ANTECEDENTS OF GROWTH IN NETWORK COMPETITION: QUALITY OR QUANTITY?

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ABSTRACT

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(Under the direction of Dr. Richard A. Bettis)

This research examines the impact of two potential antecedents of growth in high-technology, network industries. The first antecedent, installed base, is traditionally framed as a key driver of growth in these settings. The second, product quality, is thought to have only random influences on growth. This work tests the influence of both of these variables on growth in the packaged application software industry, and proposes that their relative influence may be contingent upon the network intensity of a given market or segment. In turn, installed base and timing of product release are proposed to have a significant impact on quality.

The sample for this study encompassed five segments of the packaged application software industry from 1986-1998, including word processing, spreadsheets, desktop publishing, CAD, and personal finance. Several results from the empirical analysis offer useful insights into the nature of network industries, and implications for strategic management in these domains. First, installed base size exhibits a negative relationship with growth that becomes more positive as size increases. Second, product quality is positively and significantly associated with installed base growth. Third, the impact of size on growth is shown to vary across industry segments, suggesting that the influence of network effects may not be as homogeneous as extant theory implies. Finally, installed base is associated with higher baseline product quality within periods, consistent with the notion that a large installed base confers learning-based advantages to quality.

Together, these findings indicate that competitive dynamics in network industries may be more complex than previously thought. This research extends existing theoretical and empirical work on network effects and positive feedback, and suggests new avenues for effective strategies in emerging high-technology settings.

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CHAPTER 1

INTRODUCTION

Recent theoretical work encompassing strategy and industrial organization economics suggests that in many high-technology industries, the relatively stable outcomes engendered by diminishing returns to scale are largely absent. In these settings, a single firm can enjoy robust growth and industry dominance via forces of positive feedback that tend to push the market toward the adoption of a single product or product design. Network effects, whereby consumer adoption decisions are at least partly contingent on the size of a product's installed base, are a critical component of this process. When consumers value a large cohort of fellow adopters, the firm with the largest network of previous adopters at a given time should be optimally positioned to win the battle for market dominance.

This premise has important implications for firm strategy. In competitive settings where network effects and positive feedback are evident (i.e., "network industries"), logic suggests that the ideal firm strategy is to build network size as quickly as possible (Hill, 1997). Concurrent investments or actions by the firm aimed at improving the intrinsic quality of the focal product should be ancillary concerns, as the value to consumers of a given product is reflected largely by its network size, rather than simply by some "physical attribute embodied in each unit of the good" (Bental & Spiegel, 1995).

A theoretical implication of this assertion is that products that emerge as dominant standards in network competition may not be the best ones in terms of intrinsic, stand-alone quality. While this implication has become a tenet of the literature and pedagogy on network effects, empirical efforts to validate it are surprisingly sparse (Brynjolffson & Kemerer, 1996), and have provided mixed results. Furthermore, recent findings cast some doubt on the notion of inferior products dominating high-technology markets (Liebowitz & Margolis, 1999).

This research incorporates perspectives from strategic management and industrial organization economics in developing and testing propositions about the relationships among installed base, product quality, and growth in network industry. This work offers several important contributions to the literature on strategy and network effects. First, the influence of installed base size on growth is tested in an industry setting that is often cited as an example of network-based competition and positive feedback – specifically, packaged application software. Second, the strength of the size-on-growth relationship is proposed to vary across industry segments as a result of heterogeneous *network intensities* in these segments. Third, product quality is offered and tested as a mediating variable in the relationship between size and growth in packaged software, suggesting that the role of quality may be understated by extant theory. Finally, installed base and timing of product introduction are offered as alternative drivers of quality in packaged software. Taken together, these contributions continue the trend in recent research of relaxing assumptions about the largely exogenous nature of performance outcomes in network industries (e.g., Schilling, 2002), and offer important implications for firm strategy. Furthermore, this research expands upon previous work on network effects by using continuous and longitudinal measures of both quality and performance, as opposed to the categorical, outcome-based performance measures frequently used in previous literature.

This study begins by describing the basic dynamics of network industries, and defining relevant constructs such as positive feedback, network effects, and technology lock-in. The theoretical model and hypotheses are then developed in the context of extant literature. After brief discussion of the sample, measures, and methodology, the results of the empirical tests are presented. The paper concludes with a discussion of the primary theoretical contributions of the research, as well as the limitations, possible extensions, and managerial implications of this work.

If network effects and positive feedback are indeed becoming more salient concerns for managers in various knowledge- and technology-intensive industries (Arthur, 1996; Bettis & Hitt, 1995), then understanding the unique strategic dynamics of these settings is increasingly important for strategy researchers. In building on previous theoretical and empirical work in this domain, this research adds to the growing body of knowledge on network effects and positive feedback, and offers new insights into effective firm strategies in network competition.

CHAPTER 2

LITERATURE REVIEW

2.1 "Network" Industries: Characteristics and Prevalence

Network effects are present when the value of a given product or technology to a potential consumer is at least partially contingent upon the number of people who have already adopted it (Katz & Shapiro, 1986; Farrell & Saloner, 1986). Examples of positive network effects are readily apparent in "pure" network products such as telephones, fax machines, or electronic mail, which have virtually no value in the absence of a network of consumers. In these cases, a given consumer will value a large network of fellow adopters, as this network is essential for deriving value from the product. The cumulative number of previous adopters at a given time in the product's life (i.e., the network size) is the product's *installed base*. In many high-technology markets, adopters value a large installed base due to their desire for interaction with other members of a network, but also because it serves to alleviate uncertainty about the viability of a given product (Brynjolffson & Kemerer, 1996), thus reassuring consumers that learning investments related to the product are worthwhile.

Before proceeding with a discussion of network industries, a definitional clarification merits some discussion. A large number of previous studies on the influence of network effects refer to this phenomenon as network *externalities* (e.g., Katz & Shapiro, 1985; Brynjolffson, 1996; Schilling, 2002) However, the use of the term "externality" implies a market failure resulting from agents' inability to efficiently internalize the costs and benefits of their network membership (Coase, 1960). The ostensible market failure of interest for this research, the predominance of sub-optimal products or product designs, will be discussed in greater detail later in this paper. For now, it is simply noted that the broader term network *effects* has been offered as a more apt description of network dynamics in high-technology industries (Liebowitz & Margolis, 1994). Recent literature illustrates increasingly widespread adoption of this terminology (e.g., Katz & Shapiro, 1994; Shankar & Bayus, 2003), and thus this paper uses the latter term throughout.

2.2 Positive Feedback and Path Dependence

The primacy of the installed base in the marketplace is not limited to the facile examples described previously. Indeed, Arthur (1996) contends that network effects are a salient feature of many contemporary high-technology industries. In these settings, competition is heavily influenced by positive feedback, in that each consumer adoption of a product increases the likelihood of future adoptions. As such, firms with an early lead in installed base tend to increase their lead, while those who fall behind tend to be competed out of the marketplace. Such industries are said to exhibit demand-side increasing returns to scale, as the value of a firm's product(s) increases as its installed base grows. The precise processes by which early leaders emerge in a network industry are often dependent upon random, exogenous shocks to the industry – i.e., “historical small events” (Arthur, 1989). Yet once a leading product design emerges, positive feedback tends to push a single design, and often its sponsoring firm, toward market dominance (Besen & Farrell, 1994).

The presence of positive feedback in a competitive setting not only runs counter to traditional economic notions of negative feedback and diminishing returns, but also implies specific underlying properties of a network industry. Foremost among these properties is path dependence, the notion that the present structure of the industry is strongly dependent on events in previous time periods. The conceptual linkage with network effects is quite clear – those firms with large networks at t_0 should enjoy greater growth in time t_{+1}, as their large installed base is more attractive to adopters than those of competing firms (Schilling, 2002). However, a critical issue from a strategy perspective is the precise degree of present dependence on previous conditions. If path dependence is strictly dependent on network size, which in turn may be dependent on random events or influences, then widespread adoption of inferior products becomes possible. In an attempt to address this issue, Liebowitz and Margolis (1999) identified three basic types of path dependence from the perspective of adoption decisions influenced by network effects:

Table 2.1: Three types of path dependence (Liebowitz & Margolis, 1999)

First degree: Adopters make decisions about products based on accurate information about the future, yet their decisions may seem sub-optimal at a given time in the evolution of the industry.
Second degree: Information about the viability or quality of products is unclear at the time of adoption.
Third degree: Adopter is well informed about the inferiority of a given product, but network benefits are so strong that the product is adopted. Switching and coordination costs are too great to migrate to a "superior" product.

While first- and even second-degree path dependence may seem regrettable and costly to adopters at some point in the life of the product, they are not necessarily inefficient, as adoption decisions were made based on the best available knowledge, and are remediable in nature. Third-degree path dependence, however, presents a more troubling scenario. In this case, consumers have full knowledge of the inferiority of a product, but the benefits of network membership and the possible costs incurred by adopting an alternative product are too great to overcome. Thus, network effects may foster scenarios where the value of the installed base has overwhelmed any intrinsic quality advantages offered by the product, and users are "stuck" with an inferior product. It is this artifact of third-degree path dependence that has become a tenet of the literature on network competition (Table 2.2) - if consumers truly value network size over other metrics of stand-alone product quality, then the unsettling possibility arises that products, product designs, and technological standards may emerge that are of sub-optimal quality. The next section describes several contentions in this regard.

2.3 Lock-in and Product Inferiority: Narrative Evidence

David's (1985) work effectively illustrates the theoretical arguments surrounding the process by which an apparently inferior product design virtually locks in the focal market. This historical narrative describes the evolution of the QWERTY keyboard standard. When purchasing a typewriter, each new adopter had to decide whether to make costly investments in learning a certain keyboard layout. The increasing installed base of QWERTY led adopters to believe that learning investments in this layout would allow for greater future returns to these investments, through a greater range in employment opportunities in the larger network of firms and individuals using the layout. By the time that ostensibly better layouts were introduced, users did not want to incur the switching costs associated with learning a new layout. Thus, the QWERTY design evolved into a de facto standard because consumers valued compatibility and reduced uncertainty for the emerging technology. Cowan (1990) describes a similar scenario in nuclear power technology, as light water reactors became the predominant technology due to early adoption and investments by the U.S. Navy. By the time civilian markets developed for nuclear power, light water's dominance was unassailable, even by potentially superior technologies.

These narratives have served to illustrate the unique dynamics of network industries discussed previously. Perhaps the most widely referenced of these dynamics is the aforementioned notion that network effects and positive feedback can lead to dominance by inferior or sub-optimal products in high-technology settings (Table 2.2).

Table 2.2: On the nature of product inferiority resulting from network effects

Besen & Farrell, 1994	"Because buyers want compatibility with the installed base, products that arrive later may be unable to displace poorer, but earlier standards."
Shapiro & Varian, 1999	"In a network industry, success and failure are driven as much by expectations [from network size] and luck as by the underlying value of the product."
Teece, Pisano & Shuen, 1997	"The reality is that the companies with the best products will not always win."
Schilling, 1998	"…Early technology offerings may become so entrenched that a firm offering subsequent technologies, even if they are considered technically superior, may be unable to gain a foothold…"

2.4 Strategy in Network Competition

Network industries present a compelling context for the study of firm performance, as positive feedback can enable the type of superior performance, even dominance, which strategy research seeks to identify and explain. Indeed, as proprietary product designs evolve into industry-level dominant designs (Utterback, 1996), an enormously profitable opportunity may exist for the sponsoring firm (Ferguson & Morris, 1993). However, the notion that such performance is contingent upon factors outside of the firm's realm of influence presents a difficult conundrum for strategy practitioners. Thus, a nascent literature has begun to address the role of strategy in high-technology, network-based competition. Selected results of this stream of research include the importance of an early installed base in network competition (Besen & Farrell, 1994; Hill, 1997), the avoidance of early or late market entry in determining the viability of a technology (Schilling, 2002), and the role of expectations management in network competition (Katz & Shapiro, 1994).

Despite these theoretical and prescriptive advances, managers still face a great deal of uncertainty about effective strategies in network competition. While a strategy of preemption via building an early installed base is sensible in the context of extant theory, the extent to which firms must make baseline investments in product quality remain largely unclear. As noted previously, theoretical conceptualizations and narratives of network industries describe circumstances where sub-optimal product designs came to dominate the market. Yet these conceptualizations, as well as many empirical studies of network effects, generally take an outcome-based view of competition – i.e., retrospectively delimiting winners from losers, high quality products from low quality ones. However, deriving robust implications for strategy requires a shift in focus to the process of network-based competition, and the unique characteristics and capabilities of the firms engaged in such competition.

A study of dynamic network competition over time would effectively facilitate such a shift, and largely eliminate any hindsight bias that may reinforce negative perceptions of product quality *a posteriori*. Furthermore, such an approach allows for an examination of the role of quality relative to alternative products at a given point in time, illustrating whether third-degree path dependence can indeed overwhelm consumer preferences. If product quality does indeed have an incremental impact on patterns of adoption, then investments and actions related to innovation and product quality become critical variables for the firm, and the spectrum of strategic options available to managers in network competition may be more complex than previously thought.

CHAPTER 3

THEORY DEVELOPMENT AND HYPOTHESES

3.1: Antecedents of Growth in a Network Industry: Installed Base and Product Quality

The research and narratives described in the previous chapter suggest that in network industries, consumers derive value from two aspects of a given product – its network value, and its network-independent value. For example, for certain computer applications consumers value the ability to interact and exchange files with a compatible network, as well as stand-alone product attributes such as a simple graphical interface (Brynjolffson & Kemerer, 1996). More generally, network value is a reflection of the benefits associated with a large cohort of fellow adopters (installed base) for the product, while network-independent value represents benefits conferred by intrinsic, "physical attributes embodied in each unit of the good" (Bental & Spiegel, 1995). In the most extreme cases of third-degree path dependence, a theoretical consequent of network effects is that a product's network value subsumes any network-independent benefits. As a result, quality differentiation among competing products becomes irrelevant, and adoption of inferior products and product designs may occur.

The following section incorporates a process-based, rather than outcome-based, perspective on the dynamics of network industries. A theoretical model incorporating installed base, network-independent quality, and growth is offered, and further propositions regarding effective firm strategy in network competition are described.

3.1.1 Effects of Installed Base Size on Growth: A Network-Dependent Perspective

While a broad literature in strategy and industrial organization has found mixed effects in the relationship between organizational size and growth (e.g., Penrose, 1955; Hymer and Pashigian, 1962; Evans, 1987; Hall, 1987), these studies focus primarily on manufacturing industries, in which the benefits of network effects are largely absent (Arthur, 1996). Conversely, in network industries, the size of a product's installed base beyond some critical threshold is thought to be a primary determinant of its growth. Specifically, a larger installed base confers at least three types of benefits to potential adopters:

- *Direct network benefits*: In settings where the value of the product is largely a function of the number of other individuals or firms using it, direct network effects are present (Chacko & Mitchell, 1998). Examples include telecommunications networks and certain types of computer software, wherein network participants interact frequently, and thus value compatibility with a large number of other participants.

- *Reduced uncertainty*: When product adoption requires some degree of learning investments by consumers, uncertainty about the returns to these investments can be problematic. A large installed base acts as a signal that a given product exhibits some degree of long-term viability, thereby reducing uncertainty and assuring adopters that investments in learning will be beneficial. (Brynjolffson & Kemerer, 1996),

- *Indirect effects*: A large installed base is thought to attract producers of complementary goods and services to the focal product (Schilling, 2002). For example, software vendors must decide which operating system platforms to target when developing new applications. The platform with the larger installed base offers a larger potential pool of adopters for the application, over which the vendor may be able to exploit economies of scale in production. (Chacko & Mitchell, 1998)

These dynamics of network industries suggest that the size of a product's installed base at a given time is a critical determinant of its growth. Yet surprisingly, direct tests of the impact of installed base on product adoption (i.e., the effect of a product's installed base size on its growth) are rather sparse in this domain of research. Several studies have used a product's price premium to indicate the value of compatibility with a large network (Gandal, 1994; Brynjolffson & Kemerer, 1996), and others have noted the role of network effects in driving technology adoptions at the firm level (Saloner & Shepherd, 1995; Majumdar & Venkatraman, 1998). However, this stream of research has largely neglected the seemingly most direct test of network effects – the effect of installed base on growth. If network size is indeed the primary determinant of growth in high-technology settings, a significant size-on-growth effect should provide preliminary evidence for the presence of positive feedback via network effects.

A positive relationship between installed base size and growth should provide a baseline indication that consumers in a high-technology setting value network size as a result of some or all of the associated benefits described previously. Note, however, that while a significant size-on-growth coefficient implies the presence of path dependence, it does not by itself indicate the degree of path dependence. In other words, while a significant effect may be illustrative of network value, it does not necessarily imply that the existence of such network value leads to inefficient or sub-optimal outcomes. Thus:

Hypothesis 1a: In a network industry, the larger the installed base of a product, the greater its growth in the following period.

3.1.2 Market Share as a Moderator in the Size-Growth Relationship

Chacko and Mitchell's (1998) work is one of the few empirical studies that tests a direct relationship between size and growth in a network industry. One key finding of this study is that installed base size has an increasingly positive effect on growth, but only beyond some critical mass of installed base. A plausible explanation for this finding is that below some critical threshold, network size does not fully convey the benefits of network membership to potential adopters, and thus does not adequately influence their expectations about the viability of a product. This logic is consistent with the notion that network industries tend to be "tippy" – once a firm's installed base achieves some critical mass, positive feedback increases its lead (Besen & Farrell, 1994).

The finding that a requisite critical mass is required to adequately convey network benefits to potential adopters suggests that postulating a straightforward size on growth relationship may oversimplify the nature of network dynamics. As such, it is useful to incorporate a measure of installed base relative to competing products, such as market share. Low market share indicates that a product has been unable to achieve the requisite mass to enjoy network dynamics, while a higher market share conveys broader visibility and network value to potential adopters. Thus, as market share increases, we expect to see a significant increase in the relationship between installed base size and growth. However, if we allow that some potential adopters have a natural affinity toward alternative or niche products, then the marginal costs of attracting these consumers may eventually become prohibitive. Furthermore, for virtually any product class, the number of new adopters tends to decrease as the product market matures (Bass, 1969; Mahajan, Muller & Bass, 1995). Thus, as market share continues to increase, the size on growth relationship should weaken again as the switching costs for remaining consumers become proportionally higher, and the sponsoring firm has less incentive to invest in attracting new adopters (Turner, Bettis, & DeSanctis, 2003):

Hypothesis 1b: In a network industry, the relationship between installed base and growth will be more positive at medium levels of market share than at high or low levels.

3.1.3 Effects of Product Quality on Growth: A Network-Independent Perspective

The conclusion that installed base size is the primary determinant of growth and performance outcomes in high-technology industries is not universally supported. Indeed, several empirical examinations of network industries suggest that network-independent dimensions of products play a more important role in performance outcomes than suggested by existing theory. For example, Brynjolffson and Kemerer (1996) find evidence that even when network benefits are present, consumers place a premium on certain network-independent aspects of spreadsheet software, such as the presence of a graphical interface and sorting functions.

This proposition, that adopters value the quality of network-independent characteristics of a product, is consistent with the broader contention in the strategy literature that "customers tend to be drawn to quality outputs, and form loyalties toward the providers of those outputs" (Kroll, et. al., 1999). Furthermore, high product quality relative to competitors can result in increased demand for the product (McGuire, Schneeweis & Branch, 1990), and thus positively impact the financial performance of the firm (Hendricks & Singhal, 1996; Kroll, et. al., 1999). Yet before I advance the argument that quality matters in a network industry, I will first address the precise nature of quality itself.

In the strategy literature, "quality" is a complex and multi-dimensional construct. In the specific context of network dynamics and increasing returns, I use product quality to describe characteristics of a given good in a network-independent context. More specifically, quality refers to *the superiority or inferiority of physical attributes of the* *product relative to competing products, independent of the benefits conferred by its network size.* Figure 3 provides several examples of such attributes.

Table 3.1: Examples of network-independent attributes of network products

Product	Network-Independent Attribute	Quality Metrics	Reference
Video Cassettes	Playback length	Tape capacity	Lardner, 1987
Typewriter Keyboards	Layout	Average and maximum typing speeds	David, 1985
Video games	Processor power	Clock speed, bit count	Schilling, 2003
Television	Color vs. black & white	Clarity, reliability of picture	Shapiro & Varian, 1999

This definition of quality implies several assumptions about the nature of network industries, each of which merit a brief discussion. First, this definition suggests an explicit de-coupling of network-based and network-independent sources of value to consumers, which is consistent with the logic of extant views on network effects (Table 2.2). Second, the assertion of a significant impact of quality on patterns of adoption assumes that the markets for these goods are vertically differentiated, i.e. that consumers ideally will prefer higher quality goods within segments, ceteris paribus. Finally, this research holds that software markets and segments involve one-sided or "same-side" network effects, whereby the benefits of adoption accrue largely to adopters, as opposed to two-sided networks which involve a more complex interplay of network benefits among multiple constituents (Eisenmann, Parker & Van Alstyne, 2006; Parker & Van Alstyne, 2005)

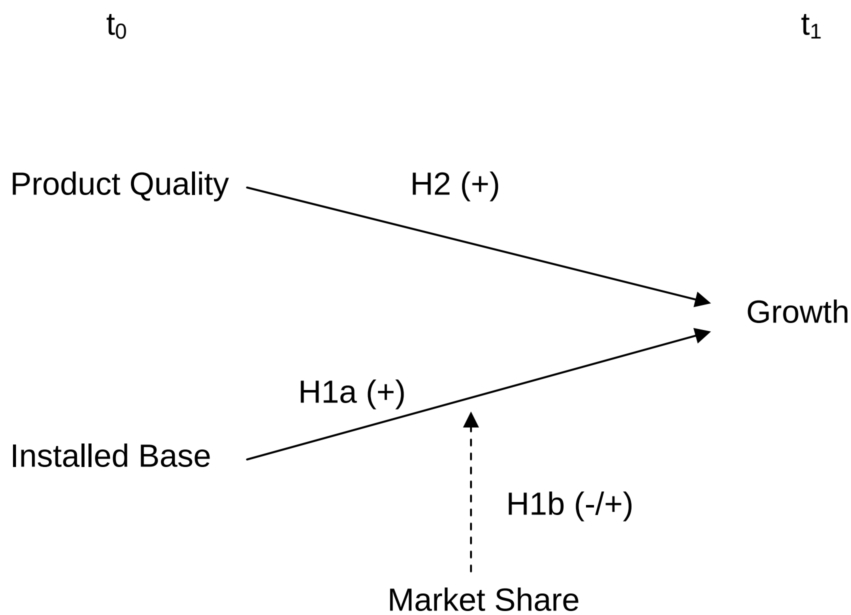
In a series of papers, Liebowitz and Margolis (1990, 1994, 1995) highlight the role of product quality in determining outcomes in network industries. The authors argue that cases of non-remediable market failure where an inferior product dominates the market must be exceedingly rare, as such outcomes must assume that consumers are unduly constrained in remediating these situations. Furthermore, they find that in settings where network effects should be strong, such as spreadsheets and word processors, dominant products tend to be those that exhibit the highest quality (Liebowitz & Margolis, 1999). This finding suggests that consumers do indeed tend to adopt the highest quality alternative, even when network benefits are evident.

These results indicate that extant theory describing market dominance by inferior products or product designs in network industries may be overlooking or underestimating the explanatory influence of product quality. One possible explanation for this phenomenon is the outcome-oriented approach implicitly advocated by much of the literature – i.e., labeling firms and technologies as winners and losers, locked-in or locked out. Such labels ascribe static characteristics to competitive settings that are fundamentally dynamic and complex in nature. Furthermore, an outcome-based orientation allows for the possibility that post hoc characterizations of product quality may be unduly influenced by hindsight bias. Recall that for conditions of third-degree (extreme) path-dependence to hold, and objectively inferior products to dominate, consumers must adopt products that are demonstrably inferior to existing alternatives at the time of the adoption decision, and must be unable or unwilling to incur the switching costs associated with migrating to the "better" product. An outcome-oriented approach to assessing the quality-dominance relationship may introduce an inordinate focus on dimensions of quality that may or may not have been relevant concerns for consumers at the time of adoption.

In summary, previous empirical findings suggest that product quality has a positive influence on both consumer preferences and firm returns, even in industries where network benefits are present. Furthermore, recent work suggests that high-quality products tend to be predominant even when consumers value network size. As such, in a network industry, the quality of network-independent attributes may play a distinct role in providing positive feedback to a given product and its sponsoring firm:

Hypothesis 2: In a network industry, the greater the quality of a product at a given time, the greater its installed base growth in the following period.

Taken together, Hypotheses 1a and 2 reflect two potential sources of positive feedback in network industries – one network-dependent (installed base size) and one network-independent (product quality), while Hypothesis 1b examines the moderating role of market share in the size on growth relationship.



3.2 Variation in Network Intensity Across Segments

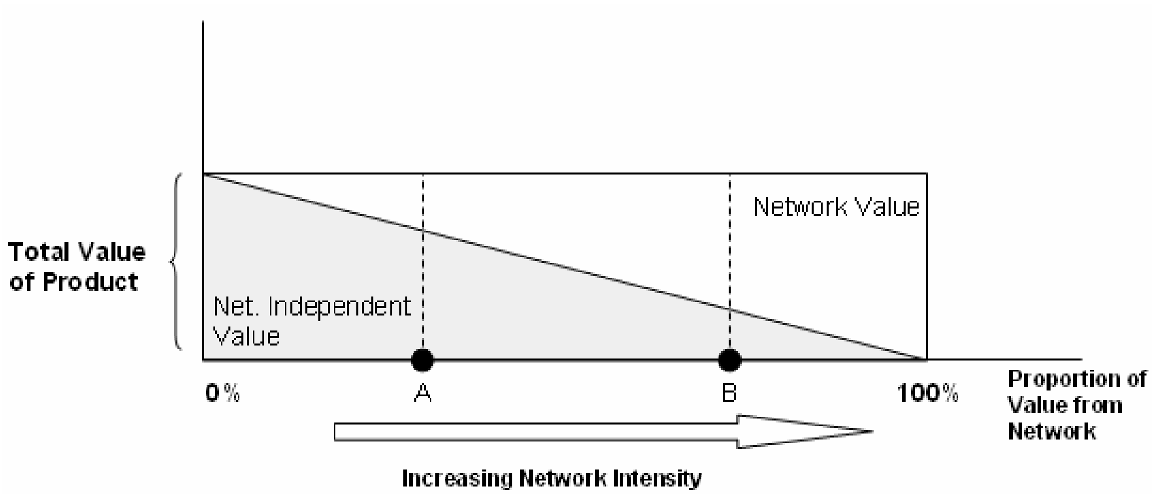
From a strategy perspective, the absolute strength of the effects of installed base and quality on growth may be less informative than their strength *relative* to each other. For example, in online auctions, we expect that installed base size plays a very strong role in driving network growth, as such auctions have almost no residual value in the absence of a network of fellow adopters[1]. However, other products, such as video game consoles, have a great deal of value to individual users in the absence of network interaction. For both online auctions and video games, consumers derive some value from

[1] This residual value can also be conceptualized as the *autarky* value of the product, or the value of the product assuming no interaction among users (Liebowitz & Margolis, 1999). For consistency, I will continue to refer to this as *network-independent value*, though I view the terms as largely interchangeable.

interacting with a network, yet in the case of video games, the proportion of total value derived from network membership is likely lower than in online auctions.

Figure 5 presents a very basic illustration of this notion, with the light region representing the proportion of a product's value that is dependent on network size, and the shaded region representing the proportion of network-independent value. If the total value of a network product is conceptualized as the sum of its network value and network-independent value, then one would expect video game consoles to lie near point A, as consumers can derive value from simply using the console, as well as the ability to exchange or play online games with fellow users. In contrast, online auctions would lie closer to point B, as the brunt of their value comes from the consumer's ability to interact with the largest possible network of users.

Figure 3.1: Illustration of network intensity



The *network intensity* of a given product can be conceptualized as the proportion of total value that consumers derive from network interaction for a given product, ceteris paribus. Understanding this intensity has several implications for strategic management. First, network intensity may explain why we often see variation in the number of product standards across network industries (Eisenmann, 2006). When network intensity is high, we would expect to see a higher prevalence of "winner-take-all" product markets, where an early leader comes to dominate the market. For a product market with lower network intensity, we would expect to see a higher incidence of multiple, evolving standards[2]. Second, network intensity may inform the firm's optimal strategy in a given market or market segment. When network intensity is high, then extant theory suggests early entry and quickly building an installed base; as network intensity decreases, competition

[2] Consider the two examples offered previously. The value of an online auction comes almost entirely from the availability of a large network, and the industry has closely approximated a classic "winner-take-all" story. The network intensity of video game consoles should be lower due to their higher network-independent value, and this has manifested in multiple, dynamic standards over the past 20+ years.

becomes increasingly focused on quality differentiation between competing products. Finally, a greater understanding of network intensity may allow for the possibility that firms can manipulate certain aspects of their products to make them more or less network intensive[3]. For example, an online auction company may try to increase the network-independent value of its product by adding a multi-service Web portal interface. Conversely, online video gaming can be viewed as an attempt to add direct network value to a stand-alone console.

In the packaged application software industry, it is reasonable to expect that network intensity varies across different product segments (Table 3.2). For instance, we expect to see stronger intensity in the word processing and spreadsheet segments, as the outputs of these applications are commonly shared within and across organizations. In contrast, applications such as desktop publishing and personal finance may be less network-intensive, as their outputs (brochures, personal financial records, etc.) tend to have value largely to a single user, or to a relatively small cohort around that focal user. Table 3.2 presents a formal presentation of this assertion, illustrating the extent to which the three dimensions of network value influence each segment. Where applicable, I have noted previous theoretical and empirical work that supports the characterizations of each segment. Note that while desktop publishing and personal finance are classified as packaged software products, there are (to my knowledge) no empirical validations of the influence of network effects in these segments, lending credence to their labels as lower-network intensity segments.

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[3] Note, however, that I have modeled network intensity as an exogenous aspect of the product market. Nonetheless, the notion that firms can manipulate network intensity is an intriguing one, and will be discussed further in Chapter 6.

Table 3.2: Network intensity in packaged application software

Segment	Direct Effects	Uncertainty/Viability Effects	Indirect Effects	Network Intensity
Word Processing (Katz & Shapiro, 1994)	High *Widespread interaction among users in the workplace, bulk corporate users*	Medium *Initial switching costs strong, but increasing compatibility, GUIs increasing the ease of switching*	Medium-High *Availability of plug-ins, accessories may draw borderline adopters*	**HIGH**
Spreadsheets (Gandal, 1995; Brynjolffoson & Kemerer, 1996)	High *Widespread interaction among users in the workplace*	Medium-High *Many complex functions, macros unique among products, raising switching costs*	Medium *Primarily interaction with external databases*	**HIGH**
CAD (Astebro, 2002)	Medium-Low *Users tend to be highly specialized; findings suggest only a modest size-on-growth impact*	Medium *High-end products can run into the thousands of dollars; design interfaces range from intuitive to highly complex*	Medium *Various plug-ins and extensions available*	**MEDIUM**
Desktop Publishing	Medium *Uses include newspaper layouts, internal corporate publications – intra-organization compatibility is more important than gross network size*	Low *Most interfaces are graphically based, similar to word processors*	Medium *Compatibility with photo, illustration software is a concern*	**LOW**
Personal Finance	Low *Prior to Internet, virtually no network interaction required*	Low *Most low-end applications require limited proprietary learning*	Medium *Initially low, increasingly prevalent with online banking and other interactions*	**LOW**

Observing significant variance in the effects of size-on-growth in these segments would provide very preliminary evidence that network intensity is heterogeneous across these industry segments. Thus, in the packaged software industry, we propose the following hypothesis relating to the influence of network intensity across product segments:

H3: The effect of installed base size on growth will increase as the network intensity of a segment increases.

3.3 Antecedents of Product Quality in a Network Industry

One obstacle to effective strategy formulation in a network industry resides in the assumption that both installed base and product quality are largely the result of random and exogenous forces in these settings. Building on the previously described theoretical model, the following section proposes two variables that may influence the quality of the firm's product releases, and thus offers further insights into the dynamics of effective strategy in network competition. The first variable, installed base size, is hypothesized to impact product quality through accumulated learning effects. The second, timing of release, is suggested to affect product quality via temporal learning effects.

3.3.1 Alternative Perspectives on Learning and Product Quality

While installed base size and product quality were hypothesized to have independent direct effects on growth, extant theory suggests a significant relationship between these two variables as well. Specifically, an organizational learning perspective suggests that size plays an important role in determining the quality of the firm's output. In addition to its role as a reflection of accumulated learning, size may confer additional advantages with respect to product quality, such as more productive research and development activities (Henderson & Cockburn, 1996), and the ability to spread fixed R&D costs over a larger output (Cohen, 1995). However, this section will focus specifically on two types of organizational learning that may affect quality: learning over production and over time.

The firm's learning orientation has been hypothesized to have a significant impact its viability in high-technology industries (Schilling, 1998) via increased absorptive capacity (Cohen & Levinthal, 1989), but the precise mechanisms by which learning occurs at the firm level remain unclear. In manufacturing-based industries, learning curves in production are thought to be an effective empirical illustration of the learning process. The basic premise of such a curve is straightforward - as firms produce more of a product, unit cost decreases at a decreasing rate (Argote & Epple, 1990; Adler & Clark, 1991). Because the rate of learning is assumed to be relatively stable across firms – roughly a 20% drop in unit costs per doubling of cumulative output – the existence of such a curve has been implied to confer first-mover advantages in multiple industries, including network industries (Arthur, 1996).

Progress in production efficiency is one metric by which firm learning can be measured, but it is not only one (Levin, 2000). The quality of the firm's output, rather than the unit cost of such output, may be an equally important metric from a strategic vantage point (Fine, 1986; Cole, 1990; Levin, 2000). From this perspective, firm learning represents more than a simple reflection of productivity- or efficiency-based knowledge gains, but also the active acquisition of quality-based knowledge (Li & Rajagopalan, 1998).

If product quality is indeed illustrative of the firm's stock of quality-based knowledge at a given point in time, then understanding the factors influencing the acquisition of this knowledge takes on increased importance. As noted previously, cumulative production is thought to be one driver of productivity-based learning. Yet cumulative output may have a similar influence on quality-based learning, as the firm gains experience in identifying and mitigating production defects, as well as a larger base of users to provide feedback on technical bugs or other design-related limitations. Though installed base is an imperfect measure of cumulative production, it does reflect some level of heterogeneity in accumulated output among competing firms. Furthermore, if knowledge acquired in production depreciates over time (Argote, Beckman & Epple, 1990), implying that more recent production is a more accurate indicator of learning, then installed base size should provide a reasonable reflection of quality-based firm learning.

In summary, theories of learning via cumulative production underlie the following hypothesis with respect to the relationship between installed base and product quality in a network industry:

Hypothesis 4: The size of a firm's installed base will be positively associated with the quality of its product releases.

Though learning over cumulative output has established a strong theoretical foundation among strategists, learning may have temporal dimensions as well. For some aspects of product quality, such as long-term reliability, time is a necessary component of learning, as the quality attribute can only be accurately discerned after a certain time lag (Levin, 2000). Furthermore, cumulative output models may be limited by their simplifying assumptions that that learning is stable and persistent over the life of production (Argote, Beckman & Epple, 1990). As such, a time-based perspective may be a more informative indicator of firm learning, as it allows for the possibility that firms actively engage in quality-based improvements over time, rather than simply absorbing incremental improvements over the life of production.

This de-coupling of learning and production experience implies that firms not only learn through their own cumulative experience, but can also by observation of the successes and failures of competing firms and products (Levin, 2000). In industries where product releases tend to be relatively generational and parallel across firms[4], such as automobiles and packaged software, the concept of "learning before doing" suggests that there may be benefits to delaying the release of product innovations. This notion is consistent with idea that first-mover status in high-technology settings may have significant disadvantages, particularly when the underlying technology and customer needs are shifting (Liberman & Montgomery, 1988). In sum, a time-based learning

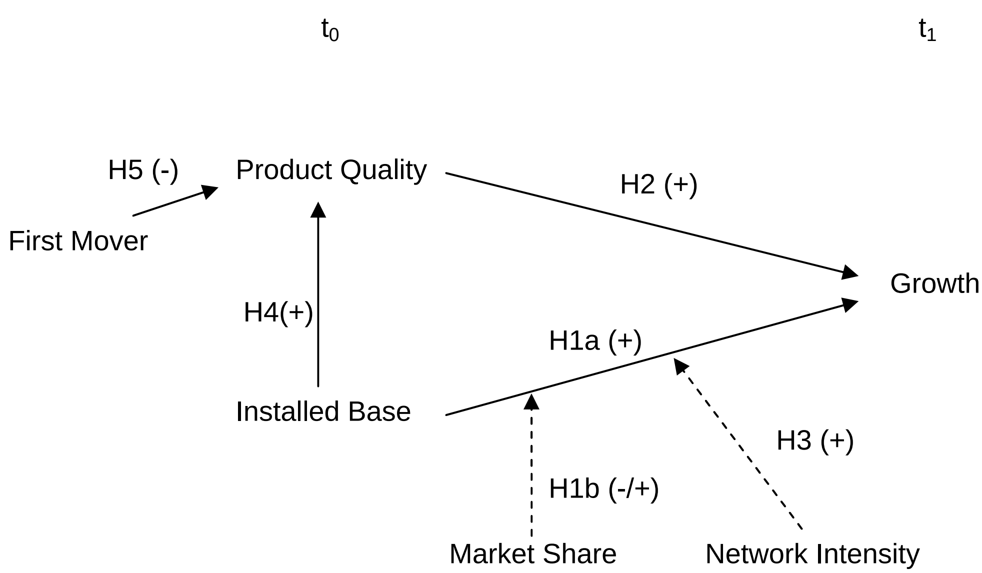
[4] See Chapter 4 for a more detailed description of generational vs. incremental product innovation.

perspective on quality provides a basis for the benefits of delaying generational product releases:

Hypothesis 5: Within generational products, first movers will tend to exhibit lower quality than later releases.

In conclusion, Hypotheses 4 and 5 frame installed base size and timing of release as factors influencing the network-independent quality of a firm's products. These hypotheses serve to complete a partially mediated model of installed base size, product quality, and growth in a network industry, and illustrate a strategic tension regarding product releases network industries, namely the trade-off between learning through experience in a market segment vs. learning by delaying a generational release.

Figure 3.2: Antecedents of quality and growth in a network industry



CHAPTER 4

METHODOLOGY

4.1 Sample

In order to test the hypotheses for this study, a sample of product releases in the packaged application software industry (NAICS 511210) was gathered. In the empirical literature, various segments of application software have been offered as representative examples of network industries (Brynjolfsson & Kemerer, 1996; Chacko & Mitchell, 1997; Liebowitz & Margolis, 1999). For this particular research, cross-sectional and time series data were gathered on a sample of software releases in five segments of packaged software from 1986-1998.

To ensure that platform effects did hold undue influence on growth patterns, the sample was limited to software compatible with the DOS/Windows operating systems. Windows-based application software first appeared sporadically in the sample in 1990, and gained a substantial foothold by 1993.

The raw sample for the study totaled 247 product-years encompassing 31 product lines in the word processing, spreadsheets, desktop publishing, CAD, and personal finance segments. Of these, installed base data was incomplete for approximately 16% of the observations, and a subset of the observations (19%) incorporated multiple imputation procedures for incomplete quality data[5]. These procedures resulted in a final sample of 207 product-years. Yearly data on market share, sales, shipments, and revenue were gathered from a dataset based on reports provided by IDC (International Data Corporation) and DataQuest, both leading providers of market research in software and other information technologies[6]. Information on product quality, product release dates, corporate parents, and general background were gathered through archival searches of software trade journals and periodicals, including *InfoWorld*, *PC World*, *PC Magazine*, *PC Week* and *Byte*.

4.2 Example of product-year observation

A typical product-year observation included information about a product's name, sponsoring firm, quality ratings, date of release, installed base, and other variables. To illustrate the nature of this data, consider the following observation, selected at random from the sample:

Table 4.1: Typical product-year observation

Product Name/Version	DisplayWrite 4.2
Year	1989
Sponsoring Firm	IBM

[5] See Chapter 5 and Appendix B for details. To ensure the integrity of the imputed values, I also compared the imputed data set with the raw data set – see Chapter 5.

[6] Special thanks to Stephen Margolis, Stan Liebowitz, Rich Bettis, and Scott Turner for assistance in tracking down this data.

Platform	DOS
Segment	Word Processing
Date of Release	August 1, 1989
***InfoWorld* Overall Quality**	4.8
Performance	.25
Documentation	.50
Ease of Use	.625
Error Handling	.50
Technical Support	.75
Value	.50
Date of Quality Review	October 30, 1989
Installed Base (t_0)	625,000
List Price	$495
Retail Price	$267
Market Share (Revenue)	8.9%
Market Share (Units)	14.3%

It is interesting to note that for the quality reviews, the overall quality ratings were not simple linear combinations of each quality dimension – i.e., the overall rating and the rating of performance, support, and other sub-dimensions were conducted independently. To ensure the baseline validity of these measures, correlations among the dimensions of quality and among multiple rating sources will be discussed in Chapter 5.

4.3 Model 1: Growth Antecedents Model

The purpose of Model 1 is to test alternative antecedents of growth in a network industry. Hypotheses 1a and 2 hold that installed base and product quality each have a significant impact on growth in a network industry. To test these hypotheses, a model was developed that incorporated each of these variables, and several control variables (Model 1).

(1) $lnS_{i,\, t+1} - lnS_{i,\, t} = \beta_0 + \beta_1 (lnS_{i,\, t}) + \beta_2 (lnS_{i,\, t})^2 + \beta_3 (Q_{i,\, t}) + \beta_4 (MS_{i,\, t}) + \beta_5 (MS_{i,\, t} * lnS_{i,\, t}) + \beta_{6 \ldots j}(CONTROLS)$

Where *S* is the size of a product's installed base, *Q* is product quality, and *MS* is the market share of the product. The specific variables in the model, as well as the logic underlying their measurement, are described in the following sections.

4.3.1 Dependent Variable

Installed Base Growth. The dependent variable of interest is installed base growth over time for a given product. Precise measures of installed base can be difficult to ascertain, as such a measure should account for both new adopters and consumers who have abandoned the product in a previous period. Following Chacko and Mitchell (1998), this study holds that lagged cumulative unit sales over a two-year period provide a reasonable approximation of a product's installed base.

Extant literature indicates that taking the difference of the logged installed bases in each time period allows for the preservation of assumptions about the normality of the distribution of the dependent variable. As such, growth is operationalized as the difference between the natural logs of size of the product's installed base at times t_0 and t_{+1}, i.e., the size of the current base less the size of the base in the previous year[7] (again following Chacko & Mitchell, 1998).

4.3.2 Independent Variables

Installed Base Size. Issues surrounding the measurement of installed base were previously discussed with respect to the dependent variable. Installed base size was measured as the natural log of cumulative unit shipments over a two-year period. A quadratic term was also included in the model, to account for possible curvilinear effects resulting from increasingly positive returns to size.

Product Quality[8]. Measures of product quality were gathered from archival issues of *InfoWorld* magazine, a publication that reviews and rates various information technologies. For each software release, *InfoWorld* provided two sets of ratings, one overall rating, and ratings in six sub-categories related to product quality: performance,

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[7] Note that in strict econometric terms, the dependent variable should be divided by the interval over which growth is being measured (*d*). Because this interval is one year (*d*=1), I have excluded it from the model for clarity. (See Evans 1987, Chacko & Mitchell 1998 for a similar rationale)

[8] In this section, I briefly describe the nature of the quality measures. For a more comprehensive discussion, see section 5.2, "On the Nature and Reliability of Quality Measures"

documentation, ease of learning, ease of use, technical support, and value. Correlations among these dimensions will be reported in Chapter 5.

The use of archival reviews in rating software assumes that such reviews are relatively unbiased – i.e., the quality rating is an accurate reflection of the product's actual quality, and that the ratings are not systematically biased or subject to excess measurement error. To test the validity of these assumptions, a sub-sample of product releases was used to calculate the reliability the quality ratings by comparing them to two other sources of independent reviews, *PC World* and *PC Magazine*. The results of these reliability estimates will be reported in Chapter 5.

Archival reviews also possess certain advantages over alternative measures of quality such as retrospective surveys or price-based indices. For example, retrospective surveys may be subject to systematic hindsight biases among respondents, while archival reviews with reliability checks should provide more unbiased estimates of quality relative to alternative technologies available at a given time.

<u>Interactive Terms</u>. To test the moderation hypothesis, interactive terms between market share and installed base and market share and quality were included in the model. In order to test Hypothesis 1b, the continuous market share variable was coded as "1" for medium market share (.34 - .66), and "0" for values lower or higher than this range.

Table 4.2: Summary of independent variables (growth model)

Variable	Definition	Measure	Type	Source
Installed Base	Active users of the focal product	Cumulative units shipped over previous two years	Continuous	IDC/DataQuest
Quality	Superiority or inferiority of physical attributes of the product relative to competing products, independent of the benefits conferred by its network size	Overall score on 10-point scale at the time of release	Continuous	*InfoWorld,* reliability checks with other journals
Market share	Percentage of the market occupied by a product in a given year	Product sales divided by market size; coded as low/ high (MS<.33, >.67 = 0) or medium (MS>.34, <.67 = 1)	Proportion	

4.3.3 Control Variables

Suite membership. Beginning in the early 1990s, many individual software applications were bundled and sold as productivity suites. While a bundling strategy may impact firm performance (Bakos & Brynjolffson, 1999), it may also make it more difficult for consumers to place a discrete value on an individual application within the suite (Katz & Shapiro, 1994).

Multi-segment firm. A firm's presence in multiple segments may have a twofold impact on performance. First, firms that compete in distinct yet related segments are thought to possess certain structural advantages over their competitors (Rumelt, 1973;

Bettis 1981). Second, such firms may be able to exploit relevant knowledge about software products and processes across multiple segments (Henderson and Cockburn, 1996 ; Tanrivierdi and Venkatraman, 2004).

Price. Product price has been characterized as a critical strategic variable in network competition (Shapiro and Varian, 1999). Yet if pricing strategy fully accounts for subsequent growth patterns, then there is little benefit in accounting for antecedents of growth outside of simple firm economies of scale. As such, list price for each product was included in the model.

Concentration. The degree of industry concentration may have a significant influence on firm innovation, profitability, and growth potential (Stigler, 1964; Buzzell, Gale and Sultan, 1975; Porter 1980). I have included one measure of concentration, the Herfindahl-Hirschman Index (HHI), which indicates the sum of the squared market shares of competitors, to control for concentration effects at the segment level (Curry and George, 1983).

Table 4.3: Summary of control variables (growth model)

Variable	Definition	Measure	Type	Source
Suite	Whether the product was released as part of a productivity suite or stand-alone	Dummy variable indicating suite membership or non-membership	Binary	Various archival sources
Multi-segment	Sponsoring firm competes in more than one segment	Dummy variable indicating single segment or multi-segment	Binary	Various archival sources

Price	List price of the focal product	Price (U.S. Dollars) of the product	Continuous	IDC/DataQuest
Concentration	Degree of concentration of the focal market segment	Herfindahl Index	Continuous	

4.4 Model 2: Network Intensity

The purpose of Model 2 is to test variation in the magnitude of size-on-growth effects across segments in a network industry. Specifically, Hypothesis 3 is tested via the interaction of a network intensity variable with installed base size to determine whether the impact of installed base on growth varies significantly as network intensity increases in a market segment:

(2) $lnS_{i,\,t+1} - lnS_{i,\,t} = \beta_0 + \beta_1 (lnS_{i,\,t}) + \beta_2 (Q_{i,\,t}) + \beta_3 (NI * lnS_{i,\,t}) + \beta_{4\ldots j}(CONTROLS)$

Where S is the size of a product's installed base, Q is the network-independent quality of the product, and NI is the network intensity of the product segment. The precise coding scheme for the network intensity variable is described in the following section.

4.4.1 Network Intensity Variable

Network Intensity. Network intensity reflects the proportion of total value that consumers derive from network interaction for a given product, ceteris paribus. Given the complexity of this construct, its use in this research is of a highly exploratory nature. As a first step toward understanding the nature and influence of network intensity, I have coded each of the five segments in two ways: first, an ordinal ranking of the segment's network intensity, and second, a broader categorical coding of "high" or "low" network intensity. Specifically, products in the word processing and spreadsheet segments were coded high, while others were coded low. The coding of each segment was based on the criteria described in Table 3.2. The first criterion is direct network effects, or the extent to which the cumulative size of the network affects product value. Second, viability effects capture the extent to which learning and/or switching costs present a significant burden for adopters, based on complexity of the focal technology. As such, the role of the network as a proxy for reducing uncertainty about the long-term viability of the product takes on increased importance. Finally, indirect effects reflect the extent to which complementary products play a role in influencing adoption decisions. Tables 3.2 and 4.4 illustrate the logic and basis for the categorical coding of each segment.

Table 4.4: Network intensity in packaged application software

Segment	Direct Effects	Uncertainty/ Viability Effects	Indirect Effects	Network Intensity	NI1	NI2
Word Processing (Katz & Shapiro, 1994)	High *Widespread interaction among users in the workplace*	Medium *Initial switching costs strong, but increasing compatibility, GUIs increasing the ease of switching*	Medium-High *Availability of plug-ins, accessories may draw borderline adopters*	**HIGH**	**5**	**1**
Spreadsheets (Gandal, 1995; Brynjolffoson & Kemerer, 1996)	High *Widespread interaction among users in the workplace*	Medium-High *Many complex functions, macros unique among products, raising switching costs*	Medium *Primarily interaction with external databases*	**HIGH**	**4**	**1**
CAD (Astebro, 2002)	Medium-Low *Users tend to be highly specialized; findings suggest low size-on-growth impact*	Medium *High-end products can run into the thousands of dollars; design interfaces range from intuitive to highly complex*	Medium *Various plug-ins and extensions available*	**MED.**	**3**	**0**
Desktop Publishing	Medium *Intra-organization compatibility is more important than gross network size*	Low *Most interfaces are graphically based, similar to word processors*	Medium *Compatibility with photo, illustration software is a concern*	**LOW**	**2**	**0**
Personal Finance	Low *Prior to Internet, virtually no network interaction required*	Low *Most low-end applications require limited proprietary learning*	Medium *Initially low, increasingly prevalent with online functions*	**LOW**	**1**	**0**

Although the dependent and independent variables included in the Network Intensity model are similar to those in the previous model, Table 4.5 provides a comprehensive overview of the specific variables and their measurement.

Table 4.5: Summary of independent variables (network intensity model)

Variable	Definition	Measure	Type	Source
Installed Base	Active users of the focal product	Cumulative units shipped over previous two years	Continuous	IDC/DataQuest
Quality	Superiority or inferiority of physical attributes of the product relative to competing products, independent of the benefits conferred by its network size	Overall score on 10-point scale at the time of release	Continuous	*InfoWorld,* reliability checks with other journals
Network Intensity	Proportion of total value that consumers derive from network interaction for a given product	Dummy variable reflecting conjectured network intensity	Dummy and Rank (Ordinal)	Archival literature
Network Intensity * Installed Base	Interaction term reflecting significant variation in size-on growth effects as network intensity changes at the segment level	Interaction term	Interaction	Multiplicative combination of individual variables

Table 4.6: Summary of control variables (network intensity model)

Variable	Definition	Measure	Type	Source
Suite	Whether the product was released as part of a productivity suite or stand-alone	Dummy variable indicating suite membership or non-membership	Binary	Various archival sources
Multi-segment	Sponsoring firm competes in more than one segment	Dummy variable indicating single segment or multi-segment	Binary	Various archival sources
Price	List price of the focal product	Price (U.S. Dollars) of the product	Continuous	IDC/DataQuest
Concentration	Degree of concentration of the focal market segment	Herfindahl Index	Continuous	

4.5 Model 3: Quality Antecedents Model

The purpose of Model 3 is to test size and timing of product release as significant antecedents of quality, thus suggesting a mediated relationship among installed base, quality, and growth in a network industry. Specifically, Hypotheses 4 and 5 hold that within periods, installed base size and timing of release have a significant impact on the quality of a given product. To test these hypotheses, Model 3 holds that:

(3) $Q_t = \beta_0 + \beta_1(lnS_{i,\,t}) + \beta_2(T_{i,\,t}) + \beta_{3..j}(CONTROLS)$

Where Q is product quality, S is the product's installed base, and T indicates first-mover or late mover status. The specific variables in the model, as well as the logic underlying their measurement, are described below.

4.5.1 Dependent Variable

Product Quality. Quality ratings from archival issues of *InfoWorld* magazine were again used to measure the quality of product releases at the time of their release. Reliability estimates were calculated using alternative sources, and will be reported in the Chapter 5.

4.5.2 Independent Variables

Installed Base Size. As in Model 1, installed base size was measured as the natural log of cumulative unit shipments over a two-year period.

First Mover Status. In order to test Hypothesis 5, the release date of each product release in the sample was recorded. Because software releases tend to be concurrent or generational in nature across firms, timing of release was calculated as the time (in months) that a product was released after the first innovation of a given generation of software. For measurement purposes, product releases were then aggregated and coded as first-movers and late-movers (non first-movers). This measure is consistent with the specific language of Hypothesis 5, that first-movers will exhibit lower quality than later ones.

Table 4.7: Summary of independent variables (quality model)

Variable	Definition	Measure	Type	Source
Installed Base	Active users of the focal product	Cumulative units shipped over previous two years	Continuous	IDC/DataQuest
First Mover	Whether the product was the first release in its segment for a given generation of products	Dummy variable indicating first mover or later release	Binary	Various archival trade journals

4.5.3 Control Variables

Previous Winner. When quality attributes are difficult to observe *a priori*, consumers may rely on a product's brand or reputation when making adoption decisions (Keller, 1993; Randall, Ulrich & Reibstein, 1998). To control for reputation effects, I included a variable indicating whether the product was the highest-rated one in the previous period (t-1).

Generational Innovation. A generational product innovation represents a significant advance in the performance of an existing product (Lawless and Anderson, 1996). In contrast, incremental product innovation tends to reinforce existing product designs, leaving the core aspects of the product unchanged (Henderson and Clark, 1990). I include a variable indicating the nature of the product based on its numbering scheme, i.e. the product was coded generational if its version represented a whole number (2, 2.0 etc.), and incremental if the version contained one or more decimal points (5.1, 5.01, etc.)

Platform. I included a variable indicating the operating system platform for which the software was designed – DOS or Windows. This variable was included to ensure that quality dimensions are not platform-dependent, and that quality reviews did not confound product-specific quality with platform-specific quality.

Table 4.8: Summary of control variables (quality model)

Variable	Definition	Measure	Type	Source
Suite	Whether the product was released as part of a productivity suite or stand-alone	Dummy variable indicating suite membership or non-membership	Binary	Various archival sources
Generational Innovation	Whether the product is a generational or incremental innovation	Dummy variable indicating whether the product is generational or incremental	Continuous	IDC/DataQuest
Previous Winner	Whether the product line was the highest rated one in the previous year (t-1)	Dummy variable indicating previous winner	Binary	*InfoWorld*
Platform	Whether the product is designed for the DOS or Windows platform	Dummy variable indicating DOS or Windows	Binary	

CHAPTER 5

EMPIRICAL RESULTS

This chapter presents the results of the descriptive and empirical methodologies described in the previous chapter. Characteristics of the sample are presented, followed by empirical results of the tests of hypotheses. Finally, limitations of the methodologies are discussed in the context of their relevance to the focal tests.

5.1 Data Overview and Descriptive Statistics

The raw sample for this study encompasses five segments of packaged application software, word processing, personal finance, spreadsheet, desktop publishing, and CAD. Table 5.1 illustrates descriptive statistics and correlation matrix for the sample.

Several features of the correlation matrix merit further discussion. First, note that growth is negatively correlated with installed base (-.37), yet it exhibits a positive association with quality (.17). Second, higher network intensity segments appear to be associated with higher baseline growth (.19), which is consistent with the notion of stronger positive feedback in these segments. Finally, it appears that multi-segment firms have significant advantages with respect to several performance metrics, including baseline quality and growth.

Table 5.1: Descriptive statistics and correlation matrix

	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Growth*	0.17	1.51									
2. Installed base*	13.98	1.94	-0.37								
3. Quality	7.35	1.31	0.17	0.35							
4. Network intensity	2.87	1.41	0.19	0.47	0.02						
5. Market share	20.72	20.01	0.28	0.62	0.42	0.25					
6. Concentration (HHI)	0.40	0.17	0.08	0.65	0.25	0.17	0.45				
7. Suite	0.21	0.41	0.01	0.44	0.32	-0.13	0.35	0.64			
8. Price	499.92	98.39	-0.20	-0.45	-0.25	-0.31	-0.17	-0.48	-0.21		
9. Multi-segment firm	0.25	0.43	0.28	0.59	0.60	0.08	0.56	0.40	0.40	-0.20	
10. First mover	0.33	0.27	-0.03	-0.16	-0.14	-0.09	-0.18	-0.15	-0.14	0.05	-0.13

* Variables are expressed in natural log form (ln), growth in differences in natural logs

Note also that the segments in the sample exhibit a relatively high degree of concentration (μ=0.40), which is indicative of the network-intensive nature of several of the segments.[9]

5.2 On the Nature and Reliability of Quality Measures

As noted in previous sections, quality has a broad and multidimensional connotation in the strategy literature. Furthermore, in evaluating the characteristics of archival products, there is a risk of hindsight bias, whereby raters' recollections may systematically influenced by the performance outcomes of the focal products (Baron & Hershey, 1988). To minimize such bias, I used quality ratings that were published at the time of product release. For 151 product releases, I was able to obtain data on both official product release dates and the date of the quality review. For this group - approximately 72% of the total sample - an average of 2.2 months of time elapsed between official product release and the initial quality review, suggesting limited opportunities for performance outcomes to influence ratings.

From an empirical perspective, the reliability of the quality measure can be tested in two contexts. The first is the convergent validity of the quality construct, or the extent to which multiple external measures of the construct are correlated (Campbell & Fiske, 1959; Pedhazur & Schmelkin, 1993). The second is that the construct is internally

[9] The U.S. Department of Justice characterizes industries between HHI .10 and .18 as "moderately concentrated", and those over HHI .18 as "concentrated". However, when gauging the competitive impact of horizontal mergers, the degree of change in HHI tends to supercede the HHI itself. See *Horizontal Merger Guidelines*, U.S. Department of Justice and Federal Trade Commission, 1992, 1997.

consistent, i.e. that measures accurately capture similar dimensions of the phenomenon over repeated observation (Cronbach, 1951; Lord & Novick, 1968).

To establish the convergent validity of the quality construct, I took a sub-sample of 15 *InfoWorld* quality ratings and compared them with those from *PC Magazine*, an alternative journal that offered user ratings of software product. The resulting average inter-measure covariance (0.78) indicates a strong degree of construct validity among alternative external measures.

A correlation matrix of the various quality dimensions was used to determine the internal consistency of the ratings (Table 5.2). Note that all sub-dimensions of quality are highly correlated with overall quality measure (all >0.50).

Table 5.2: Correlations: Quality and sub-dimensions

	1	**2**	**3**	**4**	**5**	**6**	**7**
1. Overall Quality							
2. Performance	0.58						
3. Documentation	0.61	0.38					
4. Ease of Learning	0.57	0.34	0.45				
5. Ease of Use	0.64	0.25	0.34	0.29			
6. Error Handling	0.71	0.53	0.48	0.50	0.34		
7. Technical Support	0.56	0.47	0.43	0.38	0.38	0.58	
8. Value	0.82	0.48	0.54	0.64	0.50	0.63	0.47

Finally, quality data were missing or incomplete for approximately 19% of the observations in the sample. Because these observations contained other valuable product data, I used a multiple imputation technique to approximate missing values (see Appendix B for details). Nonetheless, while specific quality rankings were absent for this portion of the sample, complete data was available for two other metrics of quality: the rank of the product's quality relative to other products, and whether the product was declared the "winner" of its class of products. To ensure the general validity of the interpolated values, I compared the final sample of actual and interpolated values with these two alternative metrics, and a reliability test indicated strong reliability among these alternative metrics ($\alpha = .88$)

5.3 Results of Longitudinal Models

Recall that three models were proposed to test the following hypotheses regarding network industries:

(1) $lnS_{i,\,t+1} - lnS_{i,\,t} = \beta_0 + \beta_1 (lnS_{i,\,t}) + \beta_2 (lnS_{i,\,t})^2 + \beta_3 (Q_{i,\,t}) + \beta_4 (MS_{i,\,t}) + \beta_5 (MS_{i,\,t} * lnS_{i,\,t}) + \beta_{6\ldots j}(CONTROLS)$

(2) $lnS_{i,\,t+1} - lnS_{i,\,t} = \beta_0 + \beta_1 (lnS_{i,\,t}) + \beta_2 (Q_{i,\,t}) + \beta_3 (NI * lnS_{i,\,t}) + \beta_{4\ldots j}(CONTROLS)$

(3) $Q_t = \beta_0 + \beta_1(lnS_{i,\,t}) + \beta_2(T_{i,\,t}) + \beta_{3..j}(CONTROLS)$

These models were developed to test the six hypotheses related to size, quality and growth in network industries.

Table 5.3: Summary of hypotheses

H1a	In a network industry, the larger the installed base of a product, the greater its growth in the following period.
H1b	In a network industry, the relationship between installed base and growth will be more positive at medium levels of market share than at high or low levels.
H2	In a network industry, the greater the quality of a product at a given time, the greater its installed base growth in the following period.
H3	The effect of installed base size on growth will increase as the network intensity of a segment increases.
H4	The size of a firm's installed base will be positively associated with the quality of its product releases.
H5	Within generational products, first movers will tend to exhibit lower quality than later releases.

Model 1 (Table 5.4) illustrates a longitudinal analysis of the antecedents of growth in a network industry, with the difference in installed bases between periods

($ln\mathrm{S}_{i,t+1} - ln\mathrm{S}_{i,t}$) as the dependent variable. When longitudinal data has panel characteristics (as in this case), OLS regression estimates can be biased if omitted the influence of omitted variables on explanatory variables is non-trivial (Hausman, 1978; Kennedy, 2003). Thus, both random effects and fixed effects models were run, with diagnostics indicating a better fit for the fixed effects model for both Model 1 and Model 2 ($p<0.001$, $p=0.002$, respectively).

Table 5.4: Model 1 (growth antecedents model)

DV = Growth ($lnS_{i,\,t+1} - lnS_{i,\,t}$)

	1	2	3
Growth Antecedents			
(*ln*) Installed Base	-3.631*** (<0.001)	-3.172*** (<0.001)	-2.939*** (0.001)
(*ln*) Installed Base^2	0.117*** (0.003)	0.095*** (<0.001)	0.085** (0.010)
(*ln*) Quality	1.286** (0.038)	0.284 (.685)	1.928** (0.025)
Interaction Terms			
Installed Base *Market Share		0.048*** (<0.001)	0.277** (0.044)
Quality*Market Share			-0.017 (0.142)
Control Variables			
Concentration (HHI)			0.802 (0.445)
Price			0.002 (0.849)
Suite			0.328 (0.332)
Multi-segment firm			1.265**

(0.047)

*p<0.10, **p<0.05, ***p<0.01

Hypothesis 1a proposes a positive relationship between installed base size and growth in a network industry. The three iterations of Model 1 illustrate a generally negative linear effect of size on growth. However, the positive coefficient on the quadratic term indicates that the effect of size on growth becomes less negative as size increases. While this result seems to run counter to theories of positive feedback and increasing returns, it is consistent with the notion a viable mass of adopters is critical in network-based competition, and positive feedback manifests only after this critical threshold is reached.[10] Nonetheless, Hypothesis 1a is not supported by the results of Model 1.

Hypothesis 1b accounts for "S-curve" effects in the product adoption process, and holds that firms with particularly low or high market shares will enjoy weaker size-on-growth benefits than those at medium levels of market share. The positive and significant coefficient on the interaction term between Market Share (where 0=low/high, 1=medium) and Installed Base (0.277, p = .04) supports Hypothesis 1b.

Hypothesis 2 proposes that a product's quality at a given time will have a positive impact on its growth in the following period. Model 1 illustrates strong support for this hypothesis, as the coefficient on quality is positive in all three iterations. Although the estimate falls below the significance threshold in the second iteration of the model, it is positive and significant in the full model with controls.

[10] This result is consistent with the findings of Chacko and Mitchell (1998), which conducts one of the few direct size-on-growth tests in the network effects literature.

Model 2 (Table 5.5) is a variation on Model 1 where network intensity is the primary measure of interest. Hypothesis 3 holds that the impact of size on growth will be increasingly positive as the network intensity of a segment increases. Hypothesis 3 is supported, as the interaction term between network intensity and installed base is positive and strongly significant when the term is included. However, the significance of the independent variables drop significantly when the interaction term is included, possibly as a result of high correlation between the rank-ordered network intensity variable and installed base (Table 5.1). To test the robustness of the finding of a significant impact of network intensity, I specified an alternative form of Model 2, where network intensity was coded high (1) if the product was a spreadsheet or word processor, and low (0) if it was a member of another segment (Table 5.6).

Table 5.5: Model 2 (network intensity model)

DV = Growth ($lnS_{i,\,t+1} - lnS_{i,\,t}$)

	1	2	3
Growth Antecedents			
(*ln*) Installed Base	-3.631*** (<0.001)	-1.394* (0.072)	-1.048 (0.270)
(*ln*) Installed Base^2	0.117*** (0.003)	0.052** (0.040)	0.047 (0.134)
(*ln*) Quality	1.286** (0.038)	0.582 (0.402)	0.831 (0.293)
Network Intensity			
Network Intensity*Installed Base		0.231*** (<0.001)	0.337** (0.001)
Control Variables			
Concentration (HHI)			-1.757 (0.214)
Price			0.002 (0.982)
Suite			-0.068 (0.825)
Multi-segment firm			0.508 (0.387)

*p<0.10, **p<0.05, ***p<0.01

Table 5.6: Model 2 (alternative specification for network intensity model)

DV = Growth ($lnS_{i,\,t+1} - lnS_{i,\,t}$)

	1	2	3
Growth Antecedents			
(*ln*) Installed Base	-3.631*** (<0.001)	-2.815*** (<0.001)	-3.245*** (<0.001)
(*ln*) Installed Base^2	0.117*** (0.003)	0.0911*** (<0.001)	0.105*** (0.001)
(*ln*) Quality	1.286** (0.038)	1.268* (0.073)	1.763** (0.029)
Network Intensity			
Network Intensity*Installed Base		0.035*** (<0.001)	0.031** (0.037)
Control Variables			
Concentration (HHI)			0.079 (0.954)
Price			0.002 (0.864)
Suite			-0.063 (0.849)
Multi-segment firm			1.054* (0.081)

*p<0.10, **p<0.05, ***p<0.01

While the parameter estimate on the network intensity interaction term is lower in the alternate model, it remains positive and significant. Thus, Hypothesis 3 is supported by both forms of the model.

Hypotheses 4 and 5 postulate the effects of installed base and first-mover status on product quality at a given time. Because these effects are hypothesized to be within-period effects, I used an OLS technique with controls to estimate Model 3:

Table 5.7: Model 3 (quality antecedents model)

DV = Quality *(Q_t)*

	1	**2**
Quality Antecedents		
(*ln*)Installed base	0.050** (0.002)	0.064** (0.011)
First-mover	-0.011 (0.847)	-0.063 (0.284)
Control Variables		
Generational innovation		-0.026 (.576)
Platform		0.113** (0.041)
Previous Winner		0.0984** (0.050)
Suite		-0.038 (0.557)

Adjusted R^2 = 0.1439, 0.1588
*p<0.10, **p<0.05, ***p<0.01

Model 3 tests alternative theories of quality-based learning in a network industry. The results support an experienced-based perspective on learning (Hypothesis 4; ß =

0.064, p=0.001). However, while the direction of the coefficient on the first-mover term is consistent with a time-based learning perspective, it is insignificant in both iterations of the model (p_1 = .85, p_2 = .28). Thus, the results do not provide sufficient support for Hypothesis 5.

5.4 Summary of Hypothesis Tests

In summary, the results do not support a positive size on growth argument in a network industry, but are consistent with the notion that the influence of size becomes more positive after a certain threshold. In contrast, product quality has a generally positive and significant impact on growth, which persists throughout the nested models. Furthermore, the results indicate that size has an increasingly positive impact on growth as the network intensity of a segment increases. Finally, cumulative experience via installed base appears to have a significant impact on the quality of a firm's product releases, while delaying releases within generational products does not appear to have a significant impact on quality.

Table 5.8: Summary of hypothesis tests

H1a	In a network industry, the larger the installed base of a product, the greater its growth in the following period.	Not supported (negative linear term, positive quadratic term)
H1b	In a network industry, the relationship between installed base and growth will be more positive at medium levels of market share than at high or low levels.	Supported
H2	In a network industry, the greater the quality of a product at a given time, the greater its installed base growth in the following period.	Supported
H3	The effect of installed base size on growth will increase as the network intensity of a segment increases.	Supported
H4	The size of a firm's installed base will be positively associated with the quality of its product releases.	Supported
H5	Within generational products, first movers will tend to exhibit lower quality than later releases.	Not Supported

5.4 Limitations

As is the case with many empirical studies in strategic management, this research was limited by several factors outside of the control of the researcher. While the preliminary results indicate support for several of the hypotheses, I note these limitations in the hope that several can be overcome in future research in this area.

First, the sample for this study was limited to a single network industry. While network intensity was tested via variation in multiple segments of the industry, a more representative cross-section of high- and low- network intensity industries may prove fruitful for future empirical research. Furthermore, though the time frame of the sample was consciously chosen for its high-growth nature, it would have been ideal to examine the industry from its inception. However, limitations in the availability of data earlier than 1986 made this approach less viable.

Second, product quality is a highly complex and multi-dimensional construct. Though I have taken reasonable steps to ensure the theoretical and empirical validity of quality, the possibility remains that critical dimensions of quality remain unaccounted. In addition, future work should involve alternative measures of quality to ensure that common-method bias is not a factor in these results.[11]

Finally, I have made a conscious trade-off between depth and breadth in developing the sample for this study. While the sample size is smaller than some comparable longitudinal studies of growth, recent studies have made similar concessions with respect to sample size in order to gain a deeper understanding of network dynamics.[12] Furthermore, to my knowledge no other study of network effects incorporates the depth of quality data that I have gathered from archival sources.

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[11] One unsettling possibility is that the actual journal reviews influence growth more than the product's "true" quality. However, the correlations of both quality dimensions and multiple journal reviews have mitigated this possibility to some extent.

[12] Consider that Chacko and Mitchell (1998) incorporates 1,673 product-year observations, yet does not measure quality-on-growth; conversely, Shankar and Bays (2003) use a sample of only 64 product-months in estimating firm-level network effects.

CHAPTER 6

DISCUSSION AND CONCLUSION

6.1 Implications for Strategic Management in Network Industries

The empirical results of this work have implications for strategic management in network industries in both the theoretical and practitioner domains. The following sections briefly describe some of these implications, and offer potential avenues for extension and future research in this domain.

6.1.1. Theoretical Implications and Extensions

Theoretical perspectives on strategy in network industries generally focus on the importance of the installed base in these settings. Yet the empirical results of this research indicate that quality of a firm's product releases plays a significant role in driving installed base growth in a network industry. More broadly, the results illustrate that the dynamics of competition and growth in network industries may be more complex than previously thought. In contrast to straightforward assumptions about positive size on growth mechanisms, I have shown that many firms in network industries can face strong negative feedback, particularly when they fail to achieve a viable installed base in the focal segment. In turn, the achievement of such viability appears to be significantly dependent upon the quality of a firm's products.

In addition to this general finding, I have shown that an existing installed base is associated with quality advantages at the segment level. This finding suggests that dominant firms in network industries may not only offer greater network-dependent value to consumers (i.e., a larger network of fellow adopters), but also greater network-independent value in the form of higher quality products. Thus, the assumed disconnect between product quality and performance outcomes in network industries may not be as strong as previous anecdotal evidence suggests. Indeed, it appears that the relationships among installed base, product quality and growth represent far more than simple luck or randomness.

Furthermore, the results show that the extent of positive feedback due to network effects varies significantly based on the characteristics of a given market or segment. This finding lends further support to the notion that network intensity can be conceptualized as the proportion of value that consumers derive from network interaction in a given setting, and has important strategic implications in various industries.

Several avenues of research may offer additional insights on the nature of network industries. First, installed base was found to have a significant association with product quality at the segment level, consistent with the notion of learning advantages from cumulative production experience. However, while larger firms may enjoy greater accumulated product knowledge, their incentives to capitalize on this knowledge merits further investigation. Specifically, in a network industry, larger firms may have less incentive to produce innovative and higher quality products as a result of their position of dominance in the segment (Christensen, 1997). Examining the relative impact of positive advantages to size against negative incentives to innovate in a network industry may provide deeper insights into the nature of product innovation in network competition.

Second, the empirical results suggest that the impact of installed base on growth tends to be more positive as installed base increases. However, the precise level at which a firm can overcome negative early feedback to enjoy increasing demand-side returns to scale, as well as the extent to which this level is heterogeneous across industries, remains unclear. Establishing both the incidence and nature of such “tipping points” in multiple contexts represents a logical next step for the literature on strategy and network effects.

Finally, the impact of new entrants on network industries merits further empirical investigation. If installed base and quality are mechanisms for growth in these settings, how can entrepreneurs overtake incumbent competitors? In other words, when installed base is zero, what other advantages might new entrants exploit to produce higher quality products, and thus overtake industry leaders?

6.1.2 Practical Implications and Extensions

This research offers several insights for strategy practitioners. First, the notion that first-mover status is vital to success in a network industry does not appear to hold in all contexts. Rather, effective strategy in network competition appears to center around managing the trade-offs involved in these settings, specifically balancing the advantages of early product release against delays which may improve product quality and impact tthe growth potential of the firm.

Second, the notion of network intensity has important implications for firm strategy. If the influence of network effects varies across competitive contexts, then the ability to accurately gauge the network intensity of a given market or segment becomes a critical firm capability. Inaccurate perceptions of network intensity can have a detrimental impact on performance, as firms may either rush to release low-quality products, or delay releases beyond the point of viability. One interesting extension in this regard is the application of network intensity to the vast number of failed Internet startups earlier this decade. A plausible hypothesis for such failures is that Web-based firms chronically overestimated the network intensity of their target industry, and that the most viable Web-based business models are those that do indeed provide strong network-based value to their customers.

Finally, this research was developed under the assumption that network intensity is a largely exogenous aspect of a given product-market. However, relaxing this assumption may provide valuable insights for strategic management. If firms can partially influence the network intensity of their products, then the manipulation of network intensity is itself a worthy avenue of future study. Using a prior example, large video-game console producers have recently added online capabilities to their core products. Future work in this domain might examine whether this represents a demand-driven evolution of the product-market, or a conscious effort by manufacturers to increase the network intensity of their products.

6.2 Conclusion

This work makes four contributions to the burgeoning literature on strategy and network effects. First, the impact of installed base on growth in a network industry was tested, and shown to be negative below a critical threshold. Second, contrary to extant theory, product quality was shown to have a positive and significant impact on installed base growth in a network industry. Third, the network intensity of segments within an industry varied significantly, suggesting that network effects do not manifest uniformly in network competition. Finally, installed base was shown to be associated with higher quality products within time periods, suggesting that the influence of installed base lies not only in its direct impact on growth, but is also partly mediated by product quality.

Taken together, these findings build on previous theoretical and empirical findings on strategy and network competition, and illustrate that the dynamics of network effects, positive feedback, and demand-side increasing returns are far more complex than simple size on growth effects. Future research in this stream will focus on the advancement of network intensity as a theoretical construct and a measurement-based tool for practitioners of strategic management.

APPENDIX A. Sample of Packaged Application Software Product Lines, 1986-1998

Word Processing	Spreadsheets	Desktop Publishing	CAD	Personal Finance
WordPerfect	Quattro	FrameMaker	TurboCAD	Quicken
Microsoft Word	Lotus 123	Ventura Publisher	Drafix CAD	Managing Your Money
DisplayWrite	Excel	PageMaker	Actrix Tech.	Money Matters
Samna Word	Wingz	Quark	AutoSketch	Money Counts
Ami Pro		Quark Xpress	MiniCAD	Microsoft Money
Word Pro			IntelliCAD	Reality
MultiMate			Corel Visual	
WordStar			X CAD	

APPENDIX B. Treatment of Missing Quality Data

Approximately 19% of the observations in the dataset contained missing or incomplete values for product quality. There appeared to be no common factor influencing whether data was present or absent, but rather a function of the idiosyncratic nature of the product reviews in the focal publications. However, because several other data points were available for these observations (installed base, growth, etc.), I attempted to remediate the missing data problem via a multiple imputation technique.

Several approaches can be used to address missing data in statistical analysis. The most convenient, casewise deletion, involves the simple removal of missing observations from the sample. Though this is a convenient approach for the researcher, it may bias the sample as the number of omissions increases (Little and Rubin, 1987; Schaefer and Graham, 2002).

One promising technique for remediation of missing data is multiple imputation, whereby each missing value is represented by a distribution of simulated values conditional upon existing data. Each of the possible alternative datasets is then analyzed to produce an estimate of the missing value, as well as a standard error and uncertainty estimate for the value (Rubin, 1996):

$$\mu = m^{-1} \sum Q^{(j)}$$

Where μ represents the missing sample value, m is the number of unique imputations, j is the vector of $1 \ldots m$ imputations, and Q is the estimate of μ. Note that this technique rests on the assumption that the data are missing at random, and the characteristics of this sample offer no plausible evidence otherwise.

Once imputed values of quality were calculated, I checked the resulting data set against two other metrics of quality to determine the validity of the imputed values. These alternative metrics were (1) the rank of the product relative to competing products and (2) whether the product was the "winner" of its product class. The resulting inter-measure correlation was as follows:

$$\alpha = \mu\,[\sigma\,(\text{IMPUTED, RANK, WINNER})] = .88$$

This average inter-measure correlation indicates a strong degree of reliability among the three alternative measures. Thus, the imputed dataset was used for analysis.

APPENDIX C. Sources of InfoWorld Quality Reviews

Infoworld quality reviews constituted the primary measure of software quality for this research. Below is a list of the issue dates used to compile the raw quality sample. Note that there are 84 dates listed. Some products were reviewed in individual articles, in which case a given date appears more than once (e.g. “Drafix CAD delivers precision: drafting tools let easy-to-use program beat out comparably priced drawing programs”, May 25, 1992). Others were reviewed as part of a broad comparison of products, in which case one date may indicate multiple reviews (e.g. “Professional word processors: Windows illuminates new features but traditional programs stay competitive”, January 7, 1991 issue). Specific issue dates included:

November 4, 1985	March 13, 1989	September 9, 1991	December 27, 1993
November 23, 1985	June 12, 1989	September 16, 1991	February 7, 1994
May 5, 1986	July 17, 1989	October 7, 1991	February 14, 1994
June 2, 1986	July 31, 1989	December 16, 1991	February 28, 1994
August 4, 1986	September 7, 1989	January 13, 1992	December 12, 1994
February 2, 1987	September 11, 1989	January 27, 1992	January 30, 1995
March 2, 1987	October 30, 1989	February 10, 1992	March 20, 1995
March 9, 1987	December 4, 1989	May 25, 1992	November 20, 1995
March 23, 1987	January 15, 1990	May 25, 1992	February 5, 1996
April 7, 1987	January 22, 1990	August 3, 1992	February 26, 1996
April 13, 1987	January 29, 1990	August 31, 1992	October 28, 1996
July 13, 1987	February 19, 1990	September 28, 1992	November 4, 1996
August 10, 1987	April 23, 1990	October 12, 1992	July 14, 1997
November 14, 1987	October 15, 1990	December 14, 1992	December 8, 1997
November 16, 1987	November 5, 1990	March 15, 1993	December 22, 1997
February 1, 1988	November 12, 1990	April 12, 1993	
March 28, 1988	December 3, 1990	April 23, 1993	
June 20, 1988	January 7, 1991	August 9, 1993	
August 29, 1988	January 28, 1991	August 23, 1993	
September 26, 1988	April 1, 1991	October 25, 1993	
October 3, 1988	April 29, 1991	November 1, 1993	

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