To Hunt or to Scavenge: Optimal Investment Strategies in the Presence of Indirect Network Effects

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ABSTRACT

What determines optimal R&D investment in a market with indirect network effects? We analyze this question in a hardware-software framework, where software firms strategically invest in quality upgrades. We find that a firm’s optimal investment depends predominantly on (1) its quality level relative to its competitors on the same hardware and on (2) the quality level of software firms on the same hardware relative to other hardware platforms. Using a dynamic model, we examine the effect of initial quality differences within and across platforms on firms’ investment behavior. We show that when quality differences across platforms are small, the network effect is strong. This stimulates investment across firms on the same platform, regardless of their past success in quality upgrading. However, if the network effect is weak, a firm’s past successful investment may increase or reduce current incentives to invest. In this case, responses to own and cross quality upgrades are determined by the overall market structure. The two different responses – increased or reduced investment, give rise to a taxonomy of optimal investment strategies. Since responses depend on market structure, we can then map a firm’s position within the market into its optimal investment strategy.

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1. INTRODUCTION

It is well established that the value of a software innovation crucially depends on the market share of compatible hardware, commonly referred to as the installed base. This has been extensively discussed in the literature (e.g., Church and Gandal, 1992) for the classic example of computer hardware and software (recall the frequently-cited battle between IBM and Apple computers). But how does the size of the installed hardware base influence optimal investment in software innovation? It turns out that the seemingly obvious answer – the larger the size of the installed base, the larger the optimal investment – is more often false than true.

Hardware-software markets typically exhibit indirect network effects—the more attractive the available software for a particular hardware, the more consumers want to buy this hardware. This, in turn, attracts more software developers to develop compatible software. Network effects, however, are not unique to the computer industry. Other frequently cited examples include the markets for video-games, DVDs, and the internet, to name examples that recently made headline news. Video-games need game-consoles like Microsoft’s X-Box or Sony’s Playstation on which to run. The more consumers who own a specific game-console, the higher the incentives for game developers to offer high-quality games for this console. DVDs need DVD players, and the more consumers who own high-definition DVD players capable of playing a particular format, the more film studios will upgrade their current DVD offerings to the new high-definition DVD standard. Finally, the more consumers who have access to the internet, the more attractive it is to develop services that can be delivered through it.

1 In a recent weblog, commentators find it noteworthy to announce whenever a software developer switches from a larger platform to a smaller one, since this indicates trust in the future of the switched-to platform. See, for example, Michaels (2006).

2 This is in contrast to direct network effects, where the size of the installed base directly influences consumers' choice of hardware. For example, the larger the size of a cellular phone network, the more attractive it is for consumers to acquire access to it. In order to capitalize on the size of their networks, service plans currently offered by major US cell-phone companies feature a switching cost: calls within a network are generally cheaper (or even free, after paying a monthly access charge) than calls to users of other networks, thereby fostering the network effect.

3 Note that all three examples above demonstrate only one side of the indirect network effect—the effect of the installed base on firms' platform choice. All three examples can be easily extended to also show the opposite side, namely the effect of software availability and quality on consumers' platform choice.
Hardware-software markets typically feature the following characteristics: software must be consumed together with compatible hardware to confer utility, and hardware generally lives longer than software. For example, game-consoles outlast more than one video-game generation, and it is usually the latest games that are in fashion and are most frequently played. The internet has outlasted the dot-com bust, which saw many internet applications come and go.

All of our examples also feature quality competition in the software market, where firms compete in quality to attract consumers. Improvements to popular video-games occur regularly and are subject to thorough reviews by the gaming community. The level of sophistication of internet services has dramatically increased, as more and more consumers browse the internet for services. In online-stores, the original sales-through-variety strategy has been complemented by a sales-through-shopping-assistance strategy. One-click shopping, individualized offerings tailored to each returning customer, recommendations, wish-lists, and wedding registries are further examples of such attempts to increase the quality of the online-shopping experience.

Indirect network effects can be driven either by variety or quality. For example, Nintendo’s dominance in the video-game market during the late 80s was mainly driven by the quality of the video-games Nintendo and its licensees offered (see Sheff, 1994). Learning from Atari’s disaster, Nintendo closely monitored the quality of every available game, ensuring that all available games were of superior quality. In converse, during the early stages of the DVD technology, the DVD market was mainly driven by variety. During this period, demand for DVD-players largely depended on the number of movies available on DVD. Rarely, however, will one find cases where only one of the drivers – variety or quality – is exclusively present. Demand for Sony Playstations depends both on the quality and variety of compatible games. Unpopular movies don’t sell DVD-players and hard-to-use internet applications do not

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4 Frequently there is also quality competition in hardware. For simplicity, we abstract in this paper from these cases.

5 See, for example, the listing of all Star Wars games at http://starwars.ugo.com/games/default.asp (accessed 01/25/06). It includes information about publication dates, the platforms for which each game was available, the publisher, as well as reviews.
easily find customers. Investment in variety in the context of platforms is well understood. We therefore focus on investment in quality upgrades when indirect network effects are present.

When software firms upgrade the quality of their products, they may attract consumers from competitors producing for the same or for a different hardware. For example, Sony’s Playstation is challenged by Microsoft’s X-box and Nintendo’s Game Cube. They may also attract consumers who have so far chosen the outside good: the attractiveness of the entire video-game market is affected by innovation in PC games or other forms of home entertainment. Currently, two DVD formats, Blu-Ray and HD-DVD, compete on becoming the standard format in the high-definition DVD market. The DVD market, however, is also challenged by other devices, at least in the portable end of this market. In recent years, hard-discs have become sizeable enough to hold movies of satisfactory quality for portable devices. The newest Apple iPod with video-capabilities will probably mark the starting point of such developments. The combination of indirect network effects with competition from the outside good creates complex dynamics in the software market, which require sophisticated investment decisions. It is these investment decisions we study in this paper.

Software firms invest in R&D based on expected future profits, taking competitive responses from other firms into account. Predicting these responses is complicated, as responses may come from competitors offering software for the same or for a different hardware. Furthermore, firms’ decisions are also affected by consumers' choices, which in turn are based on firms’ investment strategies. It is virtually impossible to solve analytically for the equilibrium of a game with such complex interaction. Consequently, following Ericson and Pakes (1995), we use numerical analysis to derive conditions for optimal investment behavior in our model.

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6 The PC can be considered either as another gaming platform or an “outside good” depending on the market definition. A study of the video-games market would only include true video-gaming platforms, for which PC-games are an outside good. An analysis of the gaming market more generally may include PCs and even the internet as competing platforms. In this case, movies may be thought of as an outside good.

7 Again, whether the iPod is seen as a different movie-platform or an outside good depends on market definition.
Intuitively, a firm’s investment behavior depends on its position in the quality race relative to its competitors both on the same and on competing platforms. One might expect a firm to invest aggressively if all firms on all platforms are roughly at similar quality levels. Conversely, a market leader that is far ahead of its competition may allow itself some complacency. It is not clear, however, whether a follower would invest strongly to catch up or would rather "give-up" and remain a follower.

In general, our results show that optimal investment depends strongly on how close the race is within as well as across platforms at any point in time. If a firm successfully increases its quality, this increases its competitive strength relative to its competitors on the same platform. It also increases the strength of its platform, overall. These changes influence the market structure and consequently the strength of competition on and between platforms. The strength of competition between platforms then determines the strength of the network effect.

Changes in market-structure can be induced by the firm itself or by a competitor. Whether a firm responds aggressively and increases its investment or instead becomes complacent depends on whether competitive forces and network effects increase or decrease as a consequence of the change in market structure. For example, a firm may invest aggressively because its own quality upgrade moved it closer to its competitors on the same platform or because it moved its platform's quality closer to that of competing platforms. A firm may also invest more aggressively because a direct competitor on the same platform upgraded its quality and therefore moved the platform that hosts both firms closer to the quality level of competing platforms.

This analysis suggests the following categorization of firms' investment behavior: for any given market structure, a firm can respond either aggressively or complacently to an increase in its own quality. Moreover, an increase in its competitor's quality can induce a similar investment behavior. Therefore, we sort firms' investment behavior into four categories, which are a combination of their type of behavior – aggressive or complacent, and its causes – an own or a competitor's increase in quality. Each market
structure can then be mapped into one of these four categories under which optimal investment behavior is either aggressive or complacent, and is either seemingly\textsuperscript{8} cooperative or non-cooperative.

We contribute to two lines of literature. First, we extend the literature on markets with network effects (e.g., Farrell and Saloner, 1985 and 1986; Katz and Shapiro, 1985, 1986 and 1992; Church and Gandal, 1992; Bresnahan & Greenstein, 1999; Gandal et al., 1999; Gandal et al., 2000; and Gandal and Dranove, 2003, among many others). While the empirical studies document the importance of network effects, the theoretical ones concentrate mainly on the long-run structure of the industry (i.e., standardization vs. variety). This paper takes a different approach and focuses on the optimal investment strategies of software firms in those markets. Within the literature on network effects, we add, in particular, to the literature on dynamic platform competition. For the computer industry, Bresnahan and Greenstein (1999) provide an excellent description of firms’ behavior in the presence of platforms. We add to their insights by analyzing the underlying drivers of investment in R&D. In addition, we use their examples to provide evidence consistent with the predictions of our model. Second, we show how the existence of platforms influences investment in R&D.\textsuperscript{9} Our within-platform results generally resemble those of Grossman and Shapiro (1987), who find that the leading firm always invests more than the follower (i.e., investment strategies are strategic substitutes). However, as in Doraszelski (2003), we find that investment strategies of firms on the same platform can be either strategic complements or strategic substitutes, depending on how strong competitive forces are from the competing platform.

The paper is organized as follows: in the next section, we describe and formally present the model. We then present the results, where we demonstrate how the existence of platforms influences the incentives of software firms to invest in quality upgrades. The results from this analysis allow us to develop a

\textsuperscript{8}The investment behavior of firms is always driven by egocentric motivations of the firm. However, aligned incentives let this behavior appear to be cooperative for certain market structures.

\textsuperscript{9}For example, Loury (1979), Lee and Wilde (1980), and Reinganum (1981, 1982, and 1983) study investment in R&D under the assumption that the probability of innovation is governed by an exponential distribution. Non-stationary R&D races were also studied by Harris and Vickers (1985) and Judd (1985), among others.
taxonomy of investment strategies. We then compare the results from our model to examples in the literature as well as to recent developments in the computer industry. The fifth section concludes.

2. THE MODEL

We present our model in three steps. In this section, we discuss the ideas that drove the model specification. Then we state the assumptions that attempt to reflect these ideas. Finally, we present a formal version of the model, which can be skipped without loss of comprehension for readers not interested in the technical details.

Our model of quality competition attempts to capture the following ideas. First, consumers’ hardware and software choices depend on current as well as expected future quality of software products. At the same time, firms’ incentives to invest in quality upgrades depend on the number of consumers who own the compatible hardware, as well as on the overall performance of all software firms in the market. Consumers are willing to pay more for higher quality. Whenever new software upgrades are available, consumers like to get the newest version as long as it is reasonably priced. Consumers keep their hardware normally for longer than just one software cycle. Therefore, they want to own the hardware for which software promises the best expected quality-price relationship. Software firms have higher incentives to upgrade if the market they can potentially address is large. This is the case if there are many consumers who already own the compatible hardware, especially if they can secure a large share of this consumer base for themselves. In order to innovate effectively, software firms frequently possess platform-specific knowledge: developing software for more than one platform can be prohibitively costly. Finally, the industry itself will be larger if it offers higher value to consumers than substitute markets do. For example, TV broadcasts, DVDs and Videos may lose attractiveness for certain age groups if new developments in the gaming industry progress further.
2.1 Model Assumptions

We try to capture these ideas with the following assumptions. We assume an infinite horizontal discrete choice model. Consumers live forever and derive utility from the consumption of software. Consumer utility increases in the quality of software and decreases in its price. We assume that software needs compatible hardware to operate, but that hardware provides no stand-alone utility. To keep the setup simple, consumers can only choose from two incompatible hardware platforms, and there are no more two software firms producing for each hardware. Every period, all consumers need to renew or replace their software licenses. Hardware has to be replaced, on average, every two periods. Therefore, every period one-half of the consumers on each platform can change their hardware. In other words, in each period, all consumers buy software, while half of them are also free to choose a different hardware – assuming it offers them a higher utility.

Successful innovation in quality upgrades depends on a firm’s level of investment. Firms base their investment decisions on discounted future profits, which depend on their own as well as their platform’s prospects. Firms with better prospects for the future will invest more and, therefore, have a higher probability of success. A successful investment increases the firm’s quality by one unit, while an unsuccessful investment becomes obsolete. Each firm’s probability of success influences other firms’ investment strategies as well as consumers’ choices. Since consumers own the hardware for two periods, they form expectations about software qualities in the future when deciding on hardware. Software quality is measured relative to the quality of the outside good. If the quality level of the outside good increases by one unit, the quality of all available software (on both platforms) decreases by one unit. To capture platform-specific knowledge of software firms, we restrict them to only one platform, and, for simplicity, to only one software product.

The timing of the game is as follows: in the first stage, consumers and firms observe current qualities of available software on both platforms as well as platforms’ market shares. Consumers choose which hardware to buy and software firms simultaneously choose how much to invest in quality. In the second
stage, firms compete in prices, and consumers buy one unit of software or the outside good. In the third stage, nature determines which firms’ investments were successful, and whether there was an increase in quality of the outside good. Note that the realization of firms’ investment affects qualities only in the following period.

2.2 Formal Analysis

We employ the same basic set-up as in Markovich and Moenius (2005) and adapt Ericson and Pakes (1995) to incorporate dynamics in consumers’ decisions. Since hardware lives for two periods but software only for one, consumers form expectations about the future. Practically speaking, they assess software on all platforms by current as well as expected future quality. Consumers then choose hardware based on the available software choices, where they take into account both quality and variety of software on a platform. All firms develop the same type of software (e.g., spreadsheets, word-processors, or office suites) and compete on quality and price. Firms invest in quality upgrades to improve their own as well as their platform’s position in the market. Investment outcomes are stochastic, and the probability of success increases in the amount of investment. Consumers live forever and both consumers and firms make their choices in discrete time, assuming an infinite horizon. Software firms specialize in one type of hardware and are unable to switch to another platform. For simplicity, we allow for no more than two platforms, $A$ and $B$, as well as no more than two software firms on each platform. Since the analysis for hardware $B$ mirrors that of $A$, we only present it for $A$.

Let $W=\{0,1,2,\ldots,K\}$ be a finite set of possible quality levels of software. Then $a_j \in W$ represents the quality of software firm $j$ producing for hardware $A$. $a = (a_1, a_2)$ is the vector of quality levels of both firms producing for hardware $A$. $\sigma$ is the market share of hardware $A$. Finally, $S = (\sigma, a, b)$ denotes the state of the industry, where $b$ is the vector of the quality levels of all firms producing for hardware $B$.

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10 $\sigma$ is the formal equivalent of the “installed base,” as defined in the introduction (also see Farrell and Saloner, 1986).
2.2.1 Demand

Consumers derive utility solely from software, which needs compatible hardware to operate. We assume that hardware itself does not provide any benefit on its own. In each period, half of the consumers who own a particular hardware are randomly selected to replace their units. These consumers can elect to either stay with the same type of hardware or switch to another one. Firms license software to consumers for one period. After that, consumers can either renew the license at the then-available quality level and price, or they can elect to switch to another software firm. Consumers who are not randomly selected for hardware choice have to select software for the hardware they already possess. For any given period, consumer $l$ who owns hardware A and holds a license from firm 1 for software with quality level $a_1$ receives utility $U_{l1}^A(a) - p_1^A = a_1 - p_1^A + \epsilon_{l1}$, where $\epsilon_{l1}$ denotes differences in software taste among consumers (e.g., within the spreadsheet market, some consumers like Lotus while others prefer Excel).

**Software Choice.** Consumers select software from the set of qualities and prices available to them. They acquire a license for one unit of software, unless the outside good provides them with higher utility, which is denoted $\epsilon_0$. We assume that consumers' preferences, $\epsilon$, are independently and identically distributed according to a standard double exponential distribution. As McFadden (1973) shows, consumer $l$ then acquires a license from firm 1 with probability:

$$D_1(a_1, a_2; p_1, p_2) = \frac{\exp(a_1 - p_1)}{1 + \exp(a_1 - p_1) + \exp(a_2 - p_2)}$$

(1)

**Derived Demand for Hardware.** Consumers who can choose hardware in a given period do so by evaluating available software qualities for each hardware platform. If consumers purchase hardware A, their expected utility is the sum of the utility from software they purchase during the two periods they own the hardware.$^{11}$ Consumer $l$'s expected utility from purchasing hardware A is then:

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$^{11}$ As noted before, consumers replace hardware on average every two years. Consequently, while some of the consumers replace hardware after one period, some hold their hardware for many periods. For simplicity, we
\[ W_i^A(\sigma,a,b) = E \{ [U_{ij}^A(a) - p_j] | \sigma,a,b \} + \beta E(\{ E \{ [U_{ij}^A(a') - p_j'] | \sigma,a,b \} \}) + \xi_i^A \] (2)

\[ E(U_{ij}^A(a)) \text{ and } E(E(U_{ij}^A(a'))) \] are a consumer’s expected utilities from licensing software \( j \) in the current period and in the next period, respectively. \( \xi_i^A \) represents consumer \( i \)'s preferences over platforms (e.g., in the operating system market, some consumers prefer the Windows platform while others favor Linux). \( a' \) and \( p_j' \) are next period’s qualities and prices, respectively. In order to assess equation (2), consumers form expectations about future availability, quality and prices of software based on the current state, \( (\sigma,a,b) \).\(^{12}\)

A consumer will choose hardware A over hardware B if and only if hardware A offers a higher expected utility than hardware B. That is, setting hardware A’s and B’s prices at \( P^A \) and \( P^B \), respectively, consumer \( i \) buys hardware A if and only if \( W_i^A(\sigma,a,b) - P^A > W_i^B(\sigma,a,b) - P^B \). Once more, we assume that consumers' preferences, \( \xi_i^k \), are distributed independently and identically and follow a standard double exponential distribution. Then, again employing McFadden (1973), consumer \( i \) purchases platform A with probability:

\[ \Psi(A,a,b;P^A,P^B) = \frac{\exp(W^A - P^A)}{\exp(W^A - P^A) + \exp(W^B - P^B)} \] (3)

Given our assumptions and eq. (3), platform A's market share follows

\[ \sigma'(\sigma,a,b;P^A,P^B) = \sigma / 2 + \Psi(\sigma,a,b;P^A,P^B) / 2 \] as its law of motion.

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\(^{12}\) See Markovich (2004) for more details.
2.2.2 The Market for Software

We now turn to the dynamics in the software market. Each software firm only develops one type of software, which is compatible with only one of the platforms. Software firms compete oligopolistically on quality and prices. If software firms want to improve the quality of their product, they need to invest. We assume that the outcome of this investment is stochastic and depends on the level of each firm’s investment. Whether the investment is successful is revealed in the following period.

Each firm's quality level in the next period is determined by three factors: its current quality level, its level of investment, and whether substitute industries improve the quality of their products. We assume that quality levels for each firm follow a Markov process – future qualities only depend on current qualities, regardless of how the firm reached this level. Consequently, if $a_j$ is firm $j$'s current quality level, $\tau_j \in \{0,1\}$ is the realization of firm $j$'s investment, and $v \in \{0,1\}$ represents the success of substitute industries in upgrading their quality, then next period’s quality level, $a_{j'}$, is described by the following Markov process: $a_{j'} = a_j + \tau_j - v$. We assume that there are no research spillovers: each firm’s probability of a successful investment increases only in its own investment. In particular, if firm $j$'s investment level is $x_j$, then its probability of success is $p(\tau_j = 1) = x_j / (1 + x_j)$.

Advances in substitute industries erode quality advantages of software. We therefore measure software qualities relative to the quality of the outside good. Any innovation in substitute industries reduces the quality advantage of all software on both platforms by one unit. We let $\delta$ denote the probability of an improvement in the quality of the outside good in each period: $p(v = 1) = \delta$. Combining firm $j$'s probability of a successful investment, given that it invests $x_j$, with the possible erosion of quality through

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13 In this paper, we only study investment strategies of software firms. Software firms, however, can also decide to enter or exit the industry, which we ignore here to keep the analysis simple. See Markovich (2004) for details.
successful innovation in substitute markets yields \((1-\delta)x_j\) as firm \(j\)'s probability to offer increased software quality next period.\(^{14}\)

Before carrying on to the firms' investment decision, we first discuss per-period profits. While investment decisions are dynamic, we assume that the pricing game is a static game with no future effects or dynamics.\(^{15}\) Firms choose prices to maximize profits in the current period and cannot strategically discount their software in order to attract more consumers in the future. All software firms on both platforms take software demand as given from equation (1) and set prices oligopolistically. The profit-maximization problem of firm 1 on platform A is thus given by:

\[
\max_{p_i \geq 0} \sigma^* M^* D_i(a_1, a_2; p_1, p_2)^* p_1
\]

where \(M > 0\) is the total size of the market and, in the interest of parsimony, we abstract from marginal and fixed costs of production. \(\sigma\) is the percentage of consumers who own platform A. The first-order condition (FOC), the derivative of (4) with respect to \(p_1\), is

\[
0 = 1 - \frac{1 + \exp(a_2 - p_2)}{1 + \exp(a_1 - p_1) + \exp(a_2 - p_2)} p_1
\]

It can be shown that there exists a unique Nash equilibrium \((p_1^*(a_1, a_2), p_2^*(a_1, a_2))\) of the pricing game (Caplin and Nalebuff, 1991). This Nash equilibrium can be computed by numerically solving the system of FOCs. The per-period profit of firm 1 in the Nash equilibrium of the pricing game is then given by \(\sigma M \pi_1(a_1, a_2)\), where

\[
\pi_1(a_1, a_2) = D_i(p_1^*(a_1, a_2), p_2^*(a_1, a_2); a_1, a_2) p_1^*(a_1, a_2)
\]

is firm 1’s profit per consumer.

\(^{14}\) All other probabilities concerning firms' quality levels can be calculated in the same fashion.
Taking the state of the industry $S = (\sigma, a, b)$ as given, incumbent software firms select optimal investment strategies by solving an intertemporal maximization problem. For example, firm 1 on platform A maximizes its expected future payoff, $V_1^A(S)$, by solving the following Bellman equation:

$$V_1^A(S) = \sup_{x \geq 0} \left[ \sigma M \pi_1 (a, p) - x_1 + \beta \sum_{a', b'} V_1^A(S') \Pr(a_1' | a_1, x_1^A) \Pr(a_2' | a_2, x_2^A(S)) \Pr(b_1' | b_1, x_1^B(S)) \Pr(b_2' | b_2, x_2^B(S)) \right]$$

where $x_1^A$ is firm 1's investment on platform A. $x_2^A$, $x_1^B$, and $x_2^B$ are defined similarly. The right-hand side of equation (4) consists of two parts: the profits from the pricing game in this period, $\sigma M \pi_1 (a, p)$, and the expected discounted value of all future profits. The expected value of future profits depends on the state of the industry, $S = (\sigma, a, b)$, as well as on all active firms' investment levels.

**Equilibrium.** Following most of the literature, we consider the Markov Perfect Equilibrium (MPE) of the game (see Maskin and Tirole, 2001). Each period, firms simultaneously decide on their investment levels given the current state of the industry, $S$, and their future expectations. Investment strategies are defined for every state of the industry, regardless of how this state has been reached.

A Markov Perfect Equilibrium for the game described above is defined by

- Investment strategies $x_j^k(\sigma, a, b)$ for $j=1,2$; $k=A,B$ and every possible state $(\sigma, a, b)$.
- Value functions $V_j^k(\sigma, a, b)$ for $i=1,2$; $k=A,B$, and every possible state $(\sigma, a, b)$.

Such that:

(i) The strategies $x_j^k(\sigma, a, b)$ are optimal given the value functions $V_j^k(\sigma, a, b)$.

(ii) For every state $S=(\sigma, a, b)$, the value functions describe the present value of profits realized when both firms play the equilibrium strategies $x_j^k(\sigma, a, b)$.

15 Despite the static nature of the pricing game and the fact that prices are independent of quality levels on the other
A full formal equilibrium definition and the computational algorithm can be found in Markovich (2004).

2.2.3 Parameterization.

We chose the following set of parameter values for the equilibrium computation. There is a total of ten consumers in the market, i.e., $M=10$. Since our focus is on software, we normalize hardware prices $P^A = P^B$ to be equal to zero. Market shares of platforms run from 0% to 100%, and are calculated in increments of 5%. We think of each period as one year and set the discount factor $\beta = 0.92$. Given these parameter values, software firms find it unprofitable to invest in quality upgrades, regardless of market structure, if they reach a quality level of $K=6$. Once a software firm has reached this quality level, it chooses not to invest at all. We therefore fix $K$ at 6.

We will present all of the results with graphs. Since it is impossible to display our results for all possible value combinations of the model, we select intermediate starting values for the graphs: each platform starts with a market share of 50%, and the level of outside competition, $\delta$, is also set to 0.5. Departing from these values only changes the relative magnitude of the effects, while the principle mechanisms stay the same.\(^\text{16}\)

Since firms can always be at one of the seven possible quality levels (0,1,2,…,6), there are 49 possible quality combinations on each platform, which cannot be easily displayed. We therefore introduce the following simplification: each combination of qualities on a platform is assigned a number indicating the sum of qualities. For example 3-3 and 4-2 are both assigned the sum 6. Since competitive efforts are the strongest when quality levels on the same platform are similar, we kept only those cases where the quality differences of firms on the same platform were either zero or one. This reduces the number of states per platform to 13. One can think of the weaker cases as delivering results "in between" the strong cases. For example, the amount of investment for the quality levels of 4-2 lies in between 3-2 and 3-3.

platform, profits do depend on the market share of the hardware a firm produces for. However, this market share is influenced by the quality levels of firms producing for the competing hardware.
3. NETWORK EFFECTS AND THE INCENTIVES TO INVEST

In order to characterize our results, we first need to distinguish between two effects exhibited by quality competition in a market with network effects. First, let us isolate the case where consumers have already made their hardware decision and assume for a moment that they cannot switch. Since hardware-market shares are fixed, software firms compatible with a certain hardware can only compete for market share within their platform. We call any effect driven by firms’ incentives while holding constant a platform's market share a competitive effect. It is well established, (see, e.g., Shaked and Sutton, 1982) that the competitive effect is strongest when there is no difference in quality levels between firms on the same platform. We define the network effect in a similar way. Consumers base their hardware choice on the observed and expected distribution of software qualities across platforms. Consequently, a platform's market share depends on the software qualities of all firms on a platform. This implies that even if a firm is not successful in upgrading its software quality, a competitor on the same platform can increase the market share of this platform through a successful quality upgrade, thus increasing the pie for both firms. Consequently, the interests of firms on the same platform are tied together. We therefore call any effect driven by firms’ incentives while holding constant relative quality levels within platforms a network effect.

The network and competitive effects may have opposite impacts on firms’ profitability. Assume that firm 1 and firm 2 compete on the same platform, and that firm 2 has been successful in upgrading its software’s quality, while firm 1 has not. This will reduce firm 1’s market share on the platform, and consequently its profits. On the other hand, this will also increase the attractiveness of the platform, overall, which – if firms on the other platform have not been successful – will increase the market share of this platform. This, in turn, has a positive effect on firm 1’s profits, as some of the switching consumers may buy firm 1’s software. This also has profit implications: in Markovich and Moenius (2005) we show that if network effects are strong enough, a firm can win additional market value through its competitors’ successful quality upgrades. That is, a firm can receive a windfall increase in market valuation through the

\[ \text{Figures with other parameter values are available upon request from the authors.} \]
innovative success of its competitor on the same platform, as long as quality differences across platforms are small. The strength of the network effect, however, depends on the difference in quality levels across platforms. The competitive effect is the strongest when there are no quality differences within a platform, and the network effect is the strongest when there are no quality differences across platforms. Therefore, it is possible to study the influence of the network and competitive effects on investment by simply studying the effects of quality differences within as well as across platforms on investment behavior.

3.1 The Effect of Quality Differences on Firms’ Investments Strategies

To see the importance of quality differences between and across platforms, we start by presenting three examples. Figure 3.1 exhibits the investment strategy of firm 2, holding the quality levels of both firms on the competing platform fixed at low (1, 1), medium (3, 3) and high (6, 6). The studied firm’s investment behavior is presented as a function of its own quality level as well as the quality level of its competitor on the same platform. Although it is tempting to describe all features of these graphs, we will highlight only two major features. First, optimal investment strongly varies with the firm’s position relative to its competitor on the same platform, as well as relative to the quality level of the competitors on the competing platform. Second, leaders invest more than followers do, as long as their lead is small. Consequently, a firm invests the most when it is the marginal leader on a slightly leading platform. If the lead is large, this may be reversed—and the follower may invest more than the leader. This is true both within and across platforms. To see this, one can compare the column where the network effect is the strongest (e.g., 3, 3 for the middle panel or 1, 1 for the left panel) with the surrounding columns.

17 Note that investment levels are positive as long as a firm’s quality level is higher than 0, but lower than six. As noted before, the highest quality level is endogenously determined to be the level at which firms find the benefits from investment to be lower than the cost of investment, and therefore choose not to invest.
3.2 Direct and Indirect Effects of Investment

In order to better understand investment behavior, we study the effect of an own and a competitor’s quality upgrade on firms’ optimal investment. In our description of the results, we will adhere to the following conventions. We call the firm of interest firm $i$ and the competing firm on the same platform $-i$. The platform compatible with firm $i$’s and firm $-i$’s software is called platform A; we call the competing platform B. $\Delta$-intra measures the quality differences within platforms, while $\Delta$-inter does so across platforms. We always measure quality differences relative to firm $i$ and to platform A. For example, if firm $i$ obtained a quality level of 2 while firm $-i$ stays at level 5, our intra-platform difference would be -3.18 If the firms on platform B exhibit quality levels 2 and 1, respectively, platform A would lead platform B by 4 quality units.

We turn now to investigate own- and cross-investment elasticities with respect to a quality upgrade. We again characterize the competitive environment by the differences in quality levels within and across platforms. The left panel in figure 3.2 shows the elasticity of firm $i$’s investment with respect to its own quality advance, which is calculated as $\frac{\Delta x_i}{\Delta a_i} \cdot \frac{a_i}{x_i}$. The right panel shows the cross elasticity: the elasticity of firm $i$’s investment with respect to firm $-i$’s quality improvement, $\frac{\Delta x_i}{\Delta a_{-i}} \cdot \frac{a_{-i}}{x_i}$.

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18 Intra-platform differences are only measured for platform A. For platform B, we always use the strongest combination of qualities as defined above. Therefore, there are no quality differences larger than 1 on platform B. That is, platform A always faces the strongest possible competition from platform B for any given quality level.
We start with own-investment elasticities. As the left panel shows, the more firm \(i\) lags behind firm \(-i\) (\(\Delta\text{-intra} < 0\)), the stronger is its investment response to its own quality upgrade. Once firm \(i\) leads, the opposite effect can be observed. The intuition behind this result is as follows: if a firm lags behind, a successful upgrade increases the probability of catching up and thus increases this firm’s incentives to invest in quality upgrades. The increase in incentives is the largest when quality differences between firms are still large. However, once a firm has become a far leader, it cannot win additional market share on its own platform – only from the other platform – decreasing the leading firm’s incentives to invest. Therefore, a far leader decreases its investment in response to its own quality increase.

Inter-platform differences affect investment as follows. In general, when quality differences across platforms are small, firms’ responses to their own increases in quality are the strongest. This is a consequence of the network effect – when platforms are close, firms increase investment to enhance the attractiveness of their platform. Once their platform is ahead or behind, incentives are lower and so is the response to an increase in a firm’s own quality.

The effect of a cross-quality increase (right panel) is quite different. A firm’s investment response to a quality upgrade by a competitor on the same platform is negative when inter-platform differences are large, and mostly positive when they are small. We set aside the positive effects, which will be
discussed in the next paragraph, and consider only the negative effects. When the reaction is negative, we see the following pattern: if a platform leads, then responses are the strongest when firms' qualities are close. This resembles the results from the R&D literature without platforms (e.g., Grossman and Shapiro, 1986). On the contrary, if the platform lags behind, the responses resemble the own-elasticity responses – the further ahead the firm, the stronger its negative response. The first pattern can be explained by the competitive effect. If a platform leads, it commands a large market share and competitors on this platform behave as if they were alone in the industry (which consists of our two platforms), and consequently reactions are the strongest when both firms on the leading platform are of similar strength. But if a platform lags behind, its market share is small; thus the more the lagging firm on this platform falls behind, the smaller are its future profit opportunities. The opposite is true for the leading firm. Recall that the attractiveness of a platform depends crucially on the survival probability of both firms on that platform. Consequently, a quality upgrade by the lagging firm strengthens its survival probability and thus the overall attractiveness of the lagging platform. Therefore, the competitive effect, which reduces incentives to invest, is partially offset by the network effect and the leading firm reacts very little to a successful quality upgrade by its competitor.

In general, cross-investment elasticities are positive when platforms are close. The response is the stronger the smaller are intra-platform differences. This pattern can be explained by the network effect. When platforms are of similar quality levels, a quality upgrade by firm \(-i\) improves the relative position of the entire platform. This, in turn, increases firm \(i\)'s incentives to upgrade its software. This is also true in the other direction: a quality upgrade by firm \(i\) leads to increased investment from firm \(-i\). Consequently, investments by the two firms on the same platform are gross complements. This relationship exists only in the neighborhood of equally strong platforms, and it is the strongest when firms are close competitors on the same platform. Once inter-platform differences increase, the competitive effect dominates and firms on the same platform find it more profitable to fight each other rather than to fight their rivals on the competing platform. We further explain this point in the next section.

In summary, the fact that consumers favor higher qualities provides an incentive for software firms to
invest in upgrading their quality. Total investment is the highest the more similar are platforms’ overall strengths. In this case, both the network effect and the competitive effect are the strongest and drive investment in the same direction. A strong network effect pushes firms on the same platform to join efforts and increase investment to improve the attractiveness of their platform. At the same time, a strong competitive effect increases the value of stepping ahead of a competitor, thereby encouraging firms to fight each other. Finally, substantial differences across as well as within platforms lower overall investment, but for different reasons: the network effect weakens when quality differences across platforms increase, while the competitive effect weakens when quality differences within platforms increase.

### 3.3 A Taxonomy of Investment Strategies

The investment behavior induced by market structure suggests the following categorization: firm $i$'s investment response to its own quality can either be aggressive, meaning that it will invest more if it successfully upgrades its quality, or complacent, implying it will decrease its level of investment. Similarly, firm $i$ may respond aggressively or complacently to an increase in its competitor's quality level.

If the two firms join forces, which is the case when both an own- and a cross-quality upgrade makes a firm aggressive, we call firm $i$ a "Pack Hunter." We call a firm that competes alone against the rest of its industry a "Lone Wolf." This happens when its own quality upgrade makes it aggressive but its competitor's quality upgrade makes it complacent. A firm that lets its competitor on the same platform do the "hunting" is called a "Puppy Wolf." This results from a positive cross-quality elasticity and a complacent reaction to its own quality upgrade (i.e., "Mom" will bring the "prey"). Finally, we call a lone wolf that does not really attack, but just half-heartedly hunts and eats what it finds, a "Scavenger." The economic determinants of this category are both negative cross- and own-quality elasticities. The above categorization can be summarized in the following table:
An increase in your competitor’s quality makes you …

An increase in your own quality makes you …

<table>
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<tr>
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<th>Aggressive</th>
<th>Complacent</th>
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<tr>
<td>aggressive</td>
<td>Pack Hunter</td>
<td>Lone Wolf</td>
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<td></td>
<td>Puppy Wolf</td>
<td>Scavenger</td>
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Table 1. Investment Strategies

Figure 3.6 plots the market structures for which we see the different types of investment behavior.

The graph shows the following: when platforms are of similar quality levels, a firm behaves as if it were "hunting" in a pack – it reacts aggressively to its own and its competitor’s quality upgrade. This

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19 Unless explicitly stated otherwise, we always refer to the competitor on the same platform in this section.
holds as long as quality differences across platforms are not too large. Moreover, firms on the leading platform like to hunt in a pack when their platform’s lead is small. A firm behaves as a "Lone Wolf" when it lags behind its competitor on a platform that is either far behind or sufficiently ahead. In this case, successful investment makes it more aggressive, since it can steal business from its competitor on the same platform. Another popular animal is the "Scavenger" – it reacts complacently to its own and its competitor’s quality upgrade. If it is the leading firm on a platform, it has no incentive to further increase its investment. It is also not jeopardized by its competitors or the other platform, so it just enjoys its life in ease. If it is on the lagging platform, it cannot win against the competing platform alone, so it just feeds on whatever market share its platform already has. Another interesting breed is the "Puppy Wolf." A firm reacts aggressively to a competitor's quality upgrade, but complacently to its own quality upgrade. This happens when platforms are competing closely but there is a large discrepancy between the quality levels of firms on the platform. In this case, the lagging firm has to catch up in order to turn a "Puppy Wolf" into a "Pack Hunter."

Note, while in some states both firms' strategic response are of the same kind – both respond aggressively or both respond complacently—this is not necessarily always the case. Take for example the state where quality differences both within and across platforms are zero. As figure 3.6 shows, in this case the two firms behave as two “Pack Hunters,” and their investment strategies are strategic complements. The two firms seem to join efforts in order to improve the attractiveness of their platform relative to the competing platform. In converse, when quality differences across platforms are zero, but, within platform, one firm is 4 quality levels ahead of its competitor, the leader behaves as a "Puppy Wolf," while the lagging firm behaves as a "Pack Hunter." In this case, the follower's investment is complementary to the leader's, but the leader's investment is a substitute for the follower's.

20 One can easily find states where both firms’ investment strategies are strategic substitutes.
4. RECONCILING THEORY AND EVIDENCE

Bresnahan and Greenstein (1999), hereafter BG, provide an excellent description and insightful analysis of the driving forces of platform development in the computer industry. Our comparatively simple model was never designed to account for all of the various influences and conditions for platform change that BG detect. Nevertheless building on their ideas, we can show how the more-detailed forces we identify in our model played out in the competition between Apple and IBM in the micro-computing market. Since we are unable to observe investment directly, we use successful quality upgrades (that hit the market) as ex-post measures of realized investment. With the help of our taxonomy, these can then be interpreted as measures of competitive efforts. Keeping this in mind, we will concentrate on two mechanisms BG discuss in reference to Apple and IBM compatible computers: (1) the intensity of competition in components and applications for the speed of innovation, and (2) the role of competitive responses. We have collected data on the quality of available components for Apple computers and IBM-compatible architectures. Our data show that, as the model predicts, platforms with higher levels of quality competition, and thus investment, manage to attract more consumers than platforms with lower levels of quality competition.

Our model predicts that the intensity of investment in quality upgrades and the resulting speed of innovation in applications and components are crucial for the success of a platform. BG provide an interesting example illustrating this point: within micro-computing, two platforms existed – the IBM-compatible PC and the Apple computer. Apple was initially far ahead of the PC in terms of market share.\(^{21}\) While IBM chose an open architecture, allowing large groups of firms to participate in technological innovation of applications and compatible components (e.g., CPUs, floppy-disc drives, screens etc.), Apple only allowed competition in the applications market. Our model predicts that Apple should suffer from a disadvantage in innovative upgrading of components, leading to lower available qualities relative to IBM.

As mentioned above, we think of hardware and software in terms of relative life duration, where we take hardware to be longer-lived and software to be the shorter-lived. Given this broad definition, since the

\(^{21}\) See [http://www.pegasus3d.com/total_share.html](http://www.pegasus3d.com/total_share.html) for exact numbers of market shares for the two systems, downloaded on 1/23/06.
components above are all shorter-lived than the computers’ architecture, components can be viewed as "software." Apple’s and IBM-compatible PC’s architectures can be then viewed as "hardware."

We managed to find reasonably useful data for CPUs, floppy discs and graphics adapters. The following three graphs provide some insight into the competitive situation in the components market for Apple and IBM-compatible computers. Remarkably, all three graphs show the same basic pattern: at almost any point in time, there were not only more component variations available for IBM-compatible machines, the components for IBM-compatibles also technically outperformed those used by Apple.\(^{22}\)

\(^{22}\) A more detailed description of the construction of the graphs as well as data sources can be found in the appendix.
While Apple users could only choose models from the Apple family, and for those models could only customize a limited set of components, users of IBM-compatible PCs could choose from a wide variety of vertically (and horizontally) differentiated models. The graphs show that there was substantial quality competition and upgrading in components on both platforms. Nevertheless, IBM-compatible machines clearly had a technical edge in all component markets over Apple’s machines for prolonged periods of

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23 Arguably, customers perceived vertical differentiation through improved quality features (like higher CPU speed, resolution of the screen, higher disc capacity) as more important than horizontal differentiation through the choice of producers who made components with roughly similar quality features.
The very recent switch of Apple to also using Intel as its main supplier of CPUs shows that Apple perceived the underperformance of its CPUs as a major disadvantage.\(^{25}\)

The situation in the applications market (e.g., word-processors, spreadsheets, etc.) during the crucial period when Apple lost most of its market share is far less clear. While the first spreadsheet, VisiCalc, was first introduced on Apple, the acquisition of VisiCalc by Lotus and the subsequent development of Lotus 1-2-3 (operable only on IBM-compatible machines) changed the balance in the market in favor of IBM. Though VisiCalc had many clones (both for the Apple and for IBM PC) none of these clones had high-enough quality to attract consumers. Lotus 1-2-3 was described by market analysts as a revolutionary product and was considered to be a "killer application" that sold IBM-compatible computers.\(^{26}\) During this period, Apple’s market share dropped from more than 15% in 1980 to about 3% by 1997 (Kwak and Yoffie, 1999). These market shares for Apple versus IBM, though not caused solely by this mechanism, are consistent with the predictions of our model.

Paradoxically, inviting competition in the component markets helped IBM-compatible PCs gain dominance in the hardware market. Overall, the higher level of competition in the component markets meant higher speed of innovation for the IBM-compatible platform relative to Apple. This, in turn, made the IBM-compatible platform more attractive for consumers. As BG point out, IBM's decision to set up an open architecture increased competition in a larger share of components markets relative to competing architectures, namely Apple, and the IBM PC became the industry standard.

Another interesting illustration of the model’s mechanics is Microsoft's recent attempts to integrate software applications into its operating system. This move, at least partially, reverses the initial disintegration (open-architecture) strategy pursued by IBM in the PC market. Microsoft’s integration

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\(^{24}\) This does not exclude that Apple machines had technical advantages at the time of introduction of particular models. Overall, however, the data points towards technological superiority of IBM-compatible machines.

\(^{25}\) Apple’s founder and CEO, Steven Jobs, claims that the switch to the new Intel CPUs doubles the speed of Apple computers relative to its preceding generation. It should be noted, however, that Jobs compares apples with pears (pun intended): Apple’s new machines use the latest in dual core technology from Intel, while the prior generation of Apple computers ran with a previous generation of CPUs, mainly from IBM. See, e.g., Flynn and Bajaj (2006).

\(^{26}\) Apple also had its "killer application" – desktop publishing. However, the mass market found spreadsheets to be much more attractive than it did desktop publishing.
strategy is consistent with our model’s predictions: as long as a firm faces competition from alternative platforms, it should invite competition on its own platform (as IBM did), thus increasing overall investment on the platform and, with this, increasing the attractiveness of the platform. However, once a firm is on the dominant platform that has established itself as the industry standard, it should suppress competition in favor of monopoly rents.

This highlights the importance of investment in quality under various circumstances. Using BG’s language, IBM's competitive effort to win market share from Apple was swift and aggressive. This can be easily translated into our investment taxonomy above: whenever competitors caught up with IBM, this triggered more aggressive behavior from IBM and its position moved from being a "Scavenger" to being a "Lone Wolf." Arguably, while Microsoft still enjoys the "Scavenger" position for some of its products (like its operating system), Intel, for example, was pushed towards being a "Lone Wolf" in its segment of components by AMD.

Three lessons, supporting BG's analysis, can be learned from this discussion. First, firms on the lagging platform (initially IBM, Intel, and Microsoft in our example) will more eagerly cooperate than firms on the dominant platform (Apple, at that stage) as long as initial quality differences across platforms are small. Firms on the lagging platform will also more eagerly invite competition in order to beat the dominant platform, while firms on the dominant platform will try to monopolize. Finally, if a competitor on the leading platform gets into the realm of a dominant firm, competitive responses will be aggressive (e.g., Intel).

5. CONCLUSIONS

In this paper, we study how the existence of competing platforms influences optimal investment strategies. We analyze two drivers of investment behavior: quality levels on the same platform and quality levels across platforms. We find that investment behavior is driven by two effects: the network effect and the competitive effect. Strong network effects coordinate investment behavior of software firms within platforms. Software firms on the same platform appear to join forces, a phenomenon that we dub “pack-hunting,” and the incentives to do so are stronger, the more equally strong the platforms are.
competitive effect increases investment of both firms on the same platform if they are of similar strength, but reduces investment if they are not. If quality differences between firms are large, a negative competitive effect can outweigh a positive network effect. This leads to a “lonely wolf” behavior for firms on the trailing or heavily contested platform or to a “scavenger” behavior on the leading, uncontested platform. While the “lonely wolf” increases its investment as long as it is successful, the “scavenger” mainly lives on past investment. Finally, the “puppy wolf,” being a leader on a leading platform has low incentives to invest heavily. In short, the existence of platforms induces noteworthy departures from standard optimal investment behavior, which can be categorized once the main drivers have been identified.

An analytical model would not allow us to address the complexity of these issues or acquire insights comparable to the ones we found. We therefore used numerical methods for our analysis. In this paper, we have analyzed the effect of market structure on optimal investment behavior in the presence of indirect network effects. Optimal investment may look different if software firms can produce for both platforms, only facing an adaptation cost. Hardware upgrades may introduce additional uncertainty, again changing optimal investment behavior. While we believe that we address the most salient issue of optimal investment in the presence of indirect network effects, we intend to investigate some of these additional issues in our future research.

REFERENCES


Appendix

Data comes from the following sources. All information about Apple computers was obtained from http://www.apple-history.com. Data on all microprocessors was downloaded from http://www.cpu-collection.de. Data on the video adapters for monitors comes from http://bugclub.org/beginners/history/MonitorsHistory.html, and finally data on floppy discs comes from http://www.fortunecity.com/marina/reach/435/storage.html. www.wikipedia.com was used as a supplementary source for all of the above items. All web pages were repeatedly accessed in the months of March to May 2005.

There is an inherent difficulty in comparing the quality of components. Any measure we might use does some injustice to certain aspects of the components we study. For example, floppy disks are characterized by capacity, size, and speed of access. However, we have no supplementary data to find out which one of these features is valued the most by consumers. Therefore, we tried to obtain as simple measures as possible that allow us to compare quality of the components used in both systems and leave it to the reader to evaluate the appropriateness of these comparisons by manipulating the raw data herself, which we are very happy to provide on request and will post on a web page later on.

Different lines of floppy discs are simply ranked by capacity. For CPU comparison, we chose the geometric mean of core speed and bus speed, ignoring the lines of processors as well as their threading capabilities. For graphics cards, we again chose the geometric mean of the resolution measured as pixels per line and column, as well as the numbers of bits the colors were coded with. While these are very rough measures, we still think that more-sophisticated measures would not lead to very different results.