones or products compatible with it (Shapiro and Varian 1999). Studies have indicated that the presence of a dominant installed base can inhibit innovation due to excess inertia in the buyers' adoption behavior (e.g., Farrell and Saloner 1986, Arthur 1989, 1994). Because there are customers who appreciate compatibility, firms that achieve backward compatibility with existing products can ensure their immediate survival at least. Furthermore, when these firms grow faster and dominate the market, there may be little room for their rivals exploring a new, incompatible technology. This suggests that exploitation could yield a better outcome than exploration.

The seeming inconsistency between the two arguments above can be cast in light of the trade-off between exploration and exploitation. In the presence of network externalities, a choice between exploration and exploitation reflects an underlying tension between performance and compatibility (Shapiro and Varian 1999). Consider a firm contemplating whether to introduce a new, incompatible architecture (e.g., RISC) for future generations of microprocessors. If the firm chooses to explore this architecture, it may greatly improve the performance of its products in the long run. However, many customers may not switch to them, because the new architecture is incompatible with existing software products or files these customers have created. Then, the firm would be exposed to a great risk in the short run.

The firm can reduce this imminent risk by exploiting the existing architecture and by ensuring backward compatibility or network benefits. For example, when Intel introduced the 486, a CISC-based microprocessor, the company was able to attract previous adopters of PCs, who might have shown inertia to switch to an incompatible RISC processor. By introducing the 486, however, Intel had to forego potential stand-alone benefits (e.g., superior price-performance ratio, faster time to market, and scalability) from RISC. What made Intel's strategic choice difficult in the early 1990s was the uncertainty of how the market would respond to the products of its rivals if they were able to widen the performance gap between RISC and CISC microprocessors in the long run. Had there been a road map regarding when network benefits outweigh stand-alone benefits, Intel's decision would have been much easier.

2.2. Network Externalities and Technological Change

Our study also addresses a controversy in the literature on network effects. Despite the popularity of the lock-in argument, critics have argued that many new, incompatible technologies have been somehow successfully introduced (Katz and Shapiro 1994). In particular, Liebowitz and Margolis (1990, 1995) argued that cases of lock-in to inferior technologies are rare in the long history of technological change. These observations raise a question of how the market makes transition between incompatible technology regimes.

In limited situations, the customer lock-in can be mitigated when "converters" are available (David and Bunn 1988). For example, Microsoft Word was introduced after WordPerfect dominated the market. But Microsoft Word was able to attract WordPerfect users because Microsoft Word was supplied with a converter that can translate a WordPerfect file into a Microsoft Word file. An economy could benefit from converters when they are costless and they can perfectly wipe out incompatibilities. Farrell and Saloner (1992), however, argued that in many cases, the tasks to achieve compatibility through converters become more complex and remain costly. Furthermore, conversion often degrades performance. Farrell and Saloner's (1992) analysis showed that the availability of converters could make matters worse if converters are costly and imperfect. Near-perfect converters with small costs can make the aforementioned dilemma disappear. In this paper, we focus on many instances where such converters are infeasible.

Garud and Karnøe (2001) noted that the understanding of Schumpeterian dynamics could throw light on how the market system escapes from lock-in. In particular, they argued that entrepreneurial firms often find ways to develop better technologies and leapfrog dominant firms. Indeed, Becker (1998) observed that monopoly positions due to lock-in tend to be frequently punctuated in high-tech industries where firms race to develop better technologies. Among the few studies that addressed this issue are Farrell and Saloner (1986) and Katz and Shapiro (1992). They found that whether the market is biased for or against new incompatible technologies depends on such variables as the date of new technology introduction, costs of the two technologies, size of the installed base of the incumbent technology, strategic pricing, and so on.

Although the impressive contribution of these studies is evident, they did not take the uncertain aspect of Schumpeterian competition into account. Instead, they resort to economic analysis based on the rationality assumption that buyers and sellers know ex ante what would happen in equilibrium. Had such a complex consequence been known in advance, Intel must not have struggled with the strategic dilemma to begin with. This assumption is rather heroic when there is fundamental uncertainty about technological change and when it is difficult to foresee how adoption patterns emerge over time. Furthermore, the perfect rationality defies the existence of the tension between exploration and exploitation. As a consequence, little is still known about how new, incompatible technologies are successfully introduced in reality (Katz and Shapiro 1994). The computational approach pioneered by Nelson and Winter (1978, 1982) and

Cyert and March (1963) permits us to fill this gap by relaxing the rationality constraint.

In addition, we construct two types of customers: power users and light users. Power users are defined to be less sensitive to compatibility than light users. Power users are also assumed to be keener on new technologies than light users. Thus, power users could be categorized as "technology enthusiasts" or "visionaries" who wish to be first to adopt a new technology (Moore 1991). In the computer industry, power users are sophisticated enough to write code and modify software on their own. Thus, they can easily switch to incompatible hardware platforms by recompiling their own source code (Khazam and Mowery 1996). On the other hand, light users could be categorized as "pragmatists" or "conservatives" who adopt innovations only after seeing the proven track records of their usefulness (Moore 1991). In the computer industry, light users usually do not write their own code and heavily rely on off-the-shelf software applications.[1] Thus, the higher performance of an incompatible computer alone adds little value for them. Much of prior work on network externalities has included the latter in the model but has excluded the former (e.g., Katz and Shapiro 1985, Farrell and Saloner 1986, Arthur 1989). We will show that there is a substantial gain by adding the new concept, power users.

3. Model

We model the dynamics of industry evolution where there are two competing technologies subject to network externalities. Initially, firms develop products based on one technology, and customers begin to adopt these products. Then, a new, competing technology emerges and offers higher potential for improving the performance of new products. However, this technology is incompatible with the existing installed base. In this situation, incumbent firms face the trade-off between compatibility and performance. Firms may choose to exploit the technology in use to ensure backward compatibility with existing products. Alternatively, firms may choose to explore the new technology to sharply increase technological performance at the cost of compatibility. Therefore, firms' strategic choices basically fall into two divergent categories: the exploration strategy vs. the exploitation strategy. Mixed strategies are possible,[2] but the key to our analysis at this point is to sort out conditions under which each ideal strategy is more conducive to the long-term survival of firms.

Figure 1 presents a blueprint about how our model works. It mainly consists of two parts: customer activities in the demand-side dynamics and firm activities in the supply-side dynamics. In the demand side, purchase and repurchase subroutines constitute customer activities. In the supply side, each firm's choice of exploration or exploitation, new product development, and firm growth and exit are three main subroutines of our simulation model. The technical details of these five subroutines will be discussed below.

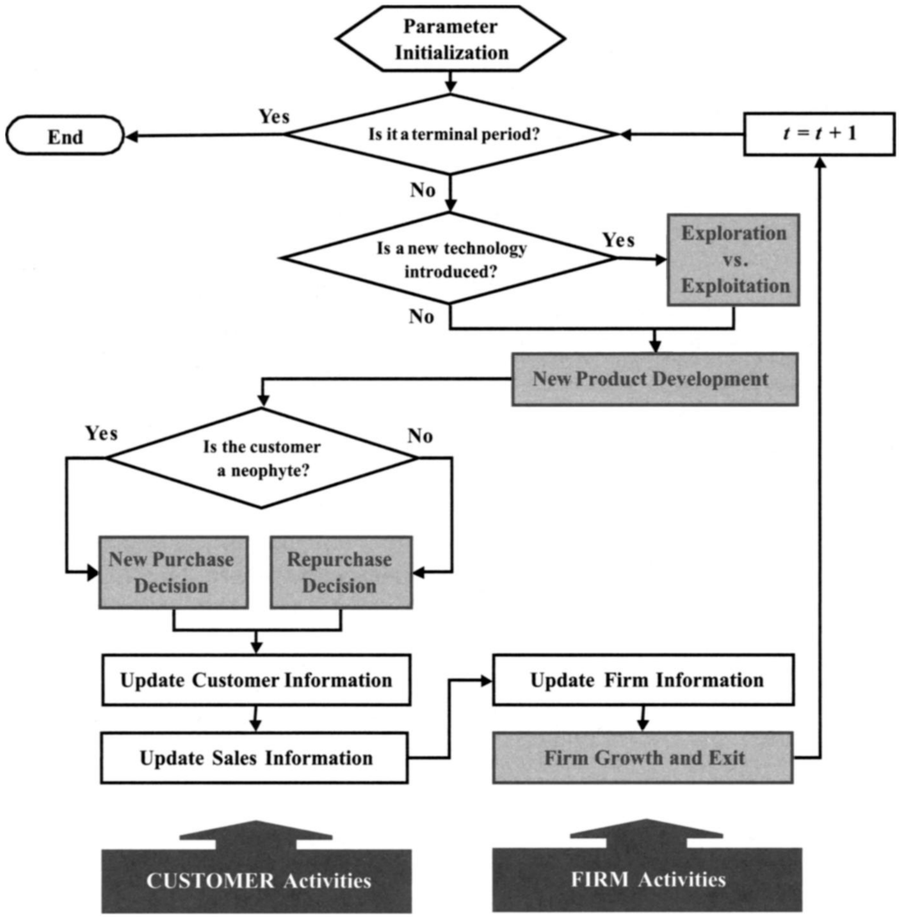
3.1. Demand-Side Dynamics: Product Adoption

First, we turn to customer activities in the demand side. Consider a product characterized by network externalities and incessant improvement of product performance over time. In the computer industry, for example, a microprocessor is subject to network externalities because customer benefits come primarily from its compatibility with software applications. Furthermore, its performance has been improved through technological changes. Thus, adoption dynamics are influenced by network benefits and changes in product performance.

[1] A referee suggested that the recompiling possibility could be considered as the presence of a converter. Then, it should be classified as an imperfect converter because its functionality is user specific. That is, the converter is not available to light users who cannot write and compile their own code, while it is available to power users due to their programming capability.

[2] Lee and Ryu (2002) examined the mixed strategies by assuming that their implementations are not too costly. In some cases, however, mixing exploration with exploitation would be prohibitively expensive. Indeed, Grove (1996, p. 104) noted: "Supporting a microprocessor architecture with all the necessary computer-related products—software, sales and technical supports—takes enormous resources. Even a company like Intel had to strain to do an adequate job with just one architecture."

Figure 1 Simulation Routines for the Model



Purchase and Repurchase Decision. The key to adoption dynamics in our model is the customer's product choice. Each customer buys either one or no unit of a product in each period. Product adoption consists of new purchases and repurchases. New purchases are generated by neophytes who have not yet adopted any product, whereas repurchases are generated by experienced customers.

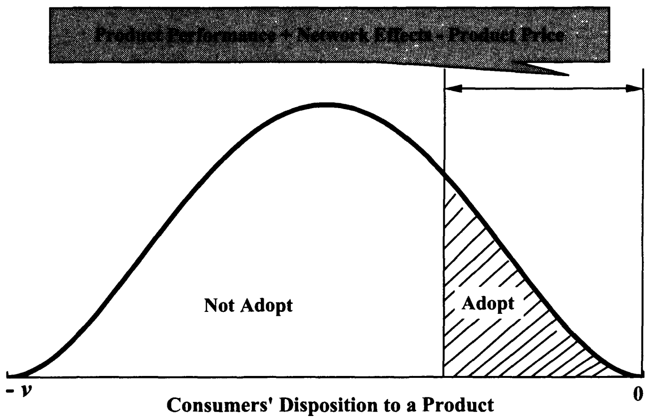
First, consider a process for new purchases. Let S_{it} denote customer i's surplus. She buys one unit of a product if $S_{it} > 0$. When there are more than one product that satisfy this condition, customer i chooses a product to maximize S_{it}. It is determined by the following four components:

$$S_{it} = q_{jt}^k + a_i n_{t-1}^k + d_i - p. \qquad (1)$$

Here, the first component q_{jt}^k represents the performance of the product that firm j produces at time t with technology k ($k \in$ {OLD, NEW}). The second component $a_i n_{t-1}^k$ represents network benefits. Like Arthur (1989) and Farrell and Saloner (1992), we assume that the network benefits grow linearly with the number of adopters.[3] In particular, the term a_i measures customer i's importance to network effects, and n_{t-1}^k is network size for technology k at time $t-1$. The third component d_i represents customer disposition toward new technology adoption. Like much of prior work (e.g., Katz and Shapiro 1985, Farrell and Saloner 1992), we assume d_i to be heterogeneous

[3] We also experiment with a nonlinear function (e.g., a logistic function), and show that dynamic behaviors of our model are not too sensitive to the linearity assumption (see Appendix B).

Figure 2 Consumer Heterogeneity and Product Adoption



among customers. In particular, customer i's timing of adoption depends on the magnitude of d_i as shown in Figure 2. If a customer is an early adopter, the value for d_i will be close to zero, whereas its value for a laggard will be low. This customer heterogeneity is assumed to follow a bell-shaped distribution in Figure 2, which is represented by a beta distribution with shape parameters (β_1, β_2), where $\beta_1 = \beta_2$ and scope parameters $[-v, 0]$.[4] This distributional assumption is widely accepted in the diffusion literature (e.g., Rogers 1995) and the marketing literature (e.g., Moore 1991, 1995). The last component p represents the price of a product. Like Winter (1971) and Arthur (1989), we assume that the price is fixed over time.[5]

Now, let us turn to a process for repurchases. An experienced customer i's surplus is

$$\begin{aligned} S_{it} &= [q_{jt}^k + a_i n_{t-1}^k + d_i] - [q^* + a_i n^* + d_i] - p \\ &= [q_{jt}^k - q^*] + a_i[n_{t-1}^k - n^*] - p, \end{aligned} \tag{2}$$

where q^* and n^* are the performance and the network benefits of the adopted product at time $t^* < t$, respectively.[6] The customer chooses one unit of product j for which (2) is largest. If (2) is not positive for all j, she buys none of the products. Unlike much of prior work (e.g., Katz and Shapiro 1985, Arthur 1989, Farrell and Saloner 1992), this repurchase process in our model allows customers to switch to an incompatible technology.

Note that the high level of network benefits can offset low product performance or vice versa. Thus, an inferior technology may be adopted when network benefits are large. Alternatively, customers may switch to a new technology when stand-alone benefits from q^{NEW} are substantially large. Unlike other models, the stand-alone benefits in our model change over time because product performance q_{jt}^k is the dynamic outcome of firm j's R&D, which will be discussed in the supply-side dynamics.

Another important distinction is that we do not assume that potential adopters know the size of an equilibrium network in advance, whereas this strong assumption is typical in other standard economic models (e.g., Katz and Shapiro 1985, 1992). Along the line of Arthur (1987, 1989), we instead assume that each customer makes a purchase (or repurchase) decision every period by looking at the number of previous adopters.[7]

Demand-Side Inertia. The demand-side inertia previously described is a force that blocks the market's transition to a new, incompatible technology. Due to the presence of this force, some firms choose not to explore a new technology. The source of such inertia in our model is customer benefits arising from the installed base for technology k. So, in the market with M customers, a measure for the demand-side inertia for technology k at time t, ϕ_t^k, is

$$\phi_t^k = \frac{\sum_i a_i n_{t-1}^k}{M}. \tag{3}$$

Power Users vs. Light Users. The customer population consists of two types: *power users* and *light users*. As defined in the previous section, power users

[4] By changing shape parameters β_1 and β_2 of a beta distribution, one can flexibly generate uniform, normal, and skewed distributions (Johnson and Kotz 1970). Our sensitivity analyses indicate that the key results of our model do not depend too much on distributional assumptions.

[5] Although prices for many products, in reality, vary over time, this feature is ignored for simplicity. Thus, our model is more relevant to markets where firms compete on the basis of R&D rather than price.

[6] Note that the second term $a_i[n_{t-1}^k - n^*]$ is zero if the alternative product is compatible with the product in use.

[7] This is the main distinction between a dynamic model and a static model. See Arthur (1987, 1999) for the detailed technical discussion.

are less sensitive to network benefits than light users. That is, $a_p < a_l$, where a_p and a_l denote power users' and light users' network sensitivities. As discussed in the previous section, power users are also early adopters in the diffusion of a new technology, while light users represent a majority of late adopters. This requires that power users' disposition values d_p be represented by values in the upper tail of the beta distribution, while the remainder in the distribution should represent light users.

3.2. Supply-Side Dynamics

We turn now to firm activities in the supply side. Central to our model is how firm j at time t generates a new product associated with q_{jt}^k, which, in turn, shapes firm j's growth. Two generic features of the model are R&D investment, and firm growth and exit, which are adopted from Nelson, and Winter's (1978, 1982) Schumpeterian models. Given these features and the demand-side dynamics, we are concerned with how a firm's choice of technology k affects firm growth and exit processes.

New Product Development. There are two types of costs: (1) R&D cost, and (2) cost for production capacity expansion. We assume that firm j invests R&D cost CR_{jt} to improve its technological capability in each period t. The decision for allocating R&D cost CR_{jt} is determined by the previous period capital, K_{jt-1} such that

$$CR_{jt} = \max(rK_{jt-1}, \tau), \tag{4}$$

where r is the percent of R&D cost on the previous capital and τ is a minimum R&D cost for staying in the industry. The larger the firm is, the more it can invest in improving its technological capability.

The term "technological capability" is used to refer to the ability to develop better performing products. Specifically, let γ_{jt}^k denote firm j's technological capability at time t. We assume that firm j's product performance q_{jt}^k is a random variable, which follows a beta distribution with shape parameters $(\gamma_{jt}^k, \delta^k)$ and scale parameters $[0, w]$. γ_{jt}^k is determined by its cumulative learning in technology in use k, which is assumed to be a function of its cumulative R&D investments (Cohen and Levinthal 1989). Then, it follows that firm j's cumulative investments for technology k increase shape parameter γ_{jt}^k at the following rate:

$$\gamma_{jt}^k = \gamma_{j0}^k + \frac{\sum_{u=0}^{t} CR_{ju}}{\theta^k}, \tag{5}$$

where θ^k specifies the difficulty of assimilation of technology k.

We further assume that q_{jt}^k is monotonically increasing in time as far as the firm stays with technology k. That is,

$$q_{jt}^k = \max(q_{jt}^k, q_{jt-1}^k). \tag{6}$$

The above dynamic equation simply says that firm j sells an improved product at time t only if R&D improves its product performance. Otherwise, the firm will sell the previous product. As firm j invests more in technology k, it becomes better able to utilize its technological potential up to the upper bound u. Firm heterogeneity in product performance results from various degrees of learning with respect to technology k.

There is another type of cost for capacity expansion. Let CP denote the cost of increasing one unit of production capacity. We assume that firm j increases one more unit of its production capacity at period t only if it sold all of its products at period $t-1$. In reality, firms may increase more than one unit of production capacity per period. However, relaxing this assumption would complicate the model without yielding substantially new insights. This simplifying assumption is also adopted in Winter's (1971) evolutionary model. Let PC_{jt} denote firm j's production capacity at period t. Then,

$$PC_{jt} = PC_{j0} + \frac{\sum_{u=0}^{t} CP_{ju}}{CP}. \tag{7}$$

As typical in other models of network externalities, variable costs in our model are ignored for simplicity (e.g., Katz and Shapiro 1985, Kristiansen 1998).

Firm Growth and Exit. The process of firm growth and exit is summarized by the time path of firm capital. The state of firm capital reflects the historical accumulation of revenue less costs over time. Thus, firm j's capital at time $t+1$ is

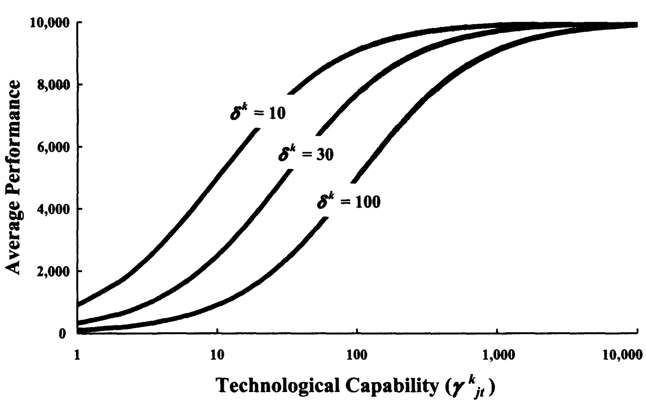
$$K_{jt+1} = K_{jt} - CR_{jt} - CP_{jt} + R_{jt}, \tag{8}$$

where R_{jt} represents firm j's revenue at time t. Firm growth, or capital accumulation, results from positive net incomes from sales of products. Firm j will have positive sales at time t only if the performance of its products satisfies a customer's need, which was previously described by customer i's surplus S_{it}. Here, revenue can increase in two ways. First, the firm can improve the performance of its products through R&D. Second, an increase in network size for the firm's technology further boosts its sales. If a firm constantly fails to satisfy customers' needs and thus has no sales of its products, its capital declines and reaches an absorbing state of insolvency. This happens when its capital is below the minimum R&D cost τ. Thus, we define the condition for exit as $K_{kt} < \tau$.

Exploration vs. Exploitation. The central issue in this paper is a tension between exploration and exploitation, which caused a strategic dilemma for Intel as previously described. Firms with the exploration strategy may benefit from superior performance over time at the cost of backward compatibility, whereas firms with the exploitation strategy may benefit from network externalities at the cost of compelling performance. In our model, the performance improvement of technology k is controlled by a tunable parameter δ^k. The smaller the value of δ, the higher the rate of improvement, as shown in Figure 3.

We assume that the new technology improves at a faster rate than the old technology. That is, $\delta^{\text{NEW}} < \delta^{\text{OLD}}$. However, when a firm first adopts a new technology, it starts from a low level of performance. As far as the firm continues to refine the new technology for a sufficiently long time, it will eventually outperform the old technology. But before it happens, the firm adopting the new technology can be driven out. The simulation results in the next section show when adopting the new technology is advantageous.

Figure 3 **Organizational Learning and Performance Improvement**



4. Results

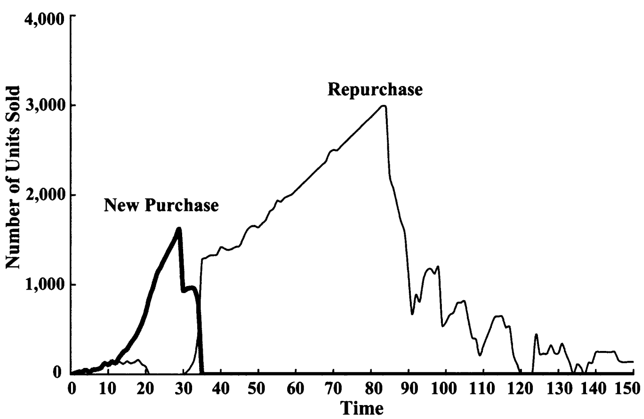
The simulation results here numerically illustrate Schumpeterian competition in the presence of network externalities. We first show the key features of the basic model. Then, we address the central research question by experimenting with selected parameters of the basic model.

4.1. Simulation of the Basic Model

As a starting point, we numerically demonstrate the behavior of the basic model, which favors exploitation over exploration. The basic model is restrictive in the sense that the two key parameters, the proportion of power users in the customer population and the timing of new technology introduction, are fixed. In the next subsection, we experiment with these parameters to show under what conditions firms with exploration outperform the others. The two key parameters in the basic model are set as follows: a new technology emerges at period 30, and there are no power users. The other details of parameter values are in Appendix A.

According to strategic responses to the new technological opportunities at period 30, we classify firms into two groups: (1) the exploration group, and (2) the exploitation group. The two groups pursue an identical strategy based on one technology at the early stage. When a new, incompatible technology emerges at period 30, 500 firms in the exploration group adopt a strategy that switches to the new technology. On the other hand, the other 500 firms in the exploitation group continue to exploit the established technology. The simulation here is to illustrate the underlying dynamics that lead to the performance gap between these two groups. To evaluate the difference in the long-run performance between the two groups, we look for three measures for each group at the end of a simulation run. Two measures are

Figure 4 **Number of Units Sold Over Time: A Typical Simulation Run**



the number of survivors and the average amount of capital. Also, by multiplying the two values together, we develop another performance measure: aggregate capital.

Let us turn to the simulation results of the basic model. Figure 4 shows the number of units sold over time in a typical simulation of the basic model. All new purchases are completed before period 40, and repurchases bolster demand at the later stage of evolution. Figure 4 suggests that demand begins to accelerate before period 20. Figure 5 shows the cumulative number of units sold over time. The dynamics are characterized by a well-known S-shaped curve with roughly three phases: (1) introduction (before period 20: a phase of slow sales growth); (2) takeoff (period 20 to 80: a phase of explosive sales growth); and (3) saturation (after period 80: a phase of a slowdown in sales growth).

In the basic model, the new technology fails to gain a footing as shown in Figure 6. This is closely associated with the installed base of the old technology, which increases along with the number of its adopters as shown in Figure 6. The new technology barely builds up its installed base. The bias toward the existing technology, in turn, affects the performances of the exploration and the exploration strategies. Table 1 shows that the group of firms exploiting the old technology outperform the group of firms exploring the new technology. The two groups have the same numbers of survivors (42 firms) in simulation period 29 just before the exploration group switches to the new technology. It is because there is no difference in strategy between the two groups before period 30. However, at period 100, there are 42 survivors in the exploitation group, whereas there are 23 survivors in the exploration group. Also, there is a substantial difference in the average amount of capital between the two groups after period 40. The average amount of capital for survivors with the exploitation strategy is larger than that for survivors with the exploration strategy.

As shown in the last row of Table 1, product performance is enhanced with a faster rate by the new technology than the old technology until period 50. Yet, since the network benefits far outweigh the benefits associated with technological superiority, the new technology fails to build up its installed base. This is reminiscent of Arthur's (1994, p. 24) informal argument: "[A]n early-start technology may already be locked in, so that a new arrival, although potentially

Figure 5 **Adoption Dynamics: A Typical Simulation Run**

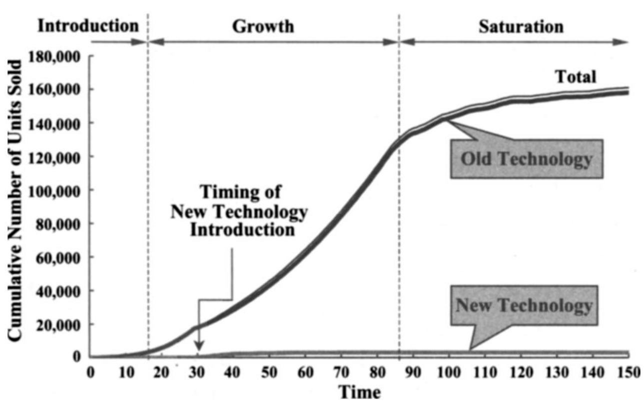


Figure 6 **Dynamics of the Installed Base: A Typical Simulation Run**

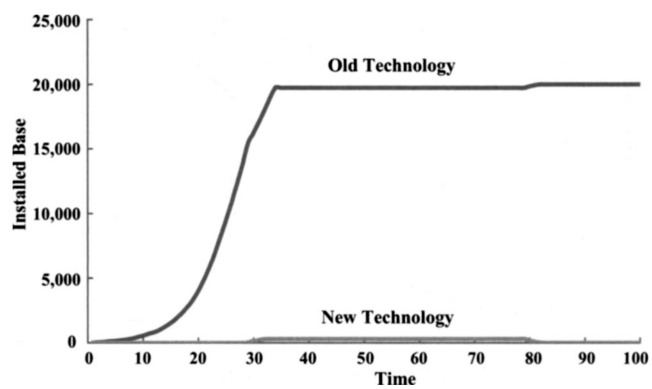


Table 1 Exploitation vs. Exploration: Results of 100 Simulation Runs of the Basic Model

Period of time	1	10	20	29	30	40	50	60	70	80	90	100
Total sales												
Exploitation	8	459	2,788	8,615	9,485	20,537	35,857	55,447	79,305	106,952	125,804	135,076
Exploration	8	477	2,908	8,834	8,834	9,897	10,837	11,357	11,824	12,105	12,195	12,245
Number of survivors												
Exploitation	500	500	45	42	42	42	42	42	42	42	42	42
Exploration	500	500	45	42	42	42	42	42	42	42	32	23
Average capital												
Exploitation	1,000	366	4,182	13,128	14,364	28,538	45,050	62,962	81,711	100,065	97,749	76,873
	(0)	(323)	(3,931)	(6,444)	(6,632)	(8,061)	(8,920)	(9,435)	(9,743)	(10,089)	(24,759)	(38,315)
Exploration	1,000	367	4,686	13,378	14,620	10,812	8,556	6,258	4,744	3,439	2,507	1,692
	(0)	(330)	(4,033)	(6,572)	(6,762)	(6,303)	(6,128)	(4,980)	(3,713)	(2,929)	(2,264)	(1,651)
Installed base												
Exploitation	16	522	4,072	15,815	16,681	19,375	19,696	19,619	19,475	19,423	19,600	19,600
Exploration	16	522	4,072	15,815	0	264	304	381	524	576	400	400
Average performance												
Exploitation	99	810	2,277	4,552	4,844	7,359	8,643	9,222	9,512	9,669	9,759	9,805
	(97)	(198)	(1,003)	(1,686)	(1,665)	(954)	(427)	(206)	(110)	(63)	(43)	(39)
Exploration	99	812	2,325	4,609	3,119	8,063	8,742	8,990	9,115	9,187	9,439	9,568
	(97)	(201)	(1,030)	(1,705)	(1,223)	(871)	(639)	(533)	(476)	(440)	(219)	(120)

Note. Standard deviations are in parentheses.

superior, cannot gain a footing." After period 50, the new technology does not progress as fast as the old technology because the exploration group could not invest in R&D as much as the exploitation group. Note that many firms leave the market before simulation period 20. This happens because many firms run out of their initially endowed capital as they consistently fail to generate positive sales.

4.2. Simulation Experiments

The simulation results of the basic model reassure the popular proposition that exploration of a new technology is not a good idea when the market builds up excess inertia for an old technology. Now, we turn to the central questions: Under what circumstances would the exploration group better perform than the exploitation group? What are the mechanisms that allow the market to overturn such inertia? To answer these questions, we experiment with the two key parameters of the basic model while holding other parameters constant: (1) the timing of the new technology introduction, and (2) the proportion of power users to light users in the customer population. A characteristic feature in the adoption dynamics is the demand-side inertia, which is measured by customer benefits due to network effects. We show that the two parameters affect dynamics of the demand-side inertia. All of the results here were obtained by running the simulation models 100 times.

Timing of New Technology Introduction. First, we report the result of a simulation experiment, which varies the timing of a new technology introduction, given that there are no power users in the market. The result in Figure 7 shows that the timing influences the demand-side inertia. Not surprisingly, the later the new technology emerges, the larger the demand-side inertia gets. In particular, the demand-side inertia seems to dramatically increase after demand for the old technology takes off. Note that demand starts to take off roughly around period 20 (again, see Figures 4 and 5).

Intuitively, the above result seems to be related to the performance of the exploration group and the exploitation group. Table 2 shows that the exploration group clearly beats the exploitation group in terms of survival rate and average capital when the new

Figure 7 Effect of the Timing of New Technology Introduction on Demand-Side Inertia

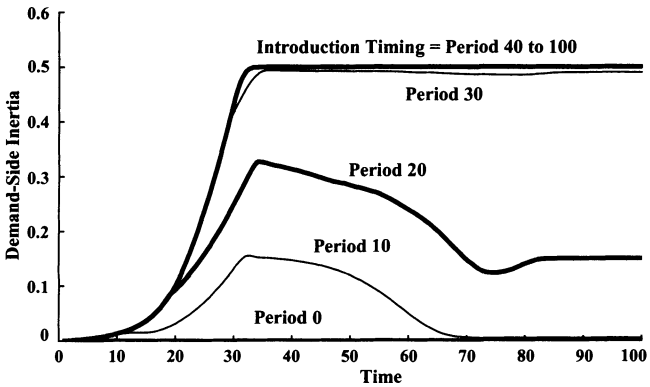
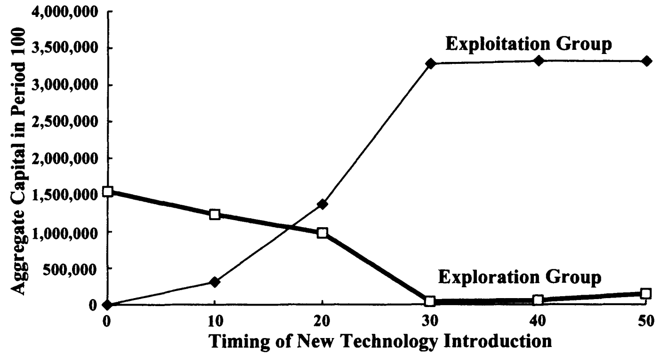


Figure 8 Effect of the Timing of New Technology Introduction on Aggregate Capital



technology is introduced before demand for the established technology takes off (or before period 20). Figure 8 also shows that as long as the new technology emerges before period 20, the aggregate amount of capital of the exploration group is larger than that of the exploitation group. However, the exploitation strategy is more effective when the new technology is introduced after period 20. The exploitation group clearly beats the exploration group in the average amount of capital and the aggregate amount of capital after period 20. As shown in Table 2, the amount of average capital of the exploration group is smaller than that of the exploitation group after period 20. The upshot is that timing of new technology introduction influences the effectiveness of exploration and exploitation.

Proportion of Power Users. We now report the results of a simulation experiment when power users are present in the market. Figure 9 shows that when there are no power users (i.e., when all customers are light users), the demand-side inertia monotonically increases in time until it reaches a plateau and stabilizes around it. On the other hand, when the proportion of power users are above 10%, the inertia systematically decays over time after it reaches a peak. Intuitively, this is possible when the exploration group with compelling performance can take away customers from the exploitation group that uses the old technology. Indeed, the erosion of the old technology's market share is clearly shown in Figure 10. When 10% of the customers are power users, the new technology takes away the market shares from the old technology, eventually cornering the market. The nonmonotonic decay of the inertia in Figure 9, thus is explained by the declining market share of the old technology.

Table 3 and Figure 11 show the proportion of power users against the performance of each group. When

Table 2 Effect of the Timing of New Technology Introduction: Results of 100 Simulation Runs

Period of time	0	10	20	30	40	50
Total sales						
Exploitation	0	44,690	88,948	135,076	134,365	135,418
Exploration	36,016	92,920	65,756	12,245	19,359	34,056
Number of survivors						
Exploitation	0	31	38	42	42	42
Exploration	500	47	30	23	42	42
Average capital						
Exploitation	0	9,890	35,941	76,873	79,915	78,395
Exploration	3,091	26,178	32,451	1,692	1,324	3,491

Figure 9 Effect of the Proportion of Power Users on Demand-Side Inertia

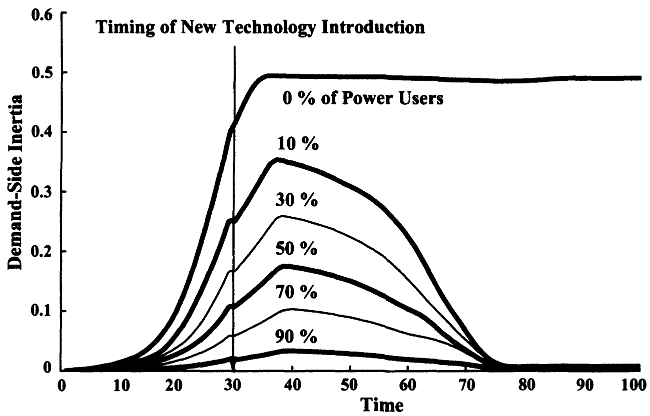
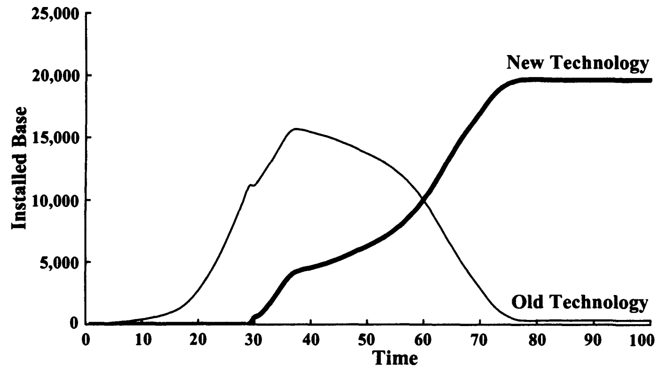


Figure 10 Dynamics of the Installed Base in the Presence of 10% of Power Users



the proportion of power users is less than 10%, the exploitation group has a greater amount of average capital than does the exploration group. When the proportion is greater than 10%, the exploration group always outperforms the exploitation group. These results indicate that the exploitation strategy is more effective when light users dominate the market. On the other hand, when power users represent a substantial proportion of the customer population, the exploration strategy is more effective. These results suggest that the power users play a critical role in sustaining new incompatible technologies.

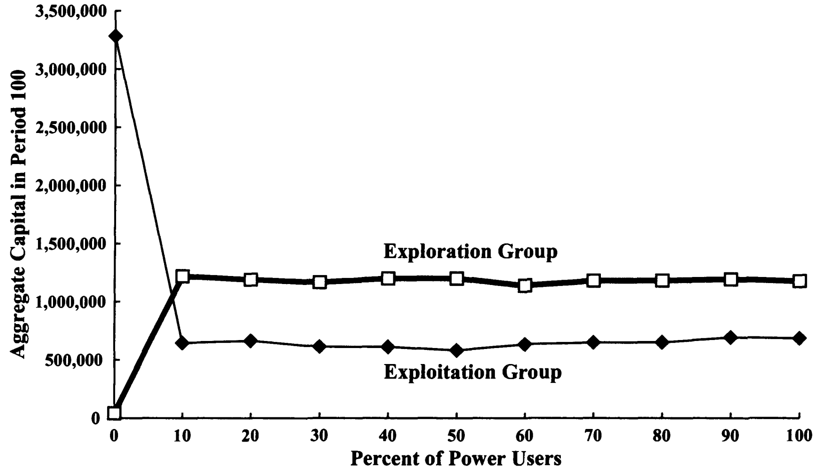
Sensitivity Analysis. We conducted additional analyses to assess how sensitive our results are to the assumption of linear network effects. In particular, we adopted a nonlinear effects function as shown in Figure B.1. The results of this analysis are shown in Appendix B. The main findings do not change much. The only notable result is that the exploration group cannot outperform the exploitation group unless the proportion of power users is greater than 30%. In the case of linear effects, the exploration group did better when this proportion was greater than 10%. The effectiveness of the exploration strategy requires additional power users in the nonlinear case because a new technology builds up network effects slowly at the beginning as shown in Figure B.1.

In addition, we ran a number of variations on key parameters such as technological opportunity for a new technology, customer disposition distribution, price, and network sensitivity (see Appendix B). Although the details of the results are not reported here, we found that our main findings are rather robust with respect to moderate changes in these parameter values.

Table 3 Effect of the Proportion of Power Users: Result of 100 Simulation Runs

Percent of power users	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Total sales											
Exploitation	135,076	59,237	58,959	57,388	56,366	54,545	56,779	57,771	57,918	59,330	58,557
Exploration	12,245	73,573	71,108	69,266	69,742	69,625	67,590	66,890	68,351	68,125	68,147
Number of survivors											
Exploitation	42	29	28	28	28	27	28	27	27	27	27
Exploration	23	30	29	27	28	28	26	26	27	27	27
Average capital											
Exploitation	76,873	22,289	23,739	21,894	21,844	21,548	22,681	24,065	24,134	25,648	25,416
Exploration	1,692	40,640	41,018	43,201	42,820	42,859	43,756	45,389	43,762	44,173	43,524

Figure 11 Effect of Proportion of Power Users on Aggregate Capital



5. Discussions and Conclusion

This study sorted out conditions under which exploration of a new, incompatible technology is conducive to firm growth in the presence of network externalities. Our findings resolve the seeming inconsistency between the learning myopia argument and the lock-in argument in the literature. The learning myopia argument emphasizes the importance of exploration for the long-term growth of the firm. Our findings support this argument when power users represent a substantial portion of the customer population or when a new technology emerges before demand for an established technology has been escalated. In these cases, the exploitation of the established technology to the exclusion of exploring a new technology is more likely to result in underperformance as expected in the literature (Levitt and March 1988, March 1991, Levinthal and March 1993, Lee and Ryu 2002). The results are consistent with the historical context of the workstation market when RISC, a new incompatible technology, challenged incumbents. Digital Equipment Corporation delayed the adoption of RISC and quickly lost its market share, whereas Sun benefited from aggressively exploring RISC. In this market, there are many power users who are able to write code and modify software on their own. The incompatibility of hardware platforms causes a small problem for them because they can easily recompile their source code. Thus, the market's migration to the new technology appeared to be smooth.

On the other hand, the lock-in argument emphasized the difficulty of establishing a market position with a new incompatible technology. Our findings support this argument when a new technology emerges after demand for an old technology has been escalated or when there are few or no power users in the customer population. In these cases, the demand evolution will show excess inertia with respect to an existing technology, because customer benefits due to network effects significantly outweigh stand-alone benefits from performance. Therefore, there is little room for the growth of firms that explore a new, incompatible technology. It turned out that Intel's strategic choice to maintain compatibility in the PC industry was sensible. Indeed, *PC Week*'s 1988 survey indicated that compatibility in the PC industry was the most important criterion for buying a PC (Yoffie 1994). In general, this market has been dominated by light users who are not sophisticated enough to write code or to modify software to run on RISC platforms. Thus, the higher performance of incompatible, RISC machines adds little value for them.

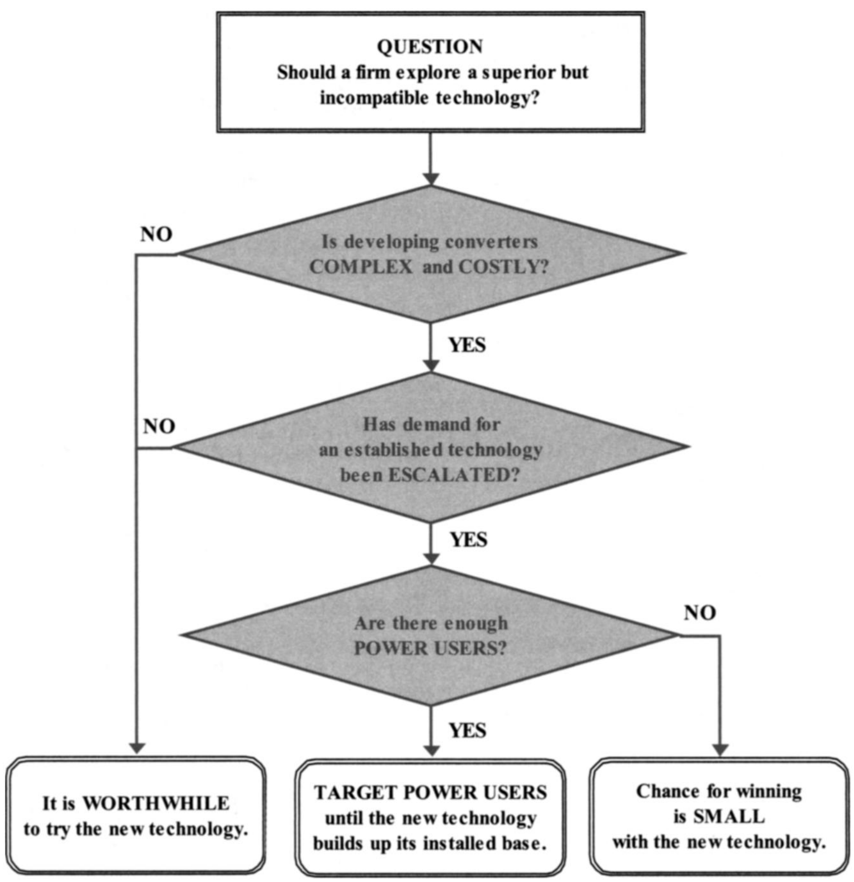
Our findings also speak to the puzzling debate regarding the lock-in argument. Despite the argument's popularity, Liebowitz and Margolis (1990, 1995) and Katz and Shapiro (1994) pointed out that historically, many new, incompatible technologies have been successfully introduced. For example, in the PC market, MS-DOS was introduced after CP/M-80 became established as the industry standard operating system (Steffens 1994). But MS-DOS was somehow able to subsequently corner the market.

Our model provides potential explanations for this puzzle when converters cannot be available. Apparently, MS-DOS was able to beat CP/M-80 in the 1980s, partly because it was the early market where technology enthusiasts or power users were more likely to enter and where the demand-side inertia should have been low. Steffens' (1994, p. 375) historical analysis is suggestive of this point: "Initially, under CP/M-80, applications software had been fairly restricted in its scope." Usually, light users, who are pragmatists or conservatives, do not enter such an immature market with limited applications available (Moore 1991).

In addition, there is a more general issue that has applicability beyond the computer industry. When a product has lock-in properties, heterogeneity among users in the extent to which they value those properties will tend to make exploration more feasible. The essence of this argument does not depend too much on the specific industry context we considered. To assess the relationship between consumer heterogeneity and efficacy of exploration, we manipulated a fraction of power users in the customer population. As previously discussed, one can consider power users as "early adopters" in Rogers' (1995) term or "technology enthusiasts" in Moore's (1991) term. In the marketing literature, these are fairly generic terms that have wide applicability.

Now, let us turn to managerial implications of our findings. Exploration vs. exploitation causes a serious strategic dilemma as illustrated in the Intel case (Grove 1996). This study provides such a firm with a strategic guideline, which is summarized in the decision tree in Figure 12. First, the firm should consider whether it could develop a converter that is not

Figure 12 Decision Tree for Technological Choice



complex and costly. If this is possible, it is a good idea for the firm to explore the new technology, because the converter will mitigate problems associated with incompatibility. If developing it is too complex or costly, the firm should consider the next question: Has the adoption of an old technology been escalated? If the answer is no, the demand-side inertia should be low and it is worthwhile to explore a new technology.

If the answer is yes, the firm should next consider whether there are enough power users. Because they are individuals with low reservation prices by definition (i.e., they are willing to pay a substantial price for a new technology), the size of this group determines staying power of firms exploring the new technology. If the company can find only a few or no power users, it is not advisable to explore the new technology. If there are a reasonably sufficient number of them, they will sponsor the firm's R&D investments as well as other operating costs for the firm to stay in business. At this stage, it may be a good idea for the firm to stay focused on the power user niche. As the firm builds up a substantial installed base over time, it may leverage this base more aggressively to penetrate into a light user segment, or often the mass market. Our suggestion here is similar to what Moore (1995, p. 27) called "bowling alley marketing" analogy: "Each niche is like a bowling pin, something that can be knocked over in itself but can also help knock over one or more additional pins."

However, the advice at this point is crude at best and needs to be further examined. Our findings are simply the logical consequences of the assumptions that we made. Although many of our assumptions are consistent with the historical contexts of the computer industry, our findings are drawn from the analysis under the restricted parameters. When some of our assumptions are violated, or when one tries to apply our findings beyond the contexts we considered, the validity of our findings is uncertain. Also, there could be other unknown mechanisms (e.g., different topologies of customer connectivity) that affect dynamics of the demand-side inertia. This possibility points to the opportunities for future studies.

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Appendix A: Parameters for the Basic Simulation Model
Our central assumption is that there exists a tension between exploration and exploitation, which can lead to a strategic dilemma for managers. To construct such a situation in a computational model, we need to fine tune three main parameters, q_{jt}^{New}, q_{jt}^{Old}, and $a_i n_{t-1}^k$. Because network benefits and performance effects jointly create this tension in our model, neither of them alone should always dominate when a customer chooses a product. If performance effects dominate, i.e., the new technology is far superior to the old technology (or $q_{jt}^{\text{NEW}} \gg q_{jt}^{\text{OLD}}$), almost all customers will choose the new technology. On the other hand, if the new technology is not superior to the old technology (i.e., $q_{jt}^{\text{NEW}} \le q_{jt}^{\text{OLD}}$), there is no need for firms to worry about the new technology. Our basic strategy for choosing the ranges for the related parameters is to exclude these two extreme cases, where the tension between exploration and exploitation should be minimal. In our model, q_{jt}^{NEW} and q_{jt}^{OLD} are stochastic outcomes from firm j's R&D, which are controlled by δ^{NEW} and δ^{OLD}. Thus, given $a_i n_{t-1}^k$, tuning the relative magnitudes of the latter two parameters can construct the situation we wish to consider. The values of all the parameters for our basic simulation model are shown below.

Demand-Side Parameters

Size of customer population: $M = 20{,}000$.

Shape parameters for the distribution of customer disposition d_i: $(\beta_1, \beta_2) = (3, 3)$.

Scope parameters for the distribution of customer disposition d_i: $[-v, 0] = [-10{,}000, 0]$.

Power users' sensitivity to compatibility: $a_p = 0.0$.

Light users' sensitivity to compatibility: $a_l = 0.5$.

Product price: $p = 100$.

Supply-Side Parameters

Initial number of firms: $N = 1{,}000$.

Initial capital: $K_{\cdot 0} = 1{,}000$.

Percent of R&D cost on the previous capital: $r = 0.05$.

Minimum R&D cost for staying in the industry: $\tau = 50$.

Initial production capacity: $PC_{\cdot 0} = 5$.

Cost of increasing one unit of production capacity: $CP = 50$.

Technology scope: $[0, w] = [0, 10{,}000]$.

Initial shape of old technology: $(\gamma_{\cdot 0}^{\text{OLD}}, \delta^{\text{OLD}}) = (0, 100)$.

Initial shape of new technology: $(\gamma_{\cdot 0}^{\text{NEW}}, \delta^{\text{NEW}}) = (0, 30)$.

Difficulty of assimilation of technology k: $\theta^k = 50$.

Appendix B: Sensitivity Analysis
Nonlinear Network Effects. We assessed the sensitivity of our results to the choice of a network effects function. As illustrated in

Figure B.1 Nonlinear Network Effects Function

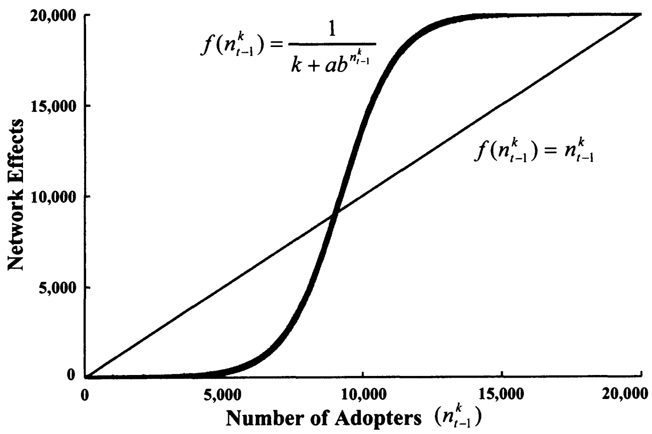


Figure B.1, we used a nonlinear effects function, $a_i f(n_{t-1}^k)$, where

$$f(n_{t-1}^k) = \frac{1}{k + ab^{n_{t-1}^k}}.$$

In particular, we tuned the values of the function's parameters with $k = 0.00005$, $a = 0.5$, and $b = 0.999$. Note that the dynamics of the system are nonlinear regardless of whether we use the linear or the nonlinear effect functions. That is, dynamics of either case show that network effects for the old technology are initially somewhat limited until a critical mass is reached. After this point, the effects become more pronounced until they approach some asymptote. The results of the sensitivity analysis are shown in Figures B.2 and B.3. Our main findings do not substantially change with the nonlinear network effects variation.

Variation in Technological Opportunity for a New Technology. We ran a variation in technological opportunity for a new technology (δ^{NEW}). Given $\delta^{OLD} = 100$, we experimented with $\delta^{NEW} = 10, 20, 30, 40$, and 50. Sensitivity analysis shows that little substantive change was detected. Our findings are rather robust with this variation.

Figure B.2 Effect of the Timing of New Technology Introduction on Aggregate Capital: Average over 100 Trials with the Nonlinear Network Effects

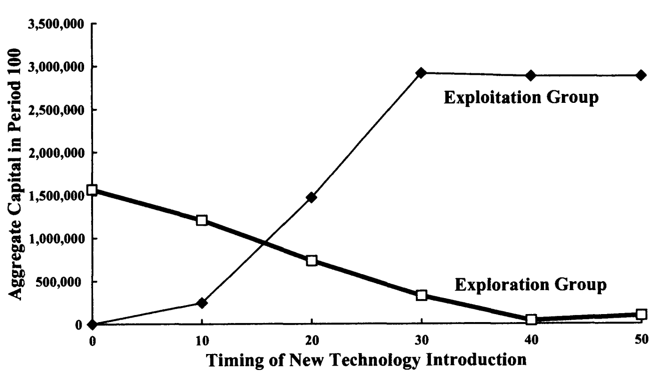
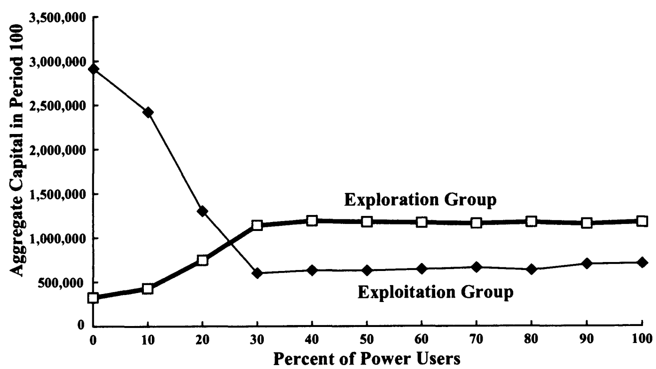


Figure B.3 Effect of the Proportion of Power Users on Aggregate Capital: Average over 100 Trails with the Nonlinear Network Effects



Customer Disposition Distribution Variation. We tested the sensitivity of our results to the distributional assumption on customer disposition d_i by varying shape parameters $(\beta_1, \beta_2) = (1, 1)$, $(3, 2)$, and $(2, 3)$. We found that our main findings were not sensitive to this variation.

Variation in Price. We tested the sensitivity of our results to the price variation with $p = 80$, 120, and 150. We found that there was no qualitative change that affects our main conclusions.

Network Sensitivity Variation. We ran a variation in light users' sensitivity to compatibility with $a_l = 0.1$, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, 0.9, and 1.0. We found that when a_l is smaller than or equal to 0.4, network effects do not seem to play a substantial role for the given time scale. The new technology always dominates, and firms exploring it will always do better than firms staying with the old technology. Because we are interested in a situation where a tension between exploration and exploitation is pronounced, we should assume away this extreme case. To construct a situation where managers like Grove (1996) face a strategic dilemma, the value of a_i appears to be at least 0.5. When it is above 0.5, the exploitation group outperforms the exploration group as was the case in the basic model.

References

Anderson, P., M. L. Tushman. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. *Admin. Sci. Quart.* **35** 604–633.

Argote, L., D. Epple. 1990. Learning curves in manufacturing. *Sci.* **247** 920–924.

——, S. L. Beckman, D. Epple. 1990. The persistence and transfer of learning in industrial settings. *Management Sci.* **36** 140–154.

Arthur, W. B. 1987. Competing technologies: An overview. G. Dosi, ed. *Technical Change and Economic Theory*. Columbia University Press, New York, 590–607.

——. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Econom. J.* **99** 116–131.

——. 1994. *Increasing Returns and Path Dependence in the Economy.* University of Michigan Press, Ann Arbor, MI.

——. 1999. Complexity and the economy. *Science* **284** 107–109.
Becker, G. S. 1998. Let the marketplace judge Microsoft. *Business Week* April **6** 26.
Botticelli, P., D. Collis, G. Pisano. 1998. Intel corporation: 1968–1997. HBS Case No. 9-797-137, Harvard Business School, Boston, MA.
Christensen, C. M. 1993. The rigid disk drive industry: A history of commercial and technological turbulence. *Bus. Hist. Rev.* **67** 531–588.
Cohen, W., D. Levinthal. 1989. Innovation and learning: The two faces of R&D. *Econom. J.* **99** 569–596.
Cyert, R., J. G. March. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall, Englewood Cliffs, NJ.
David, P. A., J. A. Bunn. 1988. The economics of gateway technologies and network evolution: Lesson from electricity supply history. *Inform. Econom. Policy* **3** 165–202.
Epple, D., L. Argote, R. Devadas. 1991. Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing. *Organ. Sci.* **2** 58–70.
Farrell, J., G. Saloner. 1986. Installed base and compatibility: innovation, product preannouncements, and predation. *Amer. Econom. Rev.* **76** 940–955.
——, ——. 1992. Converters, compatibility, and the control of interfaces. *J. Indust. Econom.* **40** 9–35.
Garud, R., P. Karnøe. 2001. Path creation as a process of mindful deviation. R. Garud, P. Karnøe, eds. *Path Dependence and Creation*. Lawrence Earlbaum Associates, Mahwah, NJ.
Grove, A. S. 1996. *Only the Paranoid Survive*. Currency, Doubleday, New York.
Henderson, R.M., K.B. Clark. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Admin. Sci. Quart.* **35** 9–30.
Holland, J. H. 1975. *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor, MI.
——. 1992. Genetic algorithms. *Sci. Amer.* (July) 66–72.
Johnson, M. L., S. Kotz. 1970. *Continuous Univariate Distributions-2*. Houghton Mifflin Company, New York.
Katz, M. L., C. Shapiro. 1985. Network externalities, competition, and compatibility. *Amer. Econom. Rev.* **75** 424–440.
——, ——. 1992. Product introduction with network externalities. *J. Indust. Eonom.* **40** 55–83.
——, ——. 1994. Systems competition and network effects. *J. Econom. Perspectives* **8** 93–115.
Khazam, J., D. C. Mowery. 1996. Tails that wag dogs: The Influence of software-based "network externalities" on the creation of dominant designs in RISC technologies. D. C. Mowery, ed. *The International Computer Software Industry: A Comparative Study of Industry Evolution and Structure*. Oxford University Press, New York, 86–103.
Kristiansen, E. C. 1998. R&D in the presence of network externalities: Timing and compatibility. *RAND J. Econom.* **29** 531–547.
Lant, T. K., S. J. Mezias. 1990. Managing discontinuous change: A simulation study of organizational learning and entrepreneurship. *Strategic Management J.* **11** 147–179.
——, ——. 1992. An organizational learning model of convergence and reorientation. *Organ. Sci.* **3** 47–71.
Lee, J. H., Y. U. Ryu. 2002. Exploration, exploitation, and adaptive rationality: The Neo-Schumpeterian perspective. *Simulation Model. Practice Theory* **10** 297–320.
Levinthal, D. A., J. G. March. 1981. A model of adaptive organizational search. *J. Econom. Behavior Organ.* **2** 307–333.
——, ——. 1993. The myopia of learning. *Strategic Management J.* **14** 95–112.
Levitt, B., J. G. March. 1988. Organization learning. *Ann. Rev. Sociology* **14** 319–340.
Liebowitz, S. J., S. E. Margolis. 1990. The fable of the keys. *J. Law Econom.* **22** 1–26.
——, ——. 1995. Path dependence, lock-in, and history. *J. Law, Econom. and Organ.* **11** 205–226.
March, J. G. 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* **2** 71–87.
Mezias, S. J., A. B. Eisner. 1997. Competition, imitation, and innovation: An organizational learning approach. *Adv. in Strategic Management* **14** 261–294.
Mezias, S. J., M. A. Glynn. 1993. The three faces of corporate renewal: Institution, revolution, and evolution. *Strategic Management J.* **14** 77–101.
Moore, G. A. 1991. *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers*. HarperBusiness, New York.
——. 1995. *Inside the Tornado: Marketing Strategies from Silicon Valley's Cutting Edge*. HarperBusiness, New York.
Nelson, R. R., S. G. Winter. 1977. Simulation of Schumpeterian competition. *Amer. Econom. Rev. Proc.* **67** 271–276.
——, ——. 1978. Force generating and limiting concentration under Schumpeterian competition. *Bell J. Econom.* **9** 524–548.
——, ——. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, MA.
Rogers, E. M. 1995. *Diffusion of Innovations*. The Free Press, New York.
Shapiro, C., H. R. Varian. 1999. *Information Rule: A Strategic Guide to the Network Economy*. Harvard Business School Press, Boston, MA.
Steffens, J. 1994. *New Games: Strategic Competition in the PC Revolution*. Pergamon Press, Seoul, South Korea.
Tripsas, M. 1997. Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. *Strategic Management J.* 18 119–142.
Utterback, J. M. 1994. *Mastering the Dynamics of Innovation: How Companies Can Seize Opportunities in the Face of Technological Change*. Harvard Business School Press, Boston, MA.
Winter, S. G. 1971. Satisficing, selection, and the innovating remnant. *Quart. J. Econom.* **85** 237–261.
Yoffie, D. B. 1994. *Strategic Management in Information Technology*. Prentice-Hall, Englewood Cliffs, NJ, 82–91.

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