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Endogenous Acceleration of Technological Change

Berlin, March 2006

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DIW Berlin
German Institute for Economic Research
Königin-Luise-Str. 5
14195 Berlin
Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
www.diw.de

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Philipp Koellinger*
Christian Schade**

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* German Institute for Economic Research (DIW Berlin), Koenigin-Luise-Str. 5, D-14195 Berlin, Germany; Email: pkoellinger@diw.de, Tel.: +49-30-89789618, Fax: +49-30-89789103

** Humboldt-Universitaet zu Berlin, Institute for Entrepreneurial Studies and Innovation Management, Spandauer Str. 1, D-10178 Berlin, Germany; Email: schade@wiwi.hu-berlin.de, Tel.: +49-30-2093-5904, Fax: +49-30-2093-5918

Abstract

Our study shows that the technological development of a firm can be subject to an endogenous acceleration mechanism. The more advanced a firm is in using a particular set of technologies, the more likely will it adopt additional, related technologies. This acceleration mechanism implies that marginal differences in early adoption decisions lead to substantial differences in technology endowment later.

This hypothesis is tested in a dataset that records the adoption times of various e-business technologies in a sample of 7,302 firms from 10 different industry sectors and 25 European countries. Estimation is carried out with a semi-parametric hazard rate model that controls for unobserved heterogeneity. The results show that the probability to adopt strictly increases with the number of previously adopted e-business technologies. Evidence for a growing digital divide among the companies in the sample is demonstrated for the period from 1994-2002.

The endogenous acceleration mechanism is a possible source of early mover advantages, if technological uncertainty and technological improvements over time are not very large and if the price of the new technologies remains roughly constant.

Keywords: Technology adoption, technological competition, complementarity, hazard rate models, IT

1 Introduction

Technology adoption is an important strategic variable for firms because it determines the type of products and services produced and how these outputs can be generated. Investments in new technologies can enable firms to change their scope of operation (e.g., to offer new products or services), while investments in new process technologies, such as computer application or automated machines, can enable firms to produce a given output at lower costs. Thus, the adoption of technologies may be crucial for the competitive advantage of a firm.

The emergence of new technologies may bring about a myriad of changes, including the adoption of various complementary technologies, accompanied by organizational changes, changes in products and services being offered, prices, quality levels, production processes, and changing supplier relationships (Schumpeter 1934, Milgrom and Roberts 1990, Milgrom, Qian, and Roberts 1991). In many cases, a newly emerging technology is not completely independent from other technologies and development trends. Instead, many technologies belong to a particular technological paradigm (Dosi 1982), which offers solutions for a selected class of real-world problems based on selected material technologies. For example, Internet-based e-business technologies offer solutions to optimize the exchange of commercially relevant information, based on communication via non-proprietary computer networks. Thus, all e-business technologies belong to the same technological paradigm and are related in the sense that they are concerned with the same class of real-world problems (making required information available at the right time and the right place as a pre-requisite to optimize workflows and decisions) and based on the same material technologies (TCP/IP computer networks).

As a consequence of these technological interdependencies, firms face not only the option to invest in one of the technologies belonging to a newly emerging paradigm, but the option to invest in the technological trajectory defined by the attributes and possibilities of the numerous technologies belonging to that paradigm. In other words, firms often invest in a development path rather than a single technology.

Our study complements the literature on technology and innovation management (including Christensen and Rosenbloom 1995, Dewar and Dutton 1986, Henderson and Clark 1990, Tushman and Anderson 1986) as well as technology adoption (for example Forman 2005, McCardle 1985, Nilakanta and Scamell 1990, Olivia 1991, Srinivasan et al. 2002, and Stoneman 2002) by integrating the supermodularity concept from economic theory (Milgrom and Roberts 1990) and empirically testing it. From our perspective, this theory is the most appropriate way to reflect technological complementarities. It has not been used in the management literature yet and an empirical test is still missing in both economics and management literature.

The theoretical part of our study (section 2) shows that progress along a technological trajectory can be subject to increasing returns under fairly general circumstances, which leads to an endogenous acceleration mechanism of technological development. This finding has important implications for the management of technological innovations, and in particular for the timing of the investment in technologies from a newly emerging trajectory. Furthermore, the empirical part of the study (sections 3, 4, and 5) demonstrates that an acceleration mechanism in technological development can actually be observed in the real world. Using data on the usage of e-business technologies from a large representative enterprise survey conducted in Nov/Dec 2003 among over 7,000 firms from 10 different industry sectors and 25 European countries, we show that (1) the hazard rate of new technology adoption strictly increases with the number of previously adopted, related technologies that do not substitute for the technology under scrutiny and (2) we demonstrate that this mechanism resulted in a growing digital divide among the firms in our sample for the period from 1994-2002.

Our results suggest (section 6) that early adopters will make continuously faster progress on a given technological trajectory, enabling them to build up a technological leadership position until they have adopted all related technologies with a positive net present value. We discuss circumstances under which this mechanism can lead to sustainable competitive advantages of early adopters.

2 Theory

2.1 Technological interdependencies

To reflect technology adoption in the presence of technological interdependencies, we apply the concept of supermodularity to a decision theoretic model based on investment principles. The focus is on the initial purchase of a new technology, hence the model abstracts from intra-firm diffusion and from the level of use of the technology by the acquirer. Without loss of generality, we also abstract from strategic interaction.[1] To analyze differences in adoption probabilities, the model simultaneously analyzes a large number (N) of companies. Let N be a number of heterogeneous, profit-maximizing firms. In addition, assume certainty with respect to expected payoffs and costs of a technology. Each firm $i = 1...N$ is characterized by a vector of $\overline{x}_i$ individual covariates. This vector captures variables indicating relevant differences between firms, e.g., firm size and market specifications. In addition, let K be a number

[1] The actual effects of competition and market structure will be included in the control variables in the empirical test. The results regarding technological interdependencies are independent from this assumption.

of related, non-substitutable technologies that belong to a joint technological paradigm (Dosi 1982): these technologies offer solutions to selected technological problems based on joint technological principles.

The pattern and direction of progress based on the paradigm is called a trajectory. The normal path of development starts with the non-availability of any of the K technologies in a firm, and progresses with the adoption of each additional technology. It is specified below how technologies could be related economically and which effects can be associated with the concept of a joint technological paradigm. But non-substitutability is the crucial assumption for the following argument.

The technological equipment of a firm can be described as follows. Define a K-component vector Y of binary variables $Y = (y_1, y_2, ..., y_k)$ with $y_j \in \{0,1\}$ and $j = 1,...,K$. Y characterizes the current endowment of a firm with any of the K related technologies. The concept of a *supermodular* function can be used to relate current technological endowment to possible investments into additional technologies. This is warranted because technologies are – in this study – discrete variables: A firm has either adopted a particular technology or not. Supermodularity is a general concept to specify changes in a function with respect to several changes in its arguments, whether they are discrete or continuous.

We say that $Y' \geq Y$ if the j-th component in Y' is not smaller than the j-th component in Y for all j. Further, we define $\max(Y', Y)$ to be the operation that takes the largest value of Y' and Y for all j. Similarly, we define $\min(Y', Y)$ to be the operation that takes the smallest value of Y' and Y for all j. $Y' > Y$ implies an increase of one or more of the K components, i.e., the adoption of one or more additional technologies belonging to the same paradigm. Also, $Y' > Y$ implies a higher position on the technological trajectory. In general, supermodularity is defined as follows:

Definition 1: A function $f : R^n \to R$ is supermodular if for all $Y, Y' \in R^n$

(1) $$[f(Y) - f(\min(Y', Y))] + [f(Y') - f(\min(Y', Y))] \leq f(\max(Y', Y)) - f(\min(Y', Y))$$

The definition implies that the sum of changes in the function when several arguments are increased separately is less than the changes resulting from increasing all arguments together. The function f is *submodular* if $-f$ is super-modular (Milgrom and Roberts 1990).

Consider the decision of a firm to invest in one or more additional technologies, given its current equipment with related technologies, such that $Y' > Y$. Technological progress is costly and consists of two separate components:

- the cost to purchase the technology p_i (e.g., hardware, software);
- the cost for complementary investments in human capital, process re-engineering, and organizational change c_i.

These two cost components can vary among firms, for example because a large firm will need more software licenses and more re-engineering efforts than a small firm. The costs for reaching Y have been decided upon in the past and are sunk. A firm that considers switching from Y to Y', $Y' > Y$, therefore considers its current technology Y as an exogenous variable. The total cost for the switch is specified as

(2) $$C_i(Y_i' \mid \overline{x}_i, Y_i) = p_i(Y_i' \mid \overline{x}_i, Y_i) + c_i(Y_i' \mid \overline{x}_i, Y_i)$$

Two cost components appear because the purchase of a new technology is only a necessary, not a sufficient condition for usage of the new technology in the production process. In order to utilize the new technology, employees have to be instructed in the use of the technology, experience and know-how has to be gained, and firms might also have to hire technical specialists to run or maintain the new technology. In addition, the introduction of a new technology often requires a re-organization of processes and structures within a firm. These adjustments lead to the additional complementary investments c_i. For example, Brynjolfsson and Hitt (2003) and Black and Lynch (2004) have confirmed the importance of such complementary investments for the case of the computerization of firms. One could also think of c_i as costs for consulting services or an initial loss of efficiency during the period of switching from the old to the new technology.

Acquisition costs C_i can depend on other technological variables in three distinct ways. First, provided that the K technologies belong to the same technological paradigm, it is possible that they will require joint complementary inputs to function properly, such as specialized labour (Acemoglu 2002, Brynjolfsson and Hitt 2002, Greenwood 1997, Krueger 1993). Second, learning-by-doing effects (Arrow 1962, Sheshinski 1967) may occur: some experience gained with the usage of one particular technology might be transferable to another related technology. In such cases, some part of c_i will not have to be paid again when a firm considers investing in an additional technology from the same paradigm, and c_i will fall if the firm is already more advanced. Third, firms that purchase more than one technology may achieve discounts on p_i. If any or all of the above apply, this will lead to lower acquisition costs for firms that are already more advanced. Thus, the presence of complementary joint inputs, learning-by-doing effects, or discounts for multiple purchases would all result in investment cost advantages for adopting an increasing number of technologies. Note that all three effects are strictly increasing in their arguments, without a natural point of inflection. Consequently, if any or all of the above effects apply, C_i will be submodular in Y_i:

Assumption 1 – (A1): The investment cost function $\mathrm{C_i(Y_i' \,|\, \overline{x}_i, Y_i)}$ is submodular in Y_i.

In addition to the adoption costs, the present value of benefits from adopting additional technologies, g_i, could also depend on the current technological endowment of the firm in two distinct ways. First, technologies could be complementary, compatible with one another and not substituting for each other in their functionalities. In this case, the payoff from installing these technologies together will be greater than installing either technology alone. Provided that our understanding holds true that the K related technologies are based on the same technological principles and are not substitutes, technological complementarities are likely to arise. This argument is also consistent with existing literature, which points out that recent IT investments can lower technical and organizational barriers to adopting new IT, thereby leading to a complementarity between recent IT investments and new technologies (Swanson 1994). Second, suppose that previous technological investments have lead to positive returns on investment, i.e. a rise in profits. This additional financial slack could enable easier access to external funding due to information asymmetries between financial intermediaries and borrowers (Abel and Blanchard 1986, Hubbard 1990, Hubbard and Kashyap 1992). Thus, previous investments in technology could lead to better financing conditions for additional investments: $Y' > Y$ would result in higher values of g_i for additional investments due to lower discount factors. Both factors – technological complementary and additional financial slack due to previous investments – lead to increasing benefits. This leads to a second assumption:

Assumption 2 – (A2): The present value of benefit flows $\mathrm{g_i(Y_i' \,|\, \overline{x}_i, Y_i)}$ is supermodular in Y_i.

However, the expected benefits from a technology will also depend on other relevant attributes of the firm, $\overline{x}_i$. For example, a Knowledge Management solution may yield benefits to a large firm with many employees, but be totally irrelevant to a micro-enterprise with just one or two employees. Thus, even though complementarities, learning-by-doing effects or an acceleration mechanism via previous investments might be present, this does not necessarily imply that all firms will adopt all K technologies. Note that neither (A1) nor (A2) specify the relation of g_i and C_i with respect to $\overline{x}_i$.

The net present value G_i of switching from Y to Y', $Y' > Y$, is defined as:

(3) $$G_i(Y_i' \mid \overline{x}_i, Y_i) = g_i(Y_i' \mid \overline{x}_i, Y_i) - C_i(Y_i' \mid \overline{x}_i, Y_i)$$

These arguments together give rise to Theorem 1.

Theorem 1: Assume (A1) and (A2), then the net present value G_i is supermodular in Y_i.

Proof: If (A1) and (A2) hold, G_i is supermodular in Y_i by definition.

Theorem 1 states that if any of the above-discussed effects apply and technologies are not substitutes, there can be an endogenous acceleration mechanism: each technology becomes more “attractive” to the firm the more related technologies it uses.

Two caveats are worthy of mention. First, theorem 1 does not imply that all firms will eventually adopt all K technologies, since G_i also depends on $\overline{x}_i$ with an undetermined effect. Second, theorem 1 also does not imply that firms will install all technologies simultaneously. A simple reason could be that prices and qualities of the technologies change at different rates over time, such that it makes sense to delay the adoption of some technologies while adopting others immediately. Also, the replacement of older technology might involve opportunity costs for the firm if the old technology still functions properly, but cannot be sold off to another user. In this case, the firm might upgrade to new technologies in an asynchronous, stepwise manner, even if the new technologies are extremely complementary (Jovanovic and Stolyarov 2000).

2.2 Dynamics of technology adoption

To study the diffusion of technologies over time, a hazard rate model can be used. Let t indicate at which point in time a firm is observed. The time from the beginning of the observation until the adoption decision is noted as T. At each point in time t, we are interested in the adoption probability of each firm, given that the firm has not adopted before t. This is the hazard rate, which is defined as

$$(4) \qquad \lambda(\mathrm{t}) = \lim_{\mathrm{dt}\to 0} \frac{\Pr\mathrm{ob}(\mathrm{t} \leq \mathrm{T} < \mathrm{t} + \mathrm{dt} \mid \mathrm{T} \geq \mathrm{t})}{\mathrm{dt}}.$$

By standard arguments, there are two functions associated with the hazard function: The *failure function* $F(t)$, which indicates the fraction of the population that has adopted at time t, and the *survivor function* $S(t)$, which states the share of the population that has not yet adopted at time t. Consequently, $\mathrm{S(t)} \equiv 1 - \mathrm{F(t)}$ and $F(t)$ is the cumulative distribution function (cdf) of all adoption events over time. The associated probability density function (pdf) is noted as $f(t)$, with $\mathrm{f(t)} = \mathrm{F}'(\mathrm{t})$. If the exact time of adoption T is only known to fall into a specific interval, a discrete time formulation is required. For this purpose, a duration of interest t can be defined to be in the vth interval so that it satisfies, $t_{v-1} \leq t < t_v$, for $\mathrm{v} = 1,\dots,\mathrm{V}$. In the last observable interval, firm i's spell $(\mathrm{i} = 1,\dots,\mathrm{N})$ for technology $\mathrm{j} = 1,\dots,\mathrm{K}$ is either complete or right censored.

Theorem 1 implies that under the assumption that none of the elements of is substituting for any other element of Y, the net present value G_{ijv} associated with each technology is increasing in the number $k_{i,-j,v-1} \in [0,1,2,...,K-1]$ of related technologies adopted in the past. The integer variable $k_{i,-j,v-1}$ counts the number of technologies belonging to Y that firm i used in the previous observation period ($v-1$). Thus, $k_{i,-j,v-1}$ is a simple proxy for how "advanced" a firm already is in using any of the K available technologies when it faces the decision to invest in technology j in period v. According to standard arguments, firms adopt new technologies if the net present value G_{ijv} is greater than zero.

(5) $$G_{ijv} > 0 \rightarrow y_{ijv} = 1$$

This leads to the central point of this paper:

Theorem 2 – Assuming (A1) and (A2), the hazard rate of adopting a technology belonging to Y is an increasing function of the number of elements of Y which have been adopted in the past.

Proof: Apply theorem 1 to (5).

Theorem 2 can be empirically tested in a hazard rate estimation model.

3 Model specification and estimation

We know that G_{ijv} depends on the observable firm-specific characteristics $\overline{x}_i$ and their level of technological development, $k_{i,-j,v-1}$. In addition, G_{ijv} might systematically depend on unobservable firm-specific characteristics. To allow for unobserved heterogeneity, a firm-specific error term u_{ij} with the following properties is introduced:

(6) $$u_{ij} \sim N(0,\sigma_u^2); \quad E[u_{ij} \mid \overline{x}_i] = 0; \quad E[u_{ij} \mid v] = 0; \quad E[u_{ij} \mid k_{i,-j,v-1}] = 0$$

The introduction of this unobservable error term allows relaxation of the assumption that only observable firm characteristics influence the adoption decision in a systematic way. Instead, we allow unobservable characteristics to have a systematic influence on adoption probability, like quality of management, organizational structure, specific characteristics of the market of operation, or an "inherent need" of firms to upgrade their technology etc., assuming that these unobservable firm-specific characteristics are normally distributed and independent of the observable variables.

Theorem 1 and Theorem 2 imply that the decision to adopt depends on the observable characteristics $\overline{x}_i$ and explicitly also on the number of previously adopted related technologies $k_{i,-j,v-1}$. In addition, diffusion processes are time-dependent. Epidemic effects, reduced uncertainty, stock effects, qualitative improvements in technology, and falling prices all lead to higher adoption probabilities in later periods. Hence, the probability to adopt is generally time-dependent following some function $h_v(t)$. Furthermore, the random unobserved firm-specific effect specified in (6) can influence the timing of adoption. Hence, a time-varying index function with the following form can be specified.

$$(7) \qquad Z_{ijv}(t) = \overline{\beta_j' x_i} + \gamma k_{i,-j,v-1} + h_{jv}(t) + u_{ij}$$

For simplicity, the index function is assumed to have a linear additive structure. Given these preliminary definitions and following the general framework of Sueyoshi (1995), the hazard function can be specified as

$$(8) \qquad \lambda_{ijv}(t, \overline{x}_i, \beta_j, k_{i,-j,v-1}, \gamma_j, u_{ij}) = h'_{jv}(t) \left\{ \frac{f_v(Z_{ijv}(t))}{1 - F_v(Z_{ijv}(t))} \right\}.$$

Note that $Z_{ijv}(t)$ is allowed to vary with time, since $k_{i,-j,v-1}$ (the number of previously adopted related technologies) is dynamic. Also note that the influence of ε_{ijv} on λ_{ijv} is a function of time and is randomly "redrawn" for each firm in each observation period, and u_{ij} captures additional firm-specific effects that do not vary with time but could have a systematic influence on the individual hazard.

To complete the specification of (8), one needs to choose $\{F, h\}$. Given that diffusion processes can be well-described by a logistic function (Griliches, 1957; Stoneman, 2002), we choose to specify F, building the logistic cdf.

The baseline hazard rate of each period can be specified as a flexible semi-parametric piecewise constant function:

(9) $$h_{jv}(t) = \alpha_{jv}\theta_{jv}$$

for all $v = 2,...,V$, choosing $v = 1$ as the reference category for estimation[2] and letting θ_{jv} be a vector of dummy variables such that $\theta_{jv} = 1$ if $t_{v-1} \leq t < t_v$ and $\theta_{jv} = 0$ otherwise. The variable α_{jv} is the period-specific hazard coefficient for technology j. This piecewise constant specification yields a flexible model with some desirable properties. It allows duration dependence to vary between observation periods, without assuming a specific functional form of $h_{jv}(t)$. Hence, the model does not assume that adoption probability strictly increases in t, and thus allow for period-specific demand shocks, for example, those due to cyclical variation. Furthermore, the model also does not assume that all firms will adopt each technology because $h_{jv}(t)$ must not necessarily go to infinity as t becomes very large. This is an important advantage vis-à-vis most fully parametric specifications of the hazard function, which assume that all firms will eventually adopt. The semi-parametric specification in (9) is more appropriate for studying the diffusion of innovations because it is only rarely the case that the entire population eventually adopts an innovation. Hence, a possible source of biased estimates is eliminated.

Equation (8) can be explicitly written as

(10) $$\lambda_{ijv} = \frac{1}{1+\exp(-\alpha_{jv}\theta_{jv} - \beta_j'\overline{x}_i - \gamma_j k_{i,-j,v-1} - u_{ij})}.$$

Because (10) depends on unobserved firm-specific effects u_{ij}, it cannot be used directly to construct the likelihood function. However, recalling (6), a conditional maximum likelihood approach is available (Wooldridge, 2002). To find a likelihood function that does not depend on u_{ij} anymore, one needs to integrate out u_{ij}, conditional on all observable covariables. Given (6), the likelihood contribution of each uncensored observation can be expressed as

(11) $$L = \int_{-\infty}^{\infty} \left[\prod_{v=1}^{V} g(y_{ijv}) \right] (1/\sigma_u)\,\phi(u_j/\sigma_u)du,$$

where $g(y_{ijv}) = F(z)^{y_{ijv}}[1-F(z)]^{1-y_{ijv}}$, F is the logistic cdf, and ϕ is the pdf of the normal distribution. Censored observations in the sample are included with values of $y_{ijv} = 0$ for all v, whereas uncensored observations are included up to the period when exit occurs and observations with $y_{ijv} = 1$ for $t > t_v$ can be dropped because they do not contain any additional information that would contribute to $\lambda(t)$. The relative importance of the unobserved effect can be measured as $\rho = \sigma_u^2/(\sigma_u^2 + 1)$, which is the proportion of the total variance contributed

2 hence maintaining in intercept term in Z

by the firm-specific variance component, since the idiosyncratic error in latent variable models is unity (Wooldridge, 2002).

4 Data

Equation (11) was estimated using a large sample of enterprise data from the Nov/Dec 2003 e-Business Market W@tch survey. The e-Business Market W@tch database is widely accepted and has been used by various official institutions, including the European Commission and the OECD (2004).

The dataset consists of 7,302 successfully completed computer-aided telephone interviews with enter-prises from 25 European countries and 10 sectors. The respondent in the enterprise targeted by the survey was normally the person responsible for ICT within the company, typically the IT manager. Alternatively, particularly in small enterprises without a separate IT unit, the managing director or owner was interviewed. Details about the sample and data collection procedures are published by the European Commission (2004). The dataset contains basic background information about each company, including size class, number of establishments, % of employees with a college degree, market share, and primary customers of the enterprise. Also, information on the adoption of 7 e-business technologies are available, including retrospective information on the time of adoption. Firms that confirmed in the interview that they currently use a particular e-business application were asked when they first started to use that technology. The ratio of missing values for these questions was always below 20% of the respective subjects, indicating that most respondents were at least able to make a fairly educated guess.

Table 1 shows some descriptive results for the occurrence of the technologies for November 2003. There are pronounced differences in the observed frequencies among the 7 e-business technologies. Online purchasing is most widely diffused (46%), whereas other solutions such as Knowledge Management (KMS) or Supply Chain Management (SCM) occur only rarely. Each of the considered 7 technologies serves a different purpose regarding supporting processes and information flows within a company, or between a company and its environment. Thus, it can be assumed that these technologies do not substitute for each other in their functionalities, which is the basic assumption underlying our theory. Only enterprises that fulfil the basic requirements for conducting e-business (based on usage of computers, Internet access, email, and WWW) are included in the sample.

Table 1 - Relative frequencies of 7 related e-business technologies, Nov 2003

Technology	**Occurrence in sample**
E-learning	9.5%
Customer Relationship Management System (CRM)	11.1%
Online purchasing	46%
Online sales	17%
Enterprise Resource Planning System (ERP)	11.5%
Knowledge Management System (KMS)	6.6%
Supply Chain Management System (SCM)	3.9%
N=5,615. Unweighted results. All firms included have computers, Internet access, and use the WWW and email. Abbreviations in ( ) indicate variable names for the regression analyses. Observations with missing values for any of the above-listed technologies are excluded from the sample.	

Information about when a technology was adopted by a company is coded in yearly intervals. 1994 was chosen as the first period of observation.[3] This is approximately the time when the Internet became available for commercial use in Europe. All adoption decisions occurring after 2002 are censored observations. Thus, there are 9 valid observations periods for each technology.

5 Results

5.1 Econometric results

In the estimation, $k_{i,-j,v-1}$ was decomposed into dummy variables to control for possible non-linear effects ($k_{i,-j,v-1} = 0$ to $k_{i,-j,v-1} = 5$).[4] The results are reported in Table 2 and 3.

[3] A few companies stated implausible adoption dates, saying that they adopted a particular e-business solution before 1994. These responses were coded as missing values. For all technologies, less than 5% of the adopters had to be excluded due to stating implausible adoption dates.

[4] Only 3 companies had adopted all 7 e-business technologies in 2002. Thus, the regression results for $k_{i,-j,v-1} = 6$ were never significant and in most cases not identified. Hence, they are not reported in the table.

Table 2 - Hazard rate regression results for 3 e-business technologies (k in 5 categories)

Co-variables	**Online sales**	**Online purchasing**	**CRM**
v = 2	1.252**	1.879**	0.601
v = 3	1.384**	2.317**	0.491
v = 4	2.223**	3.253**	1.164**
v = 5	2.834**	4.633**	1.810**
v = 6	3.299**	5.317**	1.586**
v = 7	3.631**	6.499**	2.406**
v = 8	3.865**	7.253**	2.431**
v = 9	4.284**	8.786**	3.511**
$k_{i,-j,v-1} = 1$	0.398**	0.863**	0.613**
$k_{i,-j,v-1} = 2$	0.502**	1.395**	1.143**
$k_{i,-j,v-1} = 3$	0.825**	1.922**	1.628**
$k_{i,-j,v-1} = 4$	-0.341	0.356	1.998**
$k_{i,-j,v-1} = 5$	0.867	44.260	1.409*
10-49 empl.	0.044	0.032	0.738**
50-249 empl.	0.060	0.149	0.963**
>250 empl.	0.162	0.188	1.135**
> 1 establishment	0.300**	0.548**	0.384**
Primary customers:			
other businesses	-0.473**	0.423**	0.431**
public sector	-0.600**	0.069	-0.190
no primary customers	0.058	0.114	0.170
% empl. w/ university degree	0.001	0.010**	0.013**
Market share:			
<1%	0.161	0.632**	-0.484**
1%-5%	0.414**	0.753**	-0.186
6%-10%	0.458**	0.625**	0.161
11%-25%	0.547**	0.572**	0.196
> 25%	0.340**	0.553**	0.078
Constant	-7.352**	-10.954**	-8.288**
Model diagnostics			
N obs	44,545	42,310	45,257
N groups	5,116	5,116	5,116
Log-likelihood	3,764	-7,433	-2,409
Rho	<0.01	.645	<0.01
LL-ratio test for rho=0	1.00	0.00	1.00

** denotes significance at the 95% confidence level, * denotes significance with 90% confidence. Reference categories: v = 1, $k_{i,-j,v-1} = 0$,1-9 employees, primary customers: consumers, market share: unknown. All firms included have computers, Internet access, and use the WWW and email.

Table 3 - Hazard rate regression results for 4 e-business technologies (k in 5 categories)

Co-variables	E-Learning	ERP	KM	SCM
v = 2	0.398	0.153	0.132	-0.702
v = 3	0.889	0.203	0.753	0.667
v = 4	1.824**	0.763**	0.523	1.343*
v = 5	2.118**	0.716**	1.061**	1.724**
v = 6	2.261**	1.042**	0.917**	1.751**
v = 7	3.273**	1.348**	1.750**	2.394**
v = 8	3.433**	1.068**	1.629**	1.933**
v = 9	4.630**	2.498**	2.862**	3.558**
$k_{i,-j,v-1} = 1$	0.654**	0.292**	0.425**	0.593**
$k_{i,-j,v-1} = 2$	1.136**	0.687**	0.860**	0.683**
$k_{i,-j,v-1} = 3$	1.357**	0.399	1.703**	1.254**
$k_{i,-j,v-1} = 4$	0.291	0.764	1.807**	0.699
$k_{i,-j,v-1} = 5$	1.465*	-	1.126	1.132
10-49 empl.	0.052	1.116**	0.380**	1.001**
50-249 empl.	0.234*	1.775**	0.690**	1.688**
>250 empl.	0.780**	2.359**	1.095**	2.516**
> 1 establishment	0.521**	0.189**	0.313**	0.377**
Primary customers:				
other businesses	-0.115	0.599**	0.137	0.033
public sector	0.126	-0.006	-0.030	-0.832**
no primary customers	-0.050	0.126	-0.017	-0.306
% empl. w/.university degree	0.012**	0.004**	0.012**	0.006**
Market share:				
<1%	-0.132	-0.482**	-0.171	0.199
1%-5%	0.083	-0.055	0.201	-0.358
6%-10%	-0.044	0.250	-0.165	0.500*
11%-25%	0.187	0.300**	0.299	0.118
> 25%	0.049	0.184	0.297**	0.152
Constant	-8.659**	-7.549**	-7.795**	-9.556**
Model diagnostics				
N obs	45,562	44,889	45,504	45,800
N groups	5,116	5,116	5,116	5,116
Log-likelihood	-2,111	-2,549	-1,687	-955
Rho	<0.01	<0.01	<0.01	<0.01
LL-ratio test for rho=0	1.00	1.00	1.00	1.00

** denotes significance at the 95% confidence level, * denotes significance with 90% confidence. Reference categories: v = 1, $k_{i,-j,v-1} = 0$,1-9 employees, primary customers: consumers, market share: unknown. All firms included have computers, Internet access, and use the WWW and email.

The most important result from the regression analysis is that the hazard rate for adoption increases the higher the value of $k_{i,-j,v-1}$ becomes: all significant coefficients on $k_{i,-j,v-1}$ decomposed into dummies exhibit an almost linear increase in adoption probability. Additional regressions with $k_{i,-j,v-1}$ as an ordinal variable showed positive and significant coefficients on $k_{i,-j,v-1}$ in all models. This supports Theorem 2.

Furthermore, significant size-class effects are found in the regressions. Companies with more than one establishment are more likely to adopt any of the 7 analyzed technologies. Also, large firms with many employees are systematically more likely to adopt e-business solutions that are primarily used in-house, such as CRM, E-learning, ERP and KMS. Large firms with many employees are also more likely to adopt SCM, while the size of the firm does not have a significant impact on the adoption of online sales and online purchasing. Consistent with Forman (2005), the number of establishments always has a significant positive impact on adoption probabilities, which suggests that e-business solutions are implemented to overcome regional dispersion.

Also, the results show that the primary customers served by a firm do have a systematic influence on its choice of technologies. For example, the adoption of online sales is clearly prevalent among firms that primarily serve consumers, while it is much less common among firms primarily serving other businesses or the public sector. The adoption of purchasing online, CRM, and ERP solutions is significantly more frequent among firms that have other businesses as their primary customers, and SCM adoption is less frequent for firms primarily dealing with the public sector. These findings imply that the particular business environment of a firm greatly affects the expected value of installing a particular technology – not all technologies are suitable to all kinds of firms.

In addition, the regression results show that the percent of employees with a university degree within a company always has a positive and significant influence on the hazard rate of adoption, the only exception being online sales, where the effect is not significant. Thus, a higher proportion of highly qualified staff increases the chances of e-business technology adoption. This is consistent with the view that complementary investments in human capital are an important part of technology adoption decisions (Brynjolfsson and Hitt 2002, Dewar and

Dutton 1986). Firms with better human capital resources should face lower total costs of adoption and thus higher adoption rates, ceteris paribus.

The results also show that market share (a proxy for market power) is a significant indicator for the adoption of all analyzed technologies, except for e-learning. On the one hand, firms with less than one percent market share show lower adoption rates than firms with higher market shares. On the other hand, firms with more than 25 percent of market share usually do not show the highest hazard rates for adoption, except for KMS. The peak usually occurs somewhere between the two extremes. This supports earlier findings that suggested an inverted U-shape between concentration ratios and innovative activities in markets (Aghion et al. 2005, Scherer 1967).

Finally, the estimated Rho values and their significance levels indicate that unobserved heterogeneity is never significant in the models, except for online purchasing. Thus, neither sector nor country of origin nor any other factor that is not explicitly included in our analysis has a systematic influence on adoption rates. This provides additional evidence for an endogenous acceleration mechanism because it rules out any unobserved firm-specific factors as an alternative cause for the observed effects of $k_{i,-j,v-1}$. According to the regression results, controlling for relevant technological history, time, size class, primary customers, human capital, and market share is sufficient to explain the differences in adoption rates for most e-business technologies. Interestingly, different dynamic test regressions revealed that controlling for the technological *history* ($k_{i,-j,v-1}$) of a firm makes the panel level variance component Rho insignificant, and therefore indirectly accounts for part of the variance that is otherwise captured in the country and sector dummy variables. Rather than suggesting that country and sector effects are not important, this result could imply that real economic differences among countries and sectors (institutions, regulation, competition, cyclical effects, etc.) are captured to a great extent in the investment history of firms into new technologies.

5.2 Growing digital divide

The finding that the technological development along a given trajectory of related technologies can be subject to an endogenous acceleration mechanism has some important implications. If not all firms start to adopt the new technologies at the same time, i.e., if there are some pioneer users and some followers, the endogenous acceleration mechanism will lead to growing differences in technological endowment between these groups. The differences will continue to grow until the most advanced firms do not find any additional technologies belonging to the associated paradigm that promise positive returns on investment. Only when the most advanced firms stop making progress on the trajectory will otherwise comparable follower firms be able to "catch up". Thus, when a new technological trajectory emerges, we can expect an initially growing gap in progress along the trajectory between early and late movers. Provided that technological investments do, on average, yield positive returns, this growing gap could have important consequences if early and late adopters compete directly against each other. According to standard arguments, this acceleration mechanism could benefit early adopters, allowing them to capture additional market share, thereby achieving higher profits and increasing their probability of survival in the market, ceteris paribus.

A growing digital divide among firms can be demonstrated in the data: let $k_{i,v}$ be the variable counting the number of adopted technologies belonging to the trajectory. A higher position on the trajectory is indicated by a higher number of adopted technologies. The ongoing diffusion processes should lead to higher average values of $k_{i,v}$ over time, while a growing gap will show up as a growing variance of $k_{i,v}$ over time. The results are reported in Table 4.

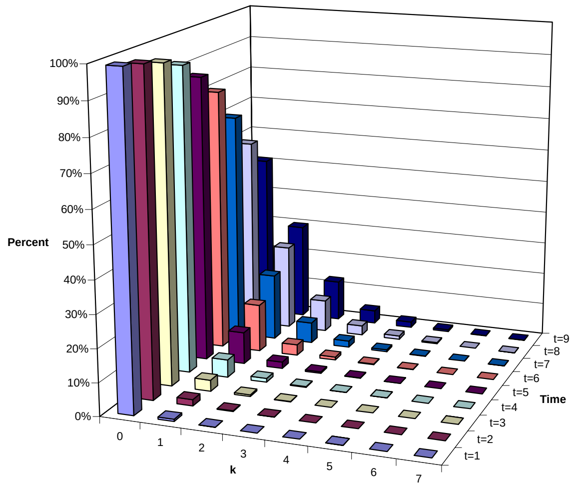
In the first observed period (1994), the mean value of $k_{i,v}$ in the sample is 0.0089. Thus, the vast majority of firms have not yet adopted any of the 7 e-business technologies at this early time. The standard deviation of $k_{i,v}$ is quite small, 0.11904. Over time, we observe an increase in the mean value of $k_{i,v}$. In 2002 it reaches 0.7854, which is still a low number considering that some very advanced firms have already adopted all 7 technologies, while the majority have still adopted none. The increase in the mean value of $k_{i,v}$ is clearly the result of the ongoing diffusion processes of all 7 technologies. The most interesting finding, however, is the increase in the standard deviation of $k_{i,v}$. Over the entire observation period, the "inequality" in technological endowment with e-business technologies is increasing in the sample. Thus, we exhibit a "growing digital divide" as suggested by the finding of an endogenous acceleration mechanism.

Table 4 - Mean value and standard deviation of k over time

	Minimum	**Maximum**	**Mean**	**Standard Deviation**
Time period				
1 (1994)	0	5	.0089	.11904
2	0	6	.0258	.19398
3	0	7	.0486	.26550
4	0	7	.0885	.36915
5	0	7	.1619	.48780
6	0	7	.2581	.61031
7	0	7	.4287	.78360
8	0	7	.6167	.91899
9 (2002)	0	7	.7854	1.029
Source: E-Business Market W@tch survey Nov/Dec 2003. N = 5,615.All firms included have computers, Internet access, and use the WWW and email.				

Figure 1 provides an illustrative representation of the phenomena. In the first period, 99% of all firms have adopted none of the 7 technologies, and 1% have adopted 1 technology. As time proceeds, the fraction of firms that have adopted no new technologies continuously decreases and the distribution spreads out, leading to higher mean values and a greater disparity in technological endowment in the early periods of the diffusion processes. In 2002, the fraction of firms that have not adopted any of the technologies is 51%, 30% have adopted one technology, 13% have adopted two technologies, and 6% have adopted more than two technologies. Clearly, the differences in technological endowment between pioneer adopters and followers have continuously increased from 1994 to 2002.

Figure 1 - Distribution of k over time



Source: E-Business Market W@tch survey Nov/Dec 2003. N=5,615.

All firms included have computers, Internet access, and use the WWW and email.

6 Discussion and implications

Our results show that current investment decisions are not independent from past investment decisions. This implies that history matters for the technological development of a firm. A decision to adopt a technology today affects the expected value of any other related technology in the future. Hence, techno-logical development can be viewed as a path dependent process where current choices of technologies become the link through which prevailing economic conditions may influence the future dimensions of technology, knowledge, and economic opportunities (Ruttan 1997).

The observation of an endogenous acceleration mechanism of technological development along a given trajectory suggests that early mover advantages can exist that are sustainable until the early mover has exhausted the possibilities of the trajectory, and followers begin to catch up – assuming they have survived. The theoretical literature on technology diffusion suggests that if early and late adopters compete on the same output market, early adopters will be able to achieve excess profits and capture additional market share until their technological advantage has been perfectly copied by all rivals (Reinganum 1981a, 1981b, Götz 1999, Quirmbach 1986). In addition, early mover advantages can be sustainable even in the long run if there is free entry and exit in the market, and if firms are not ex ante identical, for example if there are positive returns to scale, learning-by-doing effects, scarce complementary resources to the new technology, market reputation effects, or discount rates that are lower for previously more profitable companies. If first mover rents may not be completely extinguished by other, follower firms, it might be less profitable for later movers to adopt new technologies at all. Also, some firms might "pre-emptively" adopt to capture strategic advantages (Fudenberg and Tirole 1985, Ireland and Stoneman 1985). In the terminology of the resource-based view (Barney 1991), the existence of an endogenous acceleration mechanism of technological development implies that the adoption decision can lead to competitive advantages: the technological endowment of a firm belongs to its set of strategic resources. Furthermore, the current configuration of these resources systematically influences both the possibility and the return of future adoption decisions, as well as corporate performance. The presence of the acceleration mechanism implies that imitating rivals will not be able to perfectly copy these resources until the early mover has exhausted the development potential of the new technological trajectory. Furthermore, it is very likely that some of these competitive advantages will be sustainable because in reality such development processes occur over a long time span, where entry and exit to a market take place. In addition, there are numerous reasons why positive returns to scale, learning-by-doing effects, and imperfectly mobile complementary assets can exist in the real world.

From the adopters' perspective, this implies that companies must be aware of the path-dependency and the strategic role of technology investment decisions. There are two crucial questions that firms need to answer when a new technological paradigm emerges:

1. Is there an alternative technological trajectory available to solve the same problems or to build up the same strategic resources? If alternatives do exist, then the adoption decision becomes not only a problem of optimal timing, but also a choice between alternative technological development paths. In this case, firms also need to evaluate early on whether the entire industry will eventually choose one of these alternative development paths. This could be the case if there are some kind of network externalities involved that imply that only one dominant industry standard will finally emerge and firms that are on the "wrong trajectory" might lose out during competition. This scenario has beyond doubt the most severe strategic implications for a firm because it implies that "betting on the wrong horse" could put the very existence of the firm at stake. In this vein, a recent study by Forman (2005) demonstrates that investments in incompatible IT decreases the probability of adopting internet access. Hence, firms that invested in a non-internet based technological trajectory (i.e., into proprietary solutions) lost potential first mover advantages on the internet trajectory. It also implies that the decision to invest in a new trajectory depends on the firm's expectations about the behavior of other firms. Furthermore, the timing of the decision becomes subject to a difficult trade-off. On one hand, being an early mover on the "right" trajectory promises competitive advantages, not least because of a possible acceleration mechanism. On the other hand, there are some benefits to waiting to see which of the trajectories reaches critical mass and emerges as the

new industry standard. However, once this is clear, it might be too late for the firm to capture early mover advantages.

2. If no technological alternatives exist to the new paradigm, how substantial is the technological uncertainty and how probable are rapid technological improvements in the future? Both of these effects make it more attractive to delay the investment, according to diffusion theory (Stoneman 2002). However, if technological uncertainty is limited and no dramatic technological improvements can be expected for the near future, an early mover strategy will probably be the most beneficial, especially if an acceleration effect can be expected.

Arguably, these are tough questions to answer. Choosing the correct development path and the optimal time to invest are clearly decisions with far reaching consequences, requiring a very profound knowledge of technological developments and of the behavior of other market players, such as competitors, suppliers, customers, and potential new entrants. Given the complexity of the issue, firms might benefit from the knowledge of industry experts and consultants when choosing their path of action. The costs of such measures may easily be outweighed by the benefits of choosing the right technological path.

The presence of an endogenous acceleration mechanism also has some important implications for the suppliers and marketers of new technologies. Firms that have previously invested in related technologies can expect lower implementation costs and / or higher benefits from adopting additional technologies belonging to the same technological paradigm. Thus, they are more likely to make additional investments in such technologies. In other words, it should be much easier for technology suppliers to conduct further business with their existing clients or firms that are already advanced in using compatible technologies than to acquire orders from firms that are less advanced or on a different technological trajectory. This will hold until the most advanced firms have exhausted the potential benefits of the new technological trajectory and reach a saturation level. Technology providers could actively benefit from this mechanism by systematically studying and understanding the purchasing behavior of their customers and technological interdependencies. It will be easier for them to conduct additional business with existing clients if they can offer them technological solutions that are complementary to each other, rather than constituting partial or total substitutes. A quantitative analysis of the company's data on customer behavior could help the firm to optimize their product portfolio and their cross-product marketing and sales activities. Furthermore, assuming the loyalty of customers due to reduced transaction costs within a business relationship (and hence excluding an easy switch from one supplier to another), investment in the first sales of an e-business solution can be seen as an investment in a long-term relationship with a customer that finds it increasingly beneficial to adopt more and more technologies from the same paradigm.

7 Research suggestions and conclusions

A potential direction for future research would be the use of panel data that allowing control for time-varying explanatory variables and possibly also capturing entry and exit dynamics in markets. The collection of such data is clearly an ambitious project, but maybe worthwhile for further increases in our understanding of technology diffusion and its implications. Such a sample would also correct for a potential survivor bias in pseudo-panels, which is also a possible limitation of our study. However, related diffusion studies using survey data with information about the time of adoption suggested that such biases were not severe (Stoneman 2002).

On the methodological side, there seems to be potential for further research on econometric techniques that would allow controlling for the moderating effect of unobserved variables on the relationships between independent and dependent variables in the model. In addition, it would be interesting to observe the influence of additional moderating variables, such as more detailed information on market structure (typically measured as Herfindahl indices) on the acceleration effect.

We were able to provide the first empirical test of the supermodularity theory of technology adoption. We find great support for the interdependence of technology adoption decisions. Firms that are on a higher level of a technological trajectory have a larger adoption probability than firms that have as yet adopted fewer new technologies. The resulting digital divide has possibly severe economic consequences that need to be explored in more detail in future research. From a management perspective, marketers of technologies may explicitly take into account the lock-in effects of customers on a technological trajectory, whereas for users, the decision to adopt a technology from a new paradigm is a strategic long-term decision with possibly severe consequences.

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