Market-Level Information and the Diffusion of Competing Technologies: an Exploratory Analysis of the LAN Industry

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ABSTRACT

Market-level information diffused by print media may contribute to the legitimation of an emerging technology and thus influence the diffusion of competing technological standards. After analyzing more than 10 000 trade media abstracts from the Local Area Networks (LAN) industry published between 1981 and 2000, we found the presence of differential effects on the adoption of competing standards by two market-level information types: *technology* and *product availability*. The significance of these effects depends on the technology's order of entry and suggests that high-tech product managers should make strategic use of market-level information by appropriately focusing the content of their communications.

Keywords: High-technology Marketing, Diffusion, Market-Level Information, Word of Mouth, Legitimacy

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1. Introduction

In dynamic markets a firm gains competitive edge through its alertness to environmental cues, and its adeptness at environmental analysis, planning, and implementation based on an acute, unbiased perception of change in the marketplace (Dickson, 1992). This can be a daunting task in technology-related environments that are information intense and likely to contain hype and inaccuracies (Glazer, 1991; Wind and Mahajan, 1987). With the prevailing perception that information in high-tech markets is rapidly changing and the related development processes are chaotic (Cheng and Van de Ven, 1996; Quinn, 1985), players in these markets seek to reduce their uncertainty through progressively collecting and using market-information in order to make better-informed adoption decisions (Kapur, 1995). The process of collecting relevant market-level information may consist of tracking technology trends as well as changes in market participants' behaviors and in competitive market structures (Utterback and Suarez, 1993). This information can flow into the market from a variety of sources, including firms' efforts to provide information about their products, regulatory bodies (Moorman, 1998), or information intermediaries or "infomediaries", such as financial analysts, consultants, and the media (Deephouse, 2000).

While the complexity and uncertainty of high technology markets present considerable problems for market participants, very little conceptual and empirical research has been directed toward examining buyers' decision making processes in these markets (Heide and Weiss, 1995). Further, as Moorman (1998) states, the "systematic empirical investigations into the strategic implications of market information are virtually nonexistent". Although prior research has demonstrated the importance for participating firms in technology-markets to scan their environment for information that originates from multiple "players" (e.g. software and hardware vendors, consultants) and industry trade media (Maier et al., 1997), it has not examined in detail the inherent characteristics of market-level information that influence market behaviors. Since the media can facilitate or inhibit the formation of impressions through increased exposure, this market-level information derived from the media could therefore make certain technologies more legitimate than others (Suchman, 1995). A more legitimate technology would be perceived not only as more worthy, but also as more meaningful, predictable, and trustworthy, thus influencing the behavior of potential adopters.

We define market-level information as information created, shared, and exchanged by a diverse set of market participants (i.e., suppliers, vendors, buyers, industry analysts, journalists, and so forth), which is published in commercial or trade publications (print media) that act as carriers of broadcast information (Sorensen and Fleming, 2004). For this reason, print media-reported market-level information is within the public domain and generally available to anyone. In this sense, market-level information is also different from the concept of firms' market knowledge, which refers to firms' knowledge about customer and competitor behaviors, technology developments, and other environmental conditions (De Luca and Atuahene-Gima, 2007; Li and Calantone, 1998), which is disseminated to and shared by members within the firm. Moreover, market-level information is distinct from information transferred through interpersonal communications channels, such as word-of-mouth operated through individual relationships, or information conveyed through a single firm's direct marketing communications efforts, such as personal selling, that are common in industrial marketing.

Given that technology is defined by both its physical objects and more abstract technology-related information (Griffith, 1999; Rogers, 1995), a study of market-level information for high technology markets should consider and recognize the implications of these two components; something that has not explicitly been addressed by previous empirical studies examining the diffusion of competing technologies. Therefore, in this study we identify and distinguish between market-level information types and examine the extent to which the characteristics of market-level information influence the adoption-diffusion paths of competing technology standards. Specifically, we explore the impact of print media-reported market-level information in the Local Area Networks (LAN) market, which has been highly competitive and characterized by large amounts of information. In particular, we focus on the two main competing technological standards in the LAN industry that targeted PC desktops: Ethernet (the pioneer) and Token Ring (the follower). By utilizing a unique database that combines market-level information and adoption data since the inception of both standards, we assess the impact of two types of information that are mutually exclusive - one that deals with the technology standard ("technology information") and the other that deals with the availability of products that support the standard ("product availability information").

Our results indicate that there are differential information effects on the adoption of the two LAN standards. While market-level information, in general, facilitated the adoption of either technology, we found technology information to have a positive effect only on the pioneer's adoption (Ethernet) and product availability information to positively influence only the follower's adoption (Token Ring). We attribute the different information effects to differences in the perceived value and novelty of the information for the pioneer and follower technologies. Specifically, technology information for the pioneer is perceived by customers as novel and interesting and has a significant impact on the adoption of the pioneering technology. The same type of information for the follower, may be perceived as uninteresting and redundant (Sorensen and Fleming, 2004). Further, we attribute the different effects of product availability information to differences in the installed base of the two technologies; the pioneering technology, which enjoys a higher level of adoption, can signal its availability through its large installed base (i.e. network externalities effect), but the follower technology, which has a smaller installed base potentially due to late-mover disadvantages, has to strengthen its signal through complementary product availability information. Our findings also suggest that the adoption process is not driven exclusively by interpersonal, word-of-mouth communications or learning through previous adoption behavior, but rather that particular types of market-level information play an important role and need to be further studied. While this may not be a surprising result, our results highlight that the social learning process through which certain types of market-level information are shared, complements interpersonal word-of-mouth processes.

We believe that the managerial implications from this study are significant as they allow suppliers to identify the manner in which types of information influence the adoption of their technology so they can properly focus their communications and facilitate the sense making of their potential customers (Weick, 1990). Further, we respond to the wider, and repeated calls for diffusion studies in industrial markets, and in particular within a high-tech context (Mohr, 2000; Ziamou and Ratnershwar, 2002), and contribute to the diffusion literature which has been rather biased toward consumer adoption studies (Gatignon and Robertson, 1989; Midgley et al., 1992; Rogers, 1983; Rogers, 1995). The rest of the paper is organized as follows. Section 2 discusses the nature of market-level information in technological marketplaces. Section 3 introduces the focal industry of our study, Local Area Networks, and provides a description of the data. Section 4 presents the empirical analysis of the data and section 5 provides a summary of our main findings, a discussion of the managerial relevance of our study, and suggestions for future research.

2. Technological Marketplaces and Market-Level Information

Technology-based markets (e.g., modems, VCRs, DVDs, and mobile telephone systems) and their associated technologies are not created overnight, but rather develop over time (Garud and Rappa, 1994). Often, competing technologies emerge, each vying to achieve critical mass or to become the industry's dominant design (Utterback and Suarez, 1993). There are many forces that shape the evolution of competing technologies and the emergence of new product categories (e.g., VHS and Betamax formats in home video cassette recorders; CP/M and MS-DOS in PC operating systems; Lotus 1-2-3 in spreadsheet software) which also include network externalities (Katz and Shapiro, 1985) and the ability of the technology to receive organizational support from developers (Wade, 1995). More recent studies have modeled technology evolution in a new product category as a function of product-market characteristics (Agarwal and Bayus, 2002; Golder and Tellis, 1997; Srinivasan et al., 2006), and radicalness of the product category (Christensen and Bower, 1996).

Technology evolution has also been examined as a process of market sensemaking, revealed as "stories" about new technologies and products appearing in published media, such as industry trade journals (Rosa et al., 1999). Because this publicly available market-level information is dynamic, it should be monitored over time, as its shifts can potentially lead to changes in demand. However, as Moorman (1998) pointed out, market-level information is distinctly different from word-of-mouth; word-of-mouth links networks of companies or consumers where the information flow is limited to the network's interconnections and depends on the strengths of its ties (Czepiel, 1974; Granovetter, 1973). In contrast, market-level information refers to broader cues, signals, and sense making efforts reflected by the "stories" that are shared and are not constrained by network interconnections. In this regard, market-level information is an important vehicle for new technologies that lack legitimacy since it creates awareness and can shape the formation of market players' impressions about firms' new technologies; when an event, in this case new technology, becomes so familiar and well known to the general population, it is taken for granted (Hannan et al., 1995). Therefore, market-level information generates cognitive legitimacy (Aldrich and Fiol, 1994) and may play an important role in the adoption-diffusion of competing technologies which is the focus of this study.

The diffusion literature has examined several sources of information that may influence the adoption of technological innovations (Geroski, 2000) starting from interpersonal sources such as word-of-mouth, and other marketing variables such as price, advertising, and product benefits (Bass, 1969; Dodson and Muller, 1978; Horsky, 1990; Horsky and Simon, 1983). Recently, an increasing number of marketing studies have been concerned with information, but do not consider the pivotal role of market-level information in the manner defined here. For example, Golder and Tellis (2004) investigate the role of informational cascades on consumer durables adoption, but focus on information that is conveyed through the behavior of previous adopters that can outweigh an individual's private valuation. Moorman, Du, and Mela (2005) examine the effects of the Nutrition Labeling and Education Act (NLEA) on the survival and marketing strategies of firms in food categories. However, their study investigates the effects of only the presence (absence) of nutrition information without evaluating its content.

More recently, a number of studies started to examine the dynamic nature and use of customer and market-level information in new product development (NPD) decision-making contexts. Joshi and Sharma (2004) provide support for the "evolutionary" nature of firms' customer knowledge development during the innovation process. However, their study focused on internal, organizational and new product project characteristics that influence managers' customer knowledge development, as the new product evolved, rather than examining the dynamics of market knowledge structures and impacts on new technology adoption (Joshi and Sharma, 2004). Marinova (2004) shows how dynamic use of market knowledge drives a firm's innovation effort. Results from quasi field experiments based on a Markstrat Simulation exercise showed that decision maker market knowledge level, knowledge change and extent of shared knowledge influence innovation effort (Marinova, 2004). However, in this study, market knowledge comprises knowledge about customers and competitors, and market knowledge sharing was restricted to that being exchanged between managers within an organization, not the wider market. Besides, the simulated Markstrat environment only offers a microlevel perspective and cannot capture market-level knowledge dynamics in an actual evolving high-tech industry. More recently, in an empirical study of high-technology firms in China, De Luca and Atuahene-Gima (2006) provide novel insights into the complex interplay between specific market knowledge characteristics, cross-functional collaboration, and new product performance. However, both market knowledge, which was defined as the firm's knowledge of customers' behavior and needs and competitors' behavior, and its specific characteristics, which was conceptualized as the breadth, depth, tacitness, and specificity of the market knowledge held (De Luca and Atuahene-Gima, 2007:97), largely reflected the nature of the market knowledge base of the organization, as opposed to public information available to market players in the broader market. Finally, Theoharakis and Wong (2002) study the evolution of different types of market-level information over the course of a technology's lifecycle, but do not quantify its effects on technology adoption.

The market-level information we consider and defined earlier does not only capture customers' perspectives, but also contains analyses of market trends and product offerings, and interpretations of vendor announcements and can thus critically influence customer decision-making regarding the adoption of a technology. Our focus on print media-provided market-level information is based on three arguments. One, consistent with the economists' view of print-media as infomediaries, this source of information provides expert knowledge that facilitates transactions between buyers and sellers (Biglaiser, 1993). Second, drawing from social constructivist research, print media captures the information flows or "stories" shared between market players, which reveal a wider, market-level discussion and influences market players' sense making and inferences about new technologies, products, or markets. Far from being chaotic, the evolving market knowledge reflects the dynamic character of players' learning and sense making efforts, and when systematically analyzed, may reveal the shape of things to come (Theoharakis and Wong, 2002).

Although prior research has demonstrated how social structures might influence the flow of useful and credible information that market players use to construct knowledge and reduce uncertainty of market events (Rindova et al., 2006), it has placed relatively little emphasis on unraveling the precise nature or type(s) of information that drive market participants' adoption decisions. We address this gap in the literature by empirically assessing the impact of different market-level information types on technology diffusion, a task that has not been previously undertaken in the context of competing technologies. Third, survival of a technology may depend on its ability to command the appropriate levels of legitimacy and resources (Meyer and Rowan, 1977). Previous studies on media legitimation effects (e.g., Pollock and Rindova, 2003; Hannan et al., 1995:512) lead us to examine the impact of print media-reported information on new technology diffusion. The media can differentially select and frame information it communicates to the wider market, which affects the formation of market participants' perceptions and responses to emerging technologies.

3. Study Context

We focus on the Local Area Networks (LAN) industry. A LAN consists of components that form the data communications infrastructure of an organization within the geographical boundaries of a building or a campus. LANs have enabled the free flow of information across coworkers and form the information backbone of the modern firm. Specifically, we focus on the effects of market-level information on the adoption of two technologies, Ethernet and Token Ring, which competed to achieve dominance in the desktop market (i.e. connecting user PCs). These two standards were developed by different committees of the Institute for Electronic and Electrical Engineers (IEEE). In particular, the IEEE 802.3 committee published the first Ethernet specification (10BASE5) in 1983 while the IEEE 802.5 committee published the original Token Ring standard in 1985.

We use the market-level information database of Theoharakis and Wong (2002)[1], based on a quantitative content analysis of substantive abstracts from more than 800 trade journals found in the ABI Inform database, which resulted in the identification of 10 412 LAN related *market* *stories* for the period 1981-2000. The use of trade magazines was motivated by the fact that they have been consistently identified by LAN industry and academic studies (Maier et al., 1997) as the most important source of information, and that their stories reflect a variety of sources and opinions. Although Theoharakis and Wong (2002) identified four types of market stories - technology, availability, adoption and discontinuation - we focus on two of them: availability and technology. The reason is that first, there are relatively few discontinuation stories concerning the standards we study. Second, since we explicitly study the adoption of the two technological standards adoption information is essentially reflected in the adoption data (Network Interface Card connections).

The categorization effort was extensive and it was carried out by one of the authors; its reliability was tested, by presenting a sample of 100 article abstracts to eight additional judges. The judges included product and marketing managers, sales representatives, and network managers (decision makers for local area network purchases). The overall inter-judge agreement was 94% which results in a Perreault index of .96 (Perreault and Leigh, 1989) and a PRL of 1 (Rust and Cooil, 1994). An article was left unclassified if it did not fit the predefined information category. As a result, only about 15% of story participations were not placed in the originally defined information categories. While the classification of each article as positive or negative for the technology was desirable, that was highly subjective; journalists frequently present both positive and negative issues for a product or technology.

We match the market-level information data with annual adoption data obtained by the International Data Corporation LAN market reports (IDC, 1981-2000). Adoption data for each standard begin at the time when products supporting the standard were first made available (1983 for Ethernet and 1986 for Token Ring), so our dataset covers the PC LAN industry from its very beginning in terms of both market-level information and adoption data. The adoption data consist of the number of network interface card connections (NICs) for each technological standard. Although both technologies were developed to provide network connectivity, they proposed different network architectures and used different wiring systems and, consequently, their NICs

[1] Theoharakis and Wong (2002) also consider other standards such as FDDI and ATM that primarily targeted servers rather than PC desktops.

support only one technology. Since a NIC is required to connect a PC to a LAN and the two standards are incompatible with each other, the adoption of a NIC reflects a firm's decision to adopt a particular standard. With firms typically committing to only one standard, NICs are an accurate measure of the installed base of a LAN standard. Technology and product availability stories and adoption data for both standards are shown in Figures 1-3.

Figures 1-3 about here

3.1 Market-level information Types and LAN Technology Adoption

An information stimulus may have several interpretations which could be confusing to potential adopters (Daft and Lengel, 1986), especially in high technology markets where changes in the underlying technology can have a significant effect on the life cycle of products (Popper and Buskirk, 1992). However, in order to better understand information in such markets, one has to first examine the nature of technology itself. Technology consists of two components: the *physical object* and *information* that relates to the technology (Griffith, 1999; Rogers, 1995). Specifically, Griffith (1999) expects technologies to have different proportions of these components and that these components would have a different impact on technology adoption. In fact, this component typology is echoed by the technology market-level information types captured by Theoharakis and Wong (2002) that found market-level information proportions to change over the course of a technology's life cycle. For example, the primary focus of market-level information in the early stages of the technology's life cycle is on information about the technology rather than on products.

Theoharakis and Wong (2002) refer to stories where the primary topic is the technical aspects and potential of the technology (e.g. standards setting activities, technology features) as *Technology* stories. As suppliers enter the market and actively promote their products, stories evolve around product availability and specifications (Agarwal and Bayus, 2002); Theoharakis and Wong (2002) refer to this type of stories as *Product Availability* stories where the primary topic is about products, the physical objects and activities supporting the specific technology (e.g. product launch announcement, product tests). Therefore, these two categories of technology and product availability stories provide information that can be utilized as triggers for sensemaking (Griffith, 1999). However, the question of whether both types of information are equally important or effective in influencing the formation of customers' impressions and, hence, the adoption of different technologies remains unanswered.

3.2 Hypotheses Development

In emerging new product categories, irrespective of whether the market would eventually accept a single product design architecture (i.e., a dominant design) or preferred standard, the pioneer faces the challenge of legitimating its new technology. Technology sensemaking is instrumental in shaping market knowledge regarding the nature of a new technology, rendering it more comprehensible, meaningful, or desirable, and therefore more legitimate (Suchman, 1995). Through building a consensus about what the technology aspects stood for, consumers finally make sense of the technology, which is subsequently perceived as 'real' (Garud and Rappa, 1994). The amount of information for pioneers often is greater than that for followers, resulting in higher consumer confidence toward the pioneer (Kardes and Kalyanaram, 1992; Alpert and Kamins, 1995). The pioneer's successful early entry shifts buyer preference in its direction as they perceive the organization to be the first to define or be associated with the technology (Carpenter and Nakamoto, 1989; Carpenter and Nakamoto, 1994). Due to the informational advantages accruing to the pioneer and the legitimacy its technology has been able to generate, similar media-reported technology-based information for follower technologies may not affect market impression formation to the same extent as that achieved for the market pioneer.

The high levels of uncertainty characterizing high-tech industries (John et al., 1999; Moriarty and Kosnik, 1989) and hence, customers' anxiety (fear, uncertainty, and doubt) about a new technology, requires a high degree of education and information about the benefits of an innovation before the majority of the market will adopt it (Von Hippel, 1986). Consistent with von Hippel (1986), lead users (the innovators or visionaries) and early adopters are more willing to adopt the new technology for the substantive technological and psychological benefits they perceive to receive, and are more receptive to 'tech-speak' compared to the early majority and late adopters (the pragmatists comprising the market majority). In fact, first-users are closely associated with the design and early development stage of the technology (Mangematin and

Callon, 1995). Overall, in the introductory and early stages of the new technology, innovators and early adopters are more receptive than later adopters to technology arguments (Moore, 1995a; Moore, 1995b; Rogers, 1995). Indeed, in the early stages of new technology emergence, in a business-to-business, high-tech environment context, lead users are more familiar with, and faster at harnessing, the benefits accruing from emerging technological innovations, ahead of the mass of the market. They understand new technology and are more able to articulate performance criteria than later adopters (Abernathy and Utterback, 1978). Therefore, we expect that technology information will have a more pronounced effect on the adoption of the pioneering technology, since information about it should be perceived by the early adopters as novel and interesting (Kardes and Kalyanaram, 1992). Thus:

H1a: Technology information will have a positive effect on pioneering technology adoption.

In order to reduce perceived risk and facilitate the adoption of a new technology, the early majority adopters and followers require a different set of benefits and incentives, and hence are more likely to engage in and respond to information exchanges that are more customer-friendly (e.g., product availability and delivery timescales; vendor service availability). Moreover, technology information about the follower's standard may be perceived as redundant especially when it shares similar capabilities with those of the pioneer - as it is the case in the PC LAN market. This argument is further supported by the fact that previous research in high technology markets has demonstrated that a perception of rapid technological change increases the probability that the incumbent technology provider will be chosen (Heide and Weiss, 1995); new technology information transmitted by the follower raises the sense of technological uncertainty and change among customers and also reduces the follower's adoption rate in favor of the incumbent's. Heide and Weiss (1995) actually state that increasing buyers' perception of technological change, as is frequently done by followers, "actually buffers incumbent vendors from competition". In this sense, technology information has the potential of harming the adoption of follower technology. Given the preceding arguments, we offer the following hypothesis:

H1b: Technology information will have a negative effect on follower technology adoption.

Prior work has established that when an innovation is observable, i.e. the more concrete product information dominates technology information, its diffusion is accelerated (Rogers, 1995). In fact, a high volume of product availability information indicates broad vendor support and suggests the start of the technology bandwagon (Wade, 1995). It also signals to prospective customers that the technology is real and products are widely available, attenuating the fear that the technology is a case of "vaporware" that may never materialize (Bayus et al., 2001). Therefore, product availability information reduces uncertainty (Gatignon and Robertson, 1991), and communicates to the market that the technology has been implemented, enhancing its adoption rate. This perspective is consistent with previous research demonstrating that judgments of uncertainty about product performance are influenced by the availability heuristic (Folkes, 1988; Tversky and Kahneman, 1973). Since, information reporting on product availability can legitimize the technology it leads us to hypothesize that:

H2a: Product availability information will have a positive effect on technology adoption.

For products where network externalities are important, the utility to potential users increases with the number of other users that have adopted the product and may play to the advantage of the pioneer (Katz and Shapiro, 1986). The pioneer's growing or established installed base signals its ascendancy or dominance to consumers and is a great source of legitimacy. If consumers expect the technology to become the standard or to achieve dominance, then, they will be more likely to adopt it (Katz and Shapiro, 1986). In the presence of network externalities, consumers are therefore less likely to adopt a follower's unproven, incompatible technology, in the absence of extrinsic cues, such as product information and consumption experiences, or market share signals, which are more easily available for the established incumbent. Moreover, as argued earlier, due to informational advantages and the potential that a pioneering firm's legitimacy might imbue its technology with a real head start in the marketplace, followers have to rely more on extrinsic cues, such as product experiences, availability, and warranties, in order to reduce customers' perceived risk and uncertainty, and to facilitate product adoption (Bearden and Shimp, 1982).

Given that our competing LAN technologies are not compatible, competitive advantage accrues to the firm with the largest installed base (Farrell and Saloner, 1985; Katz and Shapiro, 1985). Therefore, compared to the pioneer, the follower technology not only faces an informational bias, in terms of the negative impact of technology information on adoption, but also an increased pressure to demonstrate physical evidence, i.e. products, to prove that it is real and to overcome the handicap that the incumbent has established an installed base. As a result, product availability information is a signal of product market evolution that is of even greater importance for reducing the market and technological uncertainty of the more risk-averse customer segments that enter later in the market. This is due to the fact that when competing technologies have similar capabilities, the follower needs to more rapidly convince the less innovative buyer segments that are currently in the marketplace who have a higher need to observe product applications; innovators and early adopters have for the most part adopted products based on the pioneering technology. Hence, we expect the presence of product availability information to have a stronger effect on the follower technology and propose:

H2b: The positive effect of product availability information will be stronger for the follower technology than the pioneering technology.

4. Empirical Analysis

4.1 Model Specification

The objective of our modeling approach is to capture the effects of market-level information on technology adoption, while adjusting to the limitations of the available data. Specifically, the available adoption measure is total connections for each standard, that is, total network interface connection cards. Total connections reflect a standard's installed base, consisting of first-time sales, the retained (from previous periods) installed base, and new connections due to switching from another standard. Thus, we break down the installed base for each technological standard in the following manner:

(1) $$IB_{st} = S_{st} + RS_{st} + SW_{st}$$

Where:

IB_{st} = Installed base for standard s at time t

S_{st} = First time adoptions (connections) for standard s at time t

RS_{st} = Retained installed base of standard s at time t
SW_{st} = Connections due to switching to standard s at time t
Let s=1 correspond to the Ethernet standard and s=2 to the Token Ring standard.

Due to the availability of installed base data only (left hand side of equation (1)), we need to specify models for first-time adoptions (diffusion), retention, and switching that can be exclusively expressed as functions of time and information-related variables. We will first discuss the specification of first-time adoption and then present the switching and retention specifications[2].

4.1.1 Specification of first-time adoption

Given our data limitations, our first-time adoption model should satisfy the following criteria:

i) It should have a closed-form solution in the time domain.
ii) It should be technological standard-specific while still accounting for competition between standards.
iii) It should incorporate explanatory (in our case information-related) variables.

The specification that satisfies the above criteria is a proportional hazards (PH) specification with the Bass Model (Bass, 1969) as its baseline distribution[3]. To facilitate model exposition, we first briefly discuss the proportional hazard specification and then we provide details on the Bass model of diffusion of innovation.

The proportional hazard model, due to Cox (1972), has a long history of applications not only in biostatistics, but also in the social sciences (for a relevant literature review see Seethuraman and Chintagunta 2003). It relates the *hazard rate* of an event, the instantaneous probability that an event will happen at time t given that it has not taken place prior to that time, to a set of explanatory variables or *covariates.* The hazard rate is mathematically defined as:

[2] A similar problem was encountered by Danaher, Hardie, and Putsis (2001) in their study of pricing effects on successive generations of cellular handsets, thus we follow closely their approach.

[3] An alternative specification is the model proposed by Krishnan, Bass, and Kumar (2000). This however requires the estimation of a separate set of parameters for the diffusion process before the entry of the follower (Token Ring). Since the available data are annual and the follower's technology was introduced only three years after the pioneer (Ethernet), we did not have enough observations to reliably estimate such a model.

(2) $$h(t) = \frac{f(t)}{1 - F(t)}$$

Where f(t) is the probability density function (pdf) for an event (in our case the adoption of a technological standard) and F(t) is the corresponding cumulative distribution function (cdf).

The PH formulation relates then the hazard rate to a set of covariates in the following manner:

(3) $$h(t) = h_0(t)e^{\beta' z}$$

Where h(t) denotes the hazard rate, z is a set of explanatory variables (covariates) that influence the hazard rate, β is a set of coefficients associated with z and $h_0(t)$ is the so-called "baseline" hazard rate or the hazard rate when z is set to zero. The baseline hazard rate can be considered as the underlying timing pattern for the occurrence of an event. The term "proportional" refers to the manner in which the covariates affect the baseline rate. In other words, under the PH specification, the covariates "shift" proportionally the baseline hazard rate.

In our application, we chose the Bass Model of diffusion of innovations as the baseline hazard rate model for the adoption of a technological standard. The Bass Model is perhaps the most widely known marketing model with applications that extend well beyond the marketing domain (for a review see Mahajan, Muller and Bass 1990). According to the Bass Model, the baseline hazard rate of adoption for a technological standard s is given by:

(4) $$\frac{f_s(t)}{1 - F_s(t)} = p_s + q_s F_s(t)$$

Where f_s is the density function for the timing of adoption of technology s and F_s is the corresponding cumulative distribution function (c.d.f.). The underlying premise of the model is that the hazard rate of adoption is linearly increasing in the fraction of the population that has already adopted. There are two forces that drive technology adoption, these being represented by the two terms on the right-hand side of the equation. The first force, represented by p, drives adoptions made independently of any previous adoption behavior. Individuals that make adoption decisions independently of previous adoption can be thought of as innovators, hence Bass coined p the "coefficient of innovation." The second force, represented by "qF," drives adoptions influenced by previous adopters (F(t)), and reflect imitation or interpersonal communication effects. Consistent with this interpretation, Bass (1969) coined q the "coefficient of imitation" since it captures such effects. Alternative terms were used by Lekvall and Wahlbin (1973) who labeled p and q external and internal influence respectively.

It should be noted that the interpersonal communication represented by the term "qF" need not be direct or represent private information. It may also be indirect, reflecting learning through observation of adoption behavior or information on it (Kapur, 1995; Mahajan et al., 1990). In our case, for example, publishing of information on adoption of technology standards by third-parties (e.g. marketing research firms) may generate imitation effects without requiring communication between potential and future adopters[4].

Equation (4) is a first-order differential equation and Bass (1969) has shown that its solution, in terms of F, can be expressed in the following manner:

$$F_s(t) = \frac{1 - e^{-(p_s + q_s)t}}{1 + (\frac{q_s}{p_s})e^{-(p_s + q_s)t}} \tag{5}$$

The closed-form solution of the Bass Model in the time domain satisfies our first criterion as it allows us to express first-time adoptions purely in terms of time. By assuming technology-specific imitation and innovation coefficients, we also allow for distinct diffusion paths for each technology standard, in other words for technology-specific diffusion. Technology-specific diffusion implies different market potentials for each standard, not an unreasonable assumption since the two technologies we consider here were not introduced simultaneously and were available by a different number of vendors. Competitive effects are introduced in the model using the information variables. Information effects are accommodated via the use of the proportional hazards (PH) formulation as discussed above. More specifically, the PH formulation with the Bass Model (BM) as its baseline hazard rate, referred to as the PH-BM model from hereon, leads to the following c.d.f. for first time adoption:

$$F_{sPH-BM}(t) = 1 - e^{-\Lambda_s(t)} \tag{6}$$

where Λ_s is the integrated hazard function, which takes on the following expression:

$$\Lambda_s = \sum_{j=1}^{t} \{\ln[1 - F_s(j-1) - \ln[1 - F_s(j)]\} e^{\beta_s' z_s(j)} \tag{7}$$

and $z_s=(z_{s1},\ldots,z_{sk})$ is a Kx1 vector of information-related variables for standard s and β_s is the corresponding parameter vector. The information variables are expressed as share-of voice variables, in other words relatively to competition, introducing therefore competitive effects. More specifically, *technology share-of-voice* is expressed as the ratio of technology stories for a particular standard over the total number of technological stories in the industry. Likewise, *product availability share-of-voice* is expressed as the ratio of product availability stories for a particular standard over the total number of product availability stories in the industry. Share-of-voice variables for both standards across time are shown in Figure 4. It can be easily observed that there is no apparent correlation between the type of share-of-voice (technology or availability) and time for either standard. For example, technology share of voice is not consistently larger than availability share-of-voice in the beginning of Ethernet's life cycle.[5] Thus, use of share-of-voice measures, in addition to introducing competitive effects, de-trend the information variables. Combining the PH formulation with the Bass Model also satisfies our third criterion regarding the inclusion of explanatory variables. Thus the proposed specification satisfies the three criteria we set in the beginning of the section.

Figure 4 About Here

In order to estimate the PH-BM model, it is necessary to develop an expression for first time adoptions. Following Srinivasan and Mason (1986), first-time adoptions can be expressed as:

(8) $$S_{st} = M_s[F_{sPH-BM}(t) - F_{sPH-BM}(t-1)]$$

where M_s is the market potential for each standard. Thus, through the use of a standard-specific diffusion model that allows for competition between standards and has a closed-form solution in the time domain, we are able to express first-time sales exclusively in terms of time and explanatory variables.

4.1.2 Specification of retention and switching between standards

We assume that previous adopters of a standard who do not switch to a competing standard will retain the same standard (i.e. consumers do not drop out of the market). Retention is therefore a direct consequence of the switching decision, and sales due to switching and retention will be

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[4] We would like to thank the reviewing team for suggestions on this issue.
[5] We thank the reviewing team for pointing us to this issue.

treated within the same framework. Following Danaher, Hardie, and Putsis (2001), we define sales for standard s due to retention of own customers and switching from standard s' respectively as follows:

(9) $$RS_{st} = IB_{st-1}(1-\delta_{s't})$$

(10) $$SW_{st} = IB_{s't-1}\delta_{st}$$

Where s=3-s', in other words s=1 (Ethernet) when s'=2 (Token Ring) and vice versa, and δ_{st}, $\delta_{s't}$ are switching factors that Danaher, Hardie, and Putsis (2001) coined "switching multipliers." The switching multiplier δ_{st} denotes the fraction of the installed base that switches to standard s from the competing standard s' at time t. Thus, equation (7) suggests that the fraction of the installed base of standard s at t-1 that does not switch to standard s' at t (i.e.1-$\delta_{s't}$), retains standard s at time t. Similarly, equation (8) implies that the sales of standard s due to switching from standard s' at t, are equal to the fraction δ_{st} of the installed base of standard s' at t-1 that decides to switch to standard s at t. Due to the higher growth rate of Ethernet and its eventual dominance in the LAN market, we assume that no switching takes place from Ethernet to Token Ring, i.e. δ_{2t}=0 for all t. We assume that the switching multiplier depends both on the growth of the standard adopters switch to and the growth of the standard they switch from. Specifically, the switching multiplier from Token Ring to Ethernet, $\delta_{1t,}$has the following form:

(11) $$\delta_{1t} = \begin{cases} 0 & t < T \\ \left(\dfrac{F_{1PH-BM}(t) - F_{1PH-BM}(t-1)}{1-F_{1PH-BM}(t-1)}\right)\left(1-\dfrac{F_{2PH-BM}(t) - F_{2PH-BM}(t-1)}{1-F_{2PH-BM}(t-1)}\right) & t \geq T \end{cases}$$

Where t marks time since the introduction of the first standard (Ethernet) and T denotes the time of the introduction of the second standard, Token Ring. The specification suggests that the switching multiplier is proportional to the "attraction" of Ethernet, expressed by its relative growth (first factor), but it is mitigated by the relative growth of Token Ring (second factor). In other words, the switching multiplier increases with the relative growth of Ethernet, but decreases with the relative growth of Token Ring. The latter reflects network externalities effects as the growth of the installed base of the currently adopted standard may provide a good reason for adopters not to switch to a competing standard, despite the latter's attractiveness, and, conversely, lack of growth of the current standard may accelerate switching to the competing standard[6]. Since Token Ring (the second entrant) is not introduced until T, there is no switching before that time. Treatment of the switching multiplier completes the specification of sales due to switching and retention. Using therefore the proposed specifications for first-time adoption, retention and switching, the installed base equation (1) takes the following expressions for the two standards:

For Ethernet (s=1)

$$(12) \qquad IB_{1t} = \begin{cases} M_1[F_{1PH-BM}(t) - F_{1PH-BM}(t-1)] & \mathrm{t \leq T} \\ M_1[F_{1PH-BM}(t) - F_{1PH-BM}(t-1)] + IB_{1t-1} + IB_{2t-1}\delta_{1t} & \mathrm{t > T} \end{cases}$$

For Token Ring (s=2)

$$(13) \qquad IB_{2t} = \begin{cases} 0 & \mathrm{t < T} \\ M_2[F_{2PH-BM}(t-T+1) - F_{2PH-BM}(t-T)] + IB_{2t-1}[1-\delta_{1t}] & \mathrm{t \geq T} \end{cases}$$

The Token Ring equation has one less term (connections due to switching) since we assumed $\delta_{2t}=0$ implying $SW_{2t}=0$ for all t.

4.2 Estimation Results

We estimate equations (10) and (11) simultaneously, using Seemingly Unrelated Regression (SUR). SUR accounts for correlations across the error terms of the two equations which typically leads to lower standard errors and therefore more efficient estimators (Kim et al., 1999; Pindyck and Rubinfeld, 1991). The same estimation strategy was used by Kim et al. (1999) in a similar context (diffusion of innovations). In addition to a full model incorporating both information variables, we also estimated two other benchmark models: A "null' model with no information variables and a "pooled information" model where technology and availability information were pooled in one variable using the share-of-voice measure. There are twenty observations available for each equation, a number typical of many applications of diffusion models. The estimation was carried out using the SAS PROC MODEL and the results are presented in Table 1. The three models were also compared using Wald tests to get a sense of how much it is gained using additional information variables[7].

[6] We thank the reviewing team for suggestions on this issue.
[7] We thank the editor for this suggestion.

Tables 1 and 2 About Here

Wald tests could not reject the null hypothesis of equality of the innovation coefficients p_s for the two standards; hence we used a single innovation coefficient for both Ethernet and Token Ring. We will first discuss the full model results and then compare them with those concerning the benchmark models.

4.2.1 Full Model

The market potentials of the two standards are considerably different, providing an indirect validation of our technology-specific diffusion specification. The lower market potential for Token Ring suggests that, as a result of the diffusion process, the installed base for this technology is smaller than Ethernet's. The imitation coefficient is higher for Token Ring, suggesting that the follower technology needs a stronger imitation or installed base effect to make it an attractive option as a technological standard.

Turning now to the effects of the information-related variables, the results suggest that product availability information and technology information have a differential influence on the adoption of the two technologies. More specifically, our first hypothesis regarding the effects of technology information is partially confirmed: while technology information has a positive effect on pioneering technology (Ethernet) adoption (H1a), its effect on follower technology (Token Ring) adoption (H1b) is negative as hypothesized, but is not statistically significant. Our second hypothesis on the effects of product availability information is also partially confirmed: while product availability information has a positive effect on Token Ring adoption (H2a), its effect on Ethernet is positive, but not statistically significant (H2b). Therefore, Ethernet adoption appears to be influenced only by technology information, whereas product availability information affects significantly only the adoption of Token Ring.

4.2.2 Benchmark Models

The estimates of the benchmark models concerning the Bass Model variables (p, q, M) are not dramatically different from those of the full model. More importantly, the differences between the Ethernet and Token Ring parameters are preserved: Ethernet has a bigger market potential and a smaller coefficient of imitation than Token Ring in both models. The coefficient of innovation is the same across all three models. This suggests robustness of our results. The biggest departures from the estimates of the full model are recorded by the null model, a rather expected outcome, since the latter does not account for any information (covariate effects), which may very well be absorbed by the other model parameters. For Ethernet, the information effects in the pooled information model are significant with an estimate that is larger than both the technology and the availability estimates in the full model, but closer to the availability one. The information estimate for Token Ring in the pooled information model is also closer to the availability estimate under the full model. The severity of omitting information variables will be discussed next when we explicitly compare the statistical performance of the three models.

4.2.3 Model Comparison

Square root mean standard errors ("Root MSE" in Table 1), a typical measure of model fit, suggest that, for both standards, the full model provides a better fit than the two benchmark models, offering validation for the full model specification. To further explore this issue, we compared the three models using Wald tests (Table 2). The first comparison is that between the full and the null model. This can be considered as a "significance" test for the inclusion of the two information variables. As can be seen by the statistics, the full model is favored over the no-information variable model, establishing once again the benefit of including information variables.

A more refined comparison is the one between the full and the pooled information model, which reveals some important asymmetries. Although the Wald test could not reject pooling of information variables for Ethernet, perhaps suggesting that any type of information is equally important for the pioneer, it does favor the full over the pooled model in the case of Token Ring, reinforcing the importance of separately considering the availability information for the follower. The comparison of the pooled versus the null model can be thought of as testing the significance of including *any* information variable in the model. While pooled is preferred over the null, the rather low statistic for Token Ring points to the loss of explanatory power when information effects are not considered separately (technology and availability) for that standard. It should be noted that for all these tests, significance was achieved despite the relatively low number of observations, which is typical of diffusion studies, further underlining the strength of our findings. Some of our findings will be further discussed in the next section.

5. Discussion

Our findings suggest that technology information has a positive effect on the adoption of Ethernet, consistent with our arguments that such information may be perceived as novel by potential adopters. Technology information for Token Ring, on the other hand, does not have a significant effect on its adoption possibly because such information is perceived by customers as uninteresting and redundant (Kardes and Kalyanaram, 1992). The finding that product availability information has an effect only on Token Ring adoption should be interpreted on the basis of the need for a follower technology to generate legitimacy through the dissemination of this type of information; Token Ring's installed base alone cannot adequately signal availability and the technology becomes more heavily dependent on product availability information to strengthen its signal to the market and reduce uncertainty among potential adopters. Ethernet, on the other hand, enjoys a much larger installed base and a head start in the diffusion process, due to its earlier entry. Its larger installed base appears to sufficiently communicate its availability which is an important signaling mechanism (Spence, 1973) for demonstrating product quality and dominance. However, the follower has the opportunity to partially substitute for its lack of legitimacy by supplying product availability information.

The differential information effects can thus be explained in terms of the entry timing of the two standards (early vs. late) and the differences in installed base as the market potential estimates suggested. We reason that the different effects of market-level information on the adoption of pioneer and follower technologies reflect the dynamic use of market knowledge which influences innovation adoption over time, as well as the shifting focus of market-level information sharing from the "techie" innovators and early adopters to a more risk-averse, mainstream market.

Our finding on the importance of technology information for the pioneer standard, is consistent with innovation adoption and diffusion theory indicating that innovators and early adopters in the market are more exposed to specialist media (e.g., technical and trade press), show lower anxiety toward new technology, and are more conversant on and aware of the technology aspects of an innovation (Rogers, 1995). By contrast, for a later entrant, media-provided information about the availability of its technology becomes more important. As the technology-market evolves, follower technologies have to attract the remaining potential adopters – typically, more risk-averse pragmatists, who constitute the majority of the market. Product availability information attenuates customers and producers' fear about market and technological uncertainties in several ways. It signals to the market that the innovation has materialized. In the case of a follower introducing a rival standard, which may be held suspect until legitimacy is achieved, media reporting about product availability and vendor support play an even more important role in signaling technology acceptability, as evidenced by manufacturers' adoption of the standard which has been incorporated in new products. Hence, product availability information represents a more customer-friendly perspective that appeals to the mainstream market (Moore, 1995a; Moore, 1995b; Moore, 2005).

Our results form a basis for substantive implications for competitors in high-tech industries. First, the significance of information effects should be put into perspective, since they were obtained in the presence of strong word-of-mouth effects (significant imitation coefficients). It suggests that print media-reported market-level information is an important driver of technology adoptions. This is consistent with the recommendation of Dutta, Narasimhan, and Rajiv (1999) that high-tech firms should inform consumers of their capabilities and initiatives. However, our findings highlight the differential roles of technology and product availability information on technology adoption in the context of competing technology standards. Second, firms should monitor the dynamics of market-level information usage as technology-competition in the market evolves over time. Managers should make strategic use of technology and product availability information, as their effects depend on whether standards enter the market early or late, and the size of their installed base. Pioneers should capitalize on information regarding the features and capabilities of their technology, as they have an opportunity to educate prospective customers and influence their adoption decisions. Later entrants, on the other hand, may find it difficult to affect adoption decisions through technology information, due to overlap with the pioneer's information. Instead, they should focus on leveraging product availability information especially when faced with late mover informational biases and installed base disadvantages.

6. Conclusions and Future Research

In this study we examine the effects of different information types on the diffusion of two competing technological standards in the Local Area Networks (LAN) industry. Whereas recent research identified different types of market-level information (Theoharakis and Wong, 2002), a study of their effects on the adoption of technology standards has not been previously undertaken. Our empirical application suggests that there are differential information effects on the adoption of the two standards. More specifically, technology information affects the diffusion of the pioneering technology (Ethernet) whereas product availability information affects the follower technology (Token Ring), which also has a smaller installed base.

This paper contributes across several dimensions. First, by examining the effect of different types of print media-reported market-level information on the diffusion of competing technologies, our research contributes to a very limited number of studies that provide evidence about the market performance effects of information (Moorman, 1998; Moorman et al., 2005). Second, because market-level information is external, i.e. it does not originate from the network of current and potential adopters, we were able to identify exogenous drivers of diffusion that complement internal forces such as interpersonal communication. Third, based on the empirical results, we were able to provide implications on the strategic use of market-level information. Finally, our application in a high-technology market contributes to a limited number of studies that deal with the more complex high-tech markets, although the high-tech sector accounts for a very high portion of GDP growth (Mohr, 2000).

We believe that studying market-level information effects on adoption in multiple industry sectors will provide further evidence for the direction and the magnitude of such effects, especially since market-level information research in technological environments seems to be limited. Extending the study to multiple industries will open up further possibilities for future relevant research. For example, as recent studies have examined the takeoff point of innovations (Agarwal and Bayus, 2002), one can study how market-level information is linked with market takeoff. Lastly, examining whether the effects of market-level information vary over time can provide another opportunity for potentially interesting future research. In this study, due to the relatively small number of available observations, we assumed constant market-level information effects. However, one may argue that market-level information should be more influential early in the adoption process due to the absence of strong word-of-mouth effects. In other words, since word-of-mouth effects early in the diffusion process are limited due to the low rate of adoption, market-level information should be relatively more important[8]. These potential extensions of our study will, hopefully, contribute toward a better understanding of the role of market-level information and facilitate managerial decision-making on the adoption of new technologies.

[8] Accounting for time interactions would be prohibitive for our sample size, since it requires four additional parameters in our model specification.

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Table 1: Diffusion Model Results for Ethernet and Token Ring
(t-ratios)

	Null Model No Information Variables		Pooled Information Model One (Pooled) Information Variable		Full Model Two Information Variables	
Parameter	**Ethernet**	**TR**	**Ethernet**	**TR**	**Ethernet**	**TR**
M	486526 (24.37)	31027 (9.32)	397891 (14.05)	48143 (3.96)	390176 (14.80)	49204 (4.90)
p†	0.0002 (5.60)		0.0002 (6.53)		0.0002 (4.72)	
q	0.46 (29.47)	0.71 (23.49)	0.41 (14.37)	0.56 (9.92)	0.41 (10.86)	0.60 (11.05)
Technology			0.99 (2.15)	3.13 (3.03)	0.37 (2.24)	-1.13 (-1.22)
Product Availability					0.68 (1.36)	3.43 (3.54)
Root MSE	1194	1081.9	1075.1	967.3	1069	895.5

†Wald tests could not reject the hypothesis of equality of innovation coefficients (p)

Table 2: Model Comparison
Wald Tests

	Wald Test Statistics		
Comparison	**Degrees of Freedom (df)**	**Ethernet**	**Token Ring**
Full vs. Null Significance of Information Effects	2	8.17**	9.23***
Full vs. Pooled Information Model Equality of Information Effects	1	1.54	4.84**
Pooled vs. Null	1	6.16**	3.53*

***Significant at 10% level**
****Significant at 5% level**
*****Significant at 1% level**

Figure 1: Technology and Product Availability Stories for Token Ring

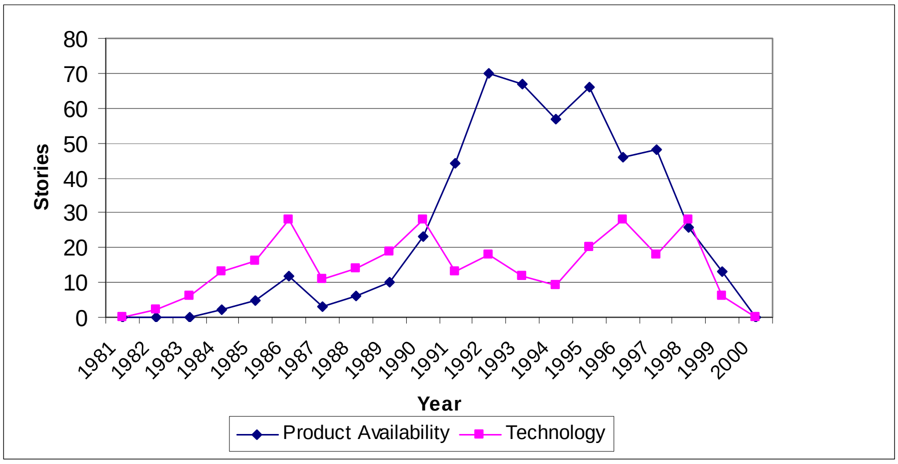


Figure 2: Technology and Product Availability Stories for Ethernet

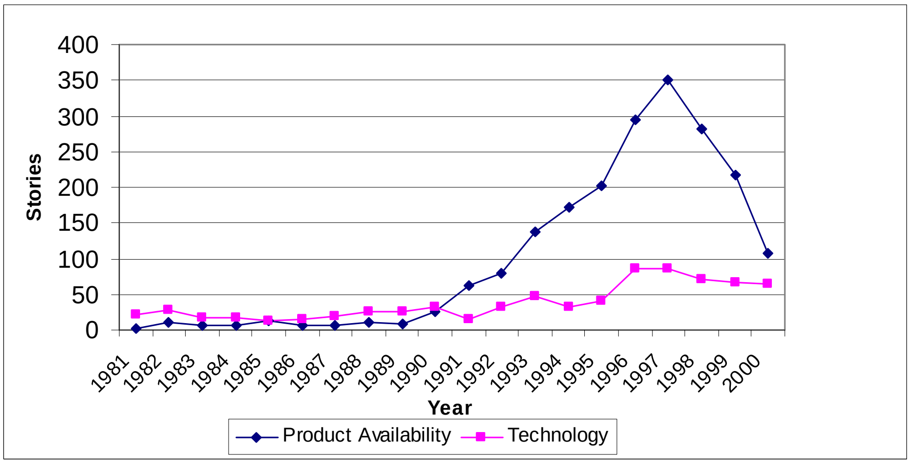


Figure 3: Installed Base Evolution for Token Ring and Ethernet

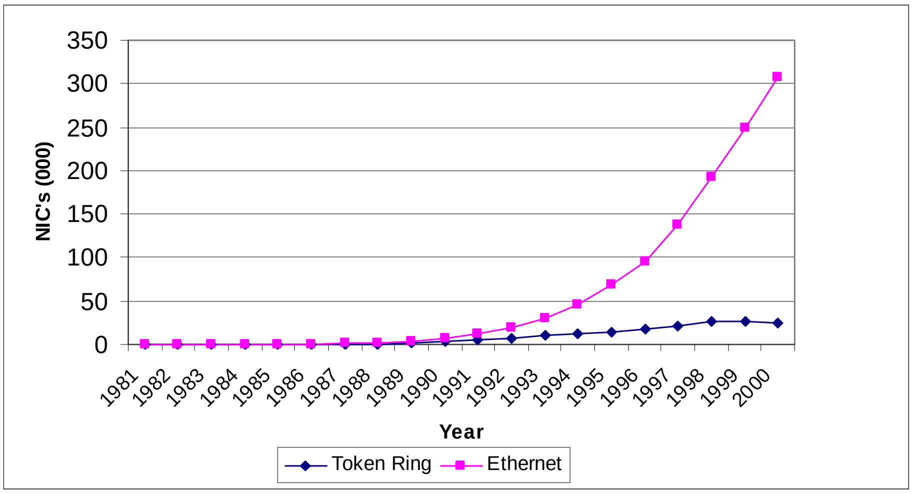
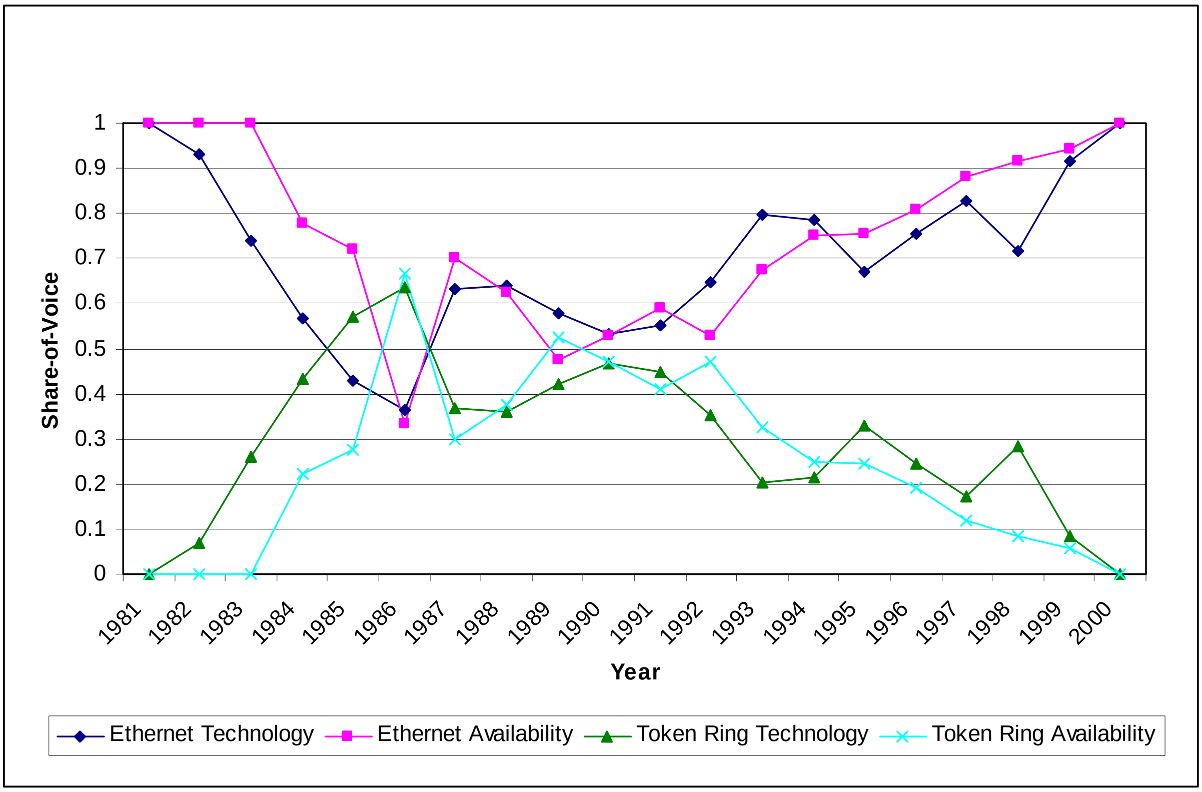


Figure 4: Ethernet and Token Shares of Voice



Acknowledgement

The authors would like to thank IDC Corporation and especially Maximilian Flisi for providing the LAN market reports that cover the complete period of investigation.