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Acceleration of Technology Adoption within Firms

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Acceleration of technology adoption within firms – Empirical evidence from e-business

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Abstract

This paper studies the diffusion of multiple related technologies among firms. The results suggest an endogenous acceleration mechanism for technology adoption: The more advanced a firm is in using a particular set of technologies, the more likely it is to adopt additional related technologies. We show that such a mechanism can occur under fairly general circumstances. If firms are not ex ante identical, the endogenous acceleration mechanism suggests a growing divergence in the technological endowment of firms in the early phases after the emergence of a new technological paradigm.

The theoretical predictions are tested with a dataset that records the adoption times of various e-business technologies in a large sample of firms from 10 different industry sectors and 25 European countries. The results show that the probability of adoption 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.

Keywords: Technology adoption, technological change, complementarity, hazard rate model, IT

JEL Codes: O33, O14

1 Introduction

Is the assumption of equal production technologies across firms in a given market or in countries around the globe plausible? Our study suggests that this is unlikely in the presence of technological progress. Our analysis of firms' dynamic adoption decisions regarding numerous technologies implies that technological divergence can occur under profit-maximization, and we report empirical evidence supporting a growing digital divide among firms for the time period from 1994-2002. This finding has important implications: the technology of a firm determines the types of products and services it can produce and the manners in which these outputs can be generated. Adopting new technologies can enable firms to change the scope of their operation (e.g., to offer new products or services), while investments in new process technologies, such as computer applications or automated machines, can enable firms to produce a given output at lower costs. Shampine's (2001) analysis of the diffusion of digital switches in the U.S. telecommunications industry provides a nice example of this. Although new technologies might bring about desirable changes, including higher productivity and growth, their diffusion among firms usually takes time (Griliches, 1957; Mansfield, 1968; Stoneman, 2002). Whatever the origin or nature of a new technology, it can only reach its full economic impact if it is actually adopted and used by firms. Thus, different adoption times and heterogeneity in production technology are likely to imply real economic consequences; for instance, such factors would affect market structures, firm performance, economic growth, and convergence.

The adoption of new technologies by firms may be accompanied by other firms' internal developments, including the adoption of various complementary technologies; organizational modifications; changes in prices, quality levels, products and services being offered, and 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) that offers solutions for a selected class of real-world problems based on selected material technologies. For example, Internet-based e-business technologies offer solutions for optimizing 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 right place as a pre-requisite to optimizing workflows and decisions); these e-business technologies are all based on the same material technologies (TCP/IP computer networks).

Technological interdependencies are likely to have a systematic effect on the adoption decisions of firms – a fact that has been largely ignored in the economics literature on technology diffusion, which tends to focus on the adoption of stand-alone technologies that are assumed to be unrelated to other technologies. Notable exceptions include Colombo and Mosconi (1995), Stoneman and Kwon (1994) and Stoneman and Toivanen (1997), who study the diffusion of production technologies with complementary attributes empirically.[1] We build upon the contributions of these authors in various ways. First, we show that acceleration of technology adoption can occur under fairly general circumstances, and we specify the necessary and sufficient conditions for this to occur. Second, we analyze the consequences of such an acceleration mechanism for technological divergence or convergence over time, both theoretically and empirically. Third, our econometric approach allows us to identify the presence of an endogenous acceleration mechanism by explicitly controlling for unobserved heterogeneity and potentially spurious state dependence.

The main hypothesis of our study is that the probability of adopting a new technology increases in a linear fashion with the number of related technologies a firm has installed previously. We call this effect the "endogenous acceleration mechanism of technology adoption." This acceleration mechanism implies that even small initial differences among firms that result in asynchronous adoption decisions can lead to increasing differences in the technological endowment of firms in the early phases after the emergence of a new technological trajectory.

The empirical part of the study (Sections 3, 4, and 5) tests our hypothesis using firm-level data on the adoption of e-business technologies from a large representative enterprise survey

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[1] A different thread in the literature, such as the work of Tomochi et al. (2005) and Arthur (1989), analyzes the diffusion of competing technologies with network externalities. The technologies we examine are not competing against each other; rather, they complement one another in different ways, which leads to entirely different adoption motives and diffusion patterns.

conducted in Nov/Dec 2003 among firms from 10 industry sectors and 25 European countries. The empirical results are consistent with our theory: we find that (1) the hazard rate of new technology adoption increases with the number of previously adopted related technologies, and (2) technological divergence among firms in our sample grows over the period from 1994-2002.

2 Theory

2.1 Profit-maximizing acceleration of technological change

Acceleration in the rate of development of a firm along a given technological trajectory can result from purely profit-maximizing rational behavior under fairly general circumstances. In addition to these profit-maximizing mechanisms, there are also behavioral reasons, which are not desirable from a profit-maximizing perspective, that can create a similar effect. We start by explaining the necessary conditions of and the logic behind a profit-maximizing acceleration mechanism.

Our analysis focuses on the initial purchase of a new technology by a firm; hence, we abstract from intra-firm diffusion and the level of use of the technology by the acquirer. Without losing generality, we also abstract from strategic interaction.[2] Our main argument is as follows: under profit maximization, the probability of adopting a new technology increases linearly with the number of previously adopted related technologies if the following two necessary conditions are satisfied:

- the technologies are related, i.e., they belong to the same technological paradigm in the sense discussed by Dosi (1982); and
- the technologies do not substitute for each other in terms of their functionalities, i.e., they are applied to different functions and processes within firms.

If these necessary conditions are fulfilled, any of the following sufficient conditions will trigger a profit-maximizing acceleration mechanism:

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

- complementarity, either directly between the technologies or indirectly via joint complementary inputs;
- learning-by-doing;
- additional financial slack due to previous successful investments in related technologies; and/or
- discounts for the purchase of more than one technology.

Note that all of the sufficient conditions above are increasing linearly in their argument. Thus, all of these effects can be described jointly using supermodular functions (Milgrom and Roberts, 1990; Milgrom, Qian, and Roberts, 1991).

To analyze differences in adoption probabilities, we analyze a large number (N) of companies simultaneously. Let N be a number of heterogeneous, profit-maximizing firms. In addition, assume certainty with respect to the 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 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. Thus, our definition of K captures the two necessary conditions mentioned above. 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.

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 respect to the K related technologies. 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 in 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. Recall the definition of supermodularity:

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

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

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

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

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

Two cost components appear because the purchase of a new technology is a necessary, but not 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 its use and gain experience and know-how; 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. Brynjolfsson and Hitt (2003) and Black and Lynch (2004) have confirmed the importance of such complementary investments in the case of computerization of firms. One could also think of c_i as the costs of 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 these will require joint complementary inputs, such as specialized labor to function properly (Acemoglu, 2002; Brynjolfsson and Hitt, 2002; Greenwood, 1997; Krueger, 1993). Second, learning-by-doing effects (Arrow, 1962; Sheshinski, 1967) may occur: some experience gained through the usage of one particular technology might be transferable to another related technology. In such cases, some part of c_i will not be incurred again when a firm considers investing in an additional technology from the same paradigm; c_i will also be reduced if the firm is already more advanced. Third, firms that purchase more than one technology may earn discounts on p_i. If any or all of the above apply, firms that are already more advanced will have lower acquisition costs. Thus, the presence of complementary joint inputs, learning-by-doing effects, and/or discounts for multiple purchases would result in investment cost advantages for adopting an increasing number of technologies. Note that all three effects are linearly 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 $\mathrm{C_i(Y_i' \mid \bar{x}_i, Y_i)}$ is submodular in Y_i.

In addition to adoption costs, the present value of the benefits of adopting additional technologies, g_i, could depend on the current technological endowment of the firm in two distinct ways. First, technologies could be complementary and compatible with one another without substituting for each other in their functionalities. In this case, the payoff from installing these technologies together is greater than the sum of the benefits gained when each technology is installed alone. Provided that the K related technologies are based on the same technological principles and are not substitutes, technological complementarities are likely to arise. Second, suppose that previous technological investments have led to positive returns on investment, i.e., an increase 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 $g_i(Y_i' \mid \overline{x}_i, Y_i)$ is supermodular in Y_i.

It must be kept in mind that 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 for a large firm with many employees but be totally irrelevant to a micro-enterprise with only 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 Proposition 1.

Proposition 1: Assume that if (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.

Proposition 1 states that if any of the above-discussed effects apply and the technologies are not substitutes, there can be an endogenous acceleration mechanism that is rational for profit-maximizing firms because each technology becomes more attractive to the firm the more related technologies it already uses.

Two caveats are worthy of mention. First, Proposition 1 does not imply that all firms will eventually adopt all K technologies, since G_i also depends on $\overline{x_i}$. Second, Proposition 1 does not imply that firms will install all technologies simultaneously. A simple reason could be that the 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. In addition, 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, step-by-step manner, even if the new technologies are extremely complementary (Jovanovic and Stolyarov, 2000).

To study the diffusion of technologies over time, we employ a hazard rate model. Let t indicate the point in time at which 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

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

If the exact time of adoption T is known only 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 *v*th interval so that it satisfies $t_{v-1} \leq t < t_v$ for $v = 1, \ldots, V$. In the last observable interval, firm *i*'s spell ($i = 1, \ldots, N$) for technology $j = 1, \ldots, K$ is either complete or right censored.

Proposition 1 implies that under the assumption that none of the elements of Y are substituting for any other element of Y, the net present value G_{ijv} associated with each technology is increasing with 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 is in using any of the K available technologies when it faces the decision to invest in technology j in period v. If firms behave as rational profit maximizers, they 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:

Proposition 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 that have been adopted in the past.

Proof: Apply Proposition 1 to equation (5).

2.2 *Non-profit-maximizing acceleration of technological change*

In addition to the profit-maximizing mechanism explained above, previous investments in technology might also induce future adoption decisions for behavioral reasons that are not compatible with profit maximization. For example, some managers might have a personal preference for using a particular kind of technology to solve certain problems. Such a preference might be due to their education and specialization (e.g., if they were originally trained as engineers or software consultants). In the presence of agency problems (Milgrom and Roberts, 1992), such idiosyncratic preferences of technology-fond managers might lead to adoption decisions that are not in accordance with profit maximization.

In addition, managers who are personally responsible for the negative consequences of previous technology investments may decide to increase the investment of resources in this previously chosen course of action, even if such behavior has the potential to compound initial losses (Staw, 1976). This effect has been widely studied in psychology and is referred to as *escalation of commitment* (Bobocel and Meyer, 1994). Such behavior is also consistent with the well-known observation of prospect theory that people will continue to put good money into bad investments due to risk-seeking in the loss domain in order to reach some subjectively given aspiration level (Kahneman and Tversky, 1979; Arkes and Blumer, 1985).

Clearly, in the presence of a given technological trajectory and previous investment decisions, such behavior of managers can lead to an acceleration of technological change at the firm level. Empirically, all of the effects discussed above would result in an observation that is consistent with Proposition 2 - an increasing effect of previous technology purchases on future adoption decisions regarding related technologies. Although it is not the aim of this article to differentiate between profit-maximizing and non-profit-maximizing reasons for adoption, we will discuss in Section 6 indirect empirical evidence indicating that the profit-maximizing mechanism predominated in the adoption of e-business technologies.

3 Model specification and estimation

The following empirical work will test for the presence of the acceleration mechanism suggested in Section 2. The main challenge in this estimation is to separate spurious state-dependence or unobserved heterogeneity from the endogenous acceleration mechanism predicted by our theory. An endogenous mechanism would be the result of earlier adoption decisions within the firm, not just a spurious correlation due to unobserved environmental or firm-specific variables that make some firms more likely to adopt then others.

We approach this challenge with a twofold strategy. First, we use the rich information available in our database to calculate the average level of e-business usage among firms in each of the 101 included markets over time. Section 4 explains this procedure in detail. The time-varying market-specific level of e-business usage will be included in the regressions as a control variable that accounts for different e-business-related technological opportunities across markets, as well as for the potential influence of imitation and the strategic interdependence of the technology adoption decisions of firms. Without controlling for the market-specific level of e-business usage, these qualitatively different factors that influence the adoption decisions of firms would be spuriously correlated with the state of e-business development for each individual firm. This would compromise the conclusions one could draw regarding the existence of the endogenous acceleration mechanism.

Second, we explicitly control for unobserved firm heterogeneity in the estimation. Our hazard rate framework allows us to test for unobserved heterogeneity under the standard random effects assumption. We supplement the estimation results with a robustness check that uses a fixed effects linear model.

Our hazard rate model is specified as follows: we are interested in the effect of the firm specific characteristics $\overline{x_i}$ on the hazard rate to adopt, λ_{ijv}. In particular, we want to test the hypothesis that the hazard rate increases in a linear fashion with the number of previously adopted related technologies $k_{i,-j,v-1}$. To allow for unobserved heterogeneity, a firm-specific error term, u_{ij}, with the following properties is introduced:

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

This is the standard random effects assumption, which states that unobservable firm-specific characteristics are normally distributed and independent of observable variables.

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

$$(7) \qquad h_{jv}(t) = \alpha_{jv}\theta_{jv}$$

for all $v = 2,...,V$, choosing $v = 1$ as the reference category for estimation[3] 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 must increase with t and thus allows for period-specific demand shocks, due to, for example, cyclical variation. Furthermore, the model also does not assume that all firms will adopt each technology because $h_{jv}(t)$ does 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 $\lambda(t) \to \infty$ as $t \to \infty$. The semi-parametric specification in (7) 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. To complete the specification of the model, we assume that the error terms in the model follow the logistic distribution, which has been shown to fit diffusion processes well (Griliches, 1957; Stoneman, 2002). The hazard rate can be explicitly written as

$$\text{(8)} \qquad \lambda_{ijv} = \frac{1}{1 + \exp(-\alpha_{jv}\theta_{jv} - \beta_j' \overline{x_{ijv}} - u_{ij})}.$$

Because (8) 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 no longer depends on u_{ij}, 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

[3] hence maintaining an intercept term

$$(9) \qquad L = \int_{-\infty}^{\infty} \left[\prod_{v=1}^{V} g(y_{ijv}) \right] (1/\sigma_u)\, \phi(u_j/\sigma_u) du\,,$$

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; 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 by the firm-specific variance component, since the idiosyncratic error in latent variable models is unity (Wooldridge, 2002). The model specification exploits the well-known fact that discrete-time hazard rate models are identical to a sequence of binary choice equations defined on the surviving population at each duration (Allison, 1982; Bover et al., 2002; Brown, 1975; Jenkins, 1995 and Sueyoshi, 1995). This allows us to estimate the model conveniently using random effects logistic regression estimation packages such as Stata.

4 Data

Equation (9) was estimated using a large sample of enterprise data originating from the Nov/Dec 2003 enterprise survey of the e-Business Market W@tch, a large-scale observatory initiative that was sponsored by the European Commission, DG Enterprise and Industry. The main purpose of the initiative was to provide reliable and methodologically-consistent empirical information about the extent and scope of e-business development and the factors affecting the speed of its growth at the sector level in an internationally comparative framework; this information was not available from other sources such as official register-based statistics or market research studies. The dataset consists of 7,302 successfully completed computer-aided telephone interviews with enterprises from 25 European countries and 10 sectors. Not all sectors were interviewed in every country. Table A1 in the Annex shows the number of successfully completed interviews for each country-sector cell, Table A2 provides the size-class distribution per sector, and Table A3 reports the definitions of the sectors included in the study. The fieldwork was carried out by specialized polling companies that mostly used computer-aided telephone interview (CATI) technology. The respondent in the enterprise targeted by the survey was normally the person responsible for IT within the company (typically the IT manager). Alternatively, particularly in small enterprises without a separate IT unit, the managing director or owner was interviewed. The number of enterprises sampled in each country-sector cell was large enough to be approximately representative of the underlying population. Details about the sample and data collection procedures are available from the European Commission (2004).

The economic conditions within each sector can differ by country. In addition, market structures and economic conditions can vary greatly between the sectors of each country. However, the economic conditions for firms operating in the same country and the same sector can be assumed to be reasonably comparable. In the dataset, each firm unambiguously belongs to a specific country-sector group of enterprises, which defines the relevant market in this study. Overall, the sample contains 101 markets (the market index in the regression model is defined as $market = 1,...,101$). On average, there are approximately 60 firms surveyed per market.

The dataset contains basic background information about each company, including size class, number of establishments, percentage of employees with a college degree, market share, and primary customers of the enterprise. In addition, information on the adoption of seven e-business technologies is 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%.

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 seven e-business technologies. Online purchasing was most widely diffused (46%), whereas other solutions such as Knowledge Management (KMS) or Supply Chain Management (SCM) occurred only rarely. Each of the seven considered 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, in accordance with the basic assumptions underlying our theory. Only enterprises that fulfill 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 seven 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, and 1994 was chosen as the first period of observation.[4] 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 nine valid observation periods for each technology.

The information about the adoption times of all firms in the sample allows us to approximate the average level of e-business usage in each market at each time period according to:

$$(10)\quad k_{i,market,v} = \frac{\sum_{i}^{N_{market}} k_{i,j,v}}{N_{market}} \text{ with } i = 1,\ldots,N_{market}.$$

$k_{i,market,v}$ is identical for all firms belonging to the same market and increases over time as more firms in each market adopt additional e-business technologies. This market-specific variable is

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

positively correlated with $k_{i,j,v}$ at values ranging between 0.18 and 0.24, indicating no issues with multicollinearity.

The dataset is not a true panel, but rather a cross-section with ex-post information about adoption times. The adoption times of the technologies are the only dynamic dimension in the data. Thus, we need to assume that our control variables (in particular, market share and size class) are strictly exogenous and that they remain constant over time. We believe that this is not a critical assumption because studies analyzing the performance impact of ICT show that the effects of ICT are mostly indirect, usually not dramatic in size, and occur only with a significant time gap of several years (Brynjolfsson and Hitt, 2003; Chan, 2000; Kohli and Devaraj, 2003). Hence, market share and size class are unlikely to change dramatically as a direct effect of ICT adoption.

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 $k_{i,-j,v-1} = 5$).[5] The results are reported in Tables 2 and 3.

The most important result is that the hazard rate for adoption increases with $k_{i,-j,v-1}$: all significant coefficients on $k_{i,-j,v-1}$ that were decomposed into dummies exhibit an almost linear increase in adoption probability. Only insignificant estimated coefficients fall outside this pattern. The very small number of firms with values of $k_{i,-j,v-1}$ greater than 4 is responsible for these insignificant coefficients.[6] An examination of the estimated standard errors of the coefficients reveals that the 95% confidence intervals around the coefficients always overlap between neighboring values of $k_{i,-j,v-1}$. For example, we cannot conclude that the hazard rate for

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

[6] The share of firms with a value of $k_{i,-j,v-1}$ equal or greater than 4 remains below 2% of the sample for all technologies in the last observed period (t = 9).

adopting online sales is smaller for firms with $k_{i,-j,v-1}$ = 4 than for firms with $k_{i,-j,v-1}$ = 3.[7] Additional estimations with $k_{i,-j,v-1}$ as an ordinal variable showed positive and significant coefficients on $k_{i,-j,v-1}$ in all models.

[7] The 95% confidence interval is approximately equal to two standard deviations above and below the estimated value. Thus, in the model for online sales, the confidence interval for $k_{i,-j,v-1}$ = 3 goes from 0.027 to 0.075 and the interval for $k_{i,-j,v-1}$ = 4 goes from -0.05 to 0.034. The intervals overlap, indicating that the lower coefficient for $k_{i,-j,v-1}$ = 4 could be random and due to the very low number of observed firms with $k_{i,-j,v-1}$ > 3.

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

Co-variables	Online sales		Online purchasing		CRM	
Time period:						
v = 2	1.497**	(0.555)	1.607**	(0.448)	0.599	(0.509)
v = 3	1.774**	(0.517)	1.838**	(0.440)	0.481	(0.518)
v = 4	2.837**	(0.445)	2.517**	(0.425)	1.146**	(0.468)
v = 5	3.694**	(0.388)	3.468**	(0.415)	1.782**	(0.442)
v = 6	4.403**	(0.336)	3.743**	(0.414)	1.524**	(0.448)
v = 7	4.953**	(0.302)	4.387**	(0.412)	2.313**	(0.432)
v = 8	5.246**	(0.286)	4.567**	(0.413)	2.233**	(0.436)
v = 9	5.799**	(0.267)	5.355**	(0.414)	3.268**	(0.444)
Other technologies used by firm :						
$k_{i,-j,v-1} = 1$	0.521**	(0.142)	0.447**	(0.077)	0.584**	(0.124)
$k_{i,-j,v-1} = 2$	0.645**	(0.274)	0.773**	(0.165)	1.083**	(0.182)
$k_{i,-j,v-1} = 3$	1.161**	(0.425)	0.856**	(0.275)	1.752**	(0.330)
$k_{i,-j,v-1} = 4$	-0.328	(0.966)	-0.176	(0.674)	2.215**	(0.565)
$k_{i,-j,v-1} = 5$	0.662	(1.614)	27.096	(5.182E+04)	1.570	(1.055)
Technology usage in market :						
$k_{i,market,v-1}$	2.072**	(0.241)	0.874**	(0.099)	0.935**	(0.179)
Company size class :						
10-49 empl.	0.003	(0.173)	0.028	(0.062)	0.764**	(0.154)
50-249 empl.	0.124	(0.181)	0.091	(0.067)	1.051**	(0.167)
>250 empl.	0.317	(0.255)	0.132	(0.095)	1.286**	(0.213)
> 1 establishment	0.519**	(0.156)	0.231**	(0.056)	0.407**	(0.113)
Primary customers:						
other businesses	-0.985**	(0.185)	0.198**	(0.058)	0.463**	(0.130)
public sector	-1.133**	(0.259)	0.090	(0.082)	-0.175	(0.192)
no primary customers	0.072	(0.210)	0.058	(0.082)	0.196	(0.174)
Human capital proxy:						
% empl. w/ university degree	0.000	(0.002)	0.004**	(0.001)	0.013**	(0.002)
Market share:						
<1%	0.314	(0.246)	0.342**	(0.086)	-0.490**	(0.219)
1%-5%	0.791**	(0.222)	0.415**	(0.080)	-0.209	(0.179)
6%-10%	0.872**	(0.252)	0.339**	(0.095)	0.180	(0.188)
11%-25%	1.007**	(0.224)	0.311**	(0.085)	0.259	(0.166)
> 25%	0.549**	(0.176)	0.282**	(0.064)	0.088	(0.129)
Constant	-11.078**	(1.488)	-7.485**	(0.417)	-8.872**	(0.700)
Model diagnostics						
N obs	44,544		42,310		45,257	
N groups	5,116		5,116		5,116	
Log-likelihood	-3,715		-7,405		-2,391	
Rho	0.701		0.077		0.225	
LL-ratio test for rho=0	0.000		0.006		0.053	

Standard errors of estimated coefficients are reported in ( ).
** 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**	
Time period:								
v = 2	0.388	(0.912)	0.152	(0.314)	0.211	(0.551)	-0.682	(1.236)
v = 3	0.868	(0.836)	0.200	(0.311)	0.953*	(0.531)	0.724	(0.889)
v = 4	1.781**	(0.759)	0.758**	(0.280)	0.803	(0.580)	1.451*	(0.838)
v = 5	2.035**	(0.746)	0.706**	(0.283)	1.407**	(0.586)	1.924**	(0.860)
v = 6	2.122**	(0.740)	1.025**	(0.270)	1.310**	(0.620)	2.031**	(0.898)
v = 7	3.026**	(0.722)	1.321**	(0.262)	2.275**	(0.663)	2.790**	(0.944)
v = 8	3.058**	(0.726)	1.022**	(0.274)	2.180**	(0.702)	2.443**	(0.997)
v = 9	4.660**	(0.712)	2.430**	(0.255)	3.651**	(0.825)	4.353**	(1.153)
Other technologies used by firm :								
$k_{i,-j,v-1} = 1$	0.619**	(0.114)	0.278**	(0.122)	0.496**	(0.194)	0.699**	(0.235)
$k_{i,-j,v-1} = 2$	1.083**	(0.148)	0.651**	(0.178)	1.073**	(0.291)	0.927**	(0.361)
$k_{i,-j,v-1} = 3$	1.304**	(0.239)	0.349	(0.389)	2.337**	(0.492)	1.710**	(0.529)
$k_{i,-j,v-1} = 4$	0.253	(0.610)	0.716	(0.788)	2.895**	(0.882)	1.206	(0.956)
$k_{i,-j,v-1} = 5$	1.472*	(0.797)	-	-	1.646	(1.706)	1.433	(1.499)
Technology usage in market :								
$k_{i,market,v-1}$	0.754**	(0.202)	0.174	(0.167)	0.515**	(0.261)	-0.736**	(0.350)
Company size class :								
10-49 empl.	0.045	(0.136)	1.114**	(0.174)	0.490**	(0.247)	1.162**	(0.413)
50-249 empl.	0.234*	(0.138)	1.774**	(0.168)	0.978**	(0.291)	1.966**	(0.530)
>250 empl.	0.790**	(0.164)	2.360**	(0.184)	1.556**	(0.401)	3.035**	(0.788)
> 1 establishment	0.504**	(0.105)	0.186**	(0.095)	0.364*	(0.190)	0.496**	(0.242)
Primary customers:								
other businesses	-0.127	(0.116)	0.599**	(0.113)	0.240	(0.213)	-0.016	(0.222)
public sector	0.135	(0.155)	0.000	(0.172)	0.033	(0.284)	-1.093**	(0.483)
no primary customers	-0.056	(0.158)	0.126	(0.162)	-0.037	(0.282)	-0.328	(0.330)
Human capital proxy:								
% empl. w/ university degree	0.011**	(0.001)	0.003**	(0.001)	0.017**	(0.004)	0.009**	(0.004)
Market share:								
<1%	-0.134	(0.190)	-0.478**	(0.219)	-0.302	(0.346)	0.248	(0.385)
1%-5%	0.066	(0.161)	-0.054	(0.161)	0.293	(0.285)	-0.469	(0.413)
6%-10%	-0.049	(0.195)	0.248	(0.162)	-0.258	(0.353)	0.613*	(0.358)
11%-25%	0.184	(0.156)	0.302**	(0.141)	0.527*	(0.287)	0.163	(0.320)
> 25%	0.037	(0.123)	0.179	(0.112)	0.396*	(0.219)	0.175	(0.246)
Constant	-8.623**	(0.722)	-7.540**	(0.298)	-10.953**	(1.925)	-11.729**	(2.719)
Model diagnostics								
N obs	45,561		44,889		45,504		45,798	
N groups	5,116		5,116		5,116		5,116	
Log-likelihood	-2,105		-2,548		-1,683		-951	
Rho	0.002		0.000		0.619		0.513	
LL-ratio test for rho=0	0.474		1.000		0.008		0.171	

Standard errors of estimated coefficients are reported in ( ).
** 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.

Thus, the estimation results reported in Tables 2 and 3 show an acceleration of technology adoption, indicating that more advanced e-business users are more likely to adopt additional e-business technologies. Our theory suggests that this acceleration effect is endogenously determined and a consequence of earlier adoption decisions, due to either profit-maximization or psychological reasons and potential agency problems. However, because of the random effects assumptions made above, we cannot rule out the possibility that the observed positive effects of $k_{i,-j,v-1}$ in Tables 2 and 3 are due to some unobserved firm-specific factors that correlate to $k_{i,-j,v-1}$ rather than a causal consequence of earlier adoption decisions. Although we find it hard to think of such factors, we conducted a robustness check using a fixed effects linear hazard rate model. Our approach and the estimation results are reported in Appendix B. The empirical results support the claim of an endogenous acceleration mechanism.

The results in Tables 2 and 3 and Appendix B also suggest significant market-specific effects in most models. In most models, a higher level of e-business usage in a given sector increases the hazard rate to adopt significantly. However, the market effect is in some cases insignificant and for SCM, it is actually significantly negative. A possible explanation for this result is a capacity limit in supply chain management systems; for example, if only a limited number of steel manufacturers can supply a manufacturer of automobiles. The logic behind such a capacity limit could be that firms at the end of a supply chain use SCM systems to optimize logistics only with their preferred suppliers, limiting excess to other potential suppliers. This idea is reasonable because installing an SCM and synchronizing IT systems among firms can only generate savings in transaction costs if actual transactions can be expected to occur.

Furthermore, significant size-class effects are found in the regressions. Companies with more than one establishment are more likely to adopt any of the seven analyzed technologies. In addition, large firms with many employees are systematically more likely to adopt e-business solutions that are used primarily 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.

In addition, 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 more prevalent among firms that primarily serve consumers, while it is much less common among firms that primarily serve 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 for all kinds of firms.

In addition, the results show that the percentage of employees with a university degree within a company always has a positive and significant influence on the hazard rate of adoption, with the exception of the case of 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 of the adoption of all analyzed technologies except 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 in the case of KMS. The peak usually occurs somewhere between the two extremes. This is consistent with an inverted U-shape relationship between market share and innovative activities in markets (Aghion et al., 2005; Scherer, 1967).

5.2 Growing digital divide

The finding that technological development along a given trajectory of related technologies can be subject to an endogenous acceleration mechanism has 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. These 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.

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 appear as a growing variance of $k_{i,v}$ over time. The results are reported in Table 4.

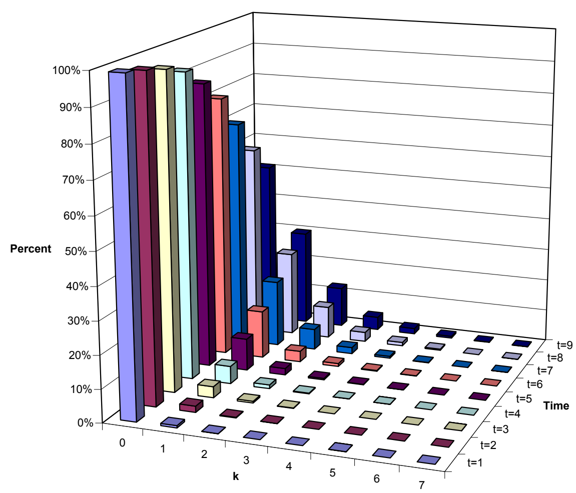
In the first observed period (1994), the mean value of $k_{i,v}$ in the sample is 0.0089. Thus, the vast majority of firms have not yet adopted any of the seven e-business technologies at this early date. The standard deviation of $k_{i,v}$ is quite small, 0.11904. Over time, we observe an increase in 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 seven technologies; the majority have adopted none. The increase in the mean value of $k_{i,v}$ is clearly the result of the ongoing diffusion processes of all seven 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 see a growing digital divide, as suggested by the endogenous acceleration mechanism.

Table 4 - Mean value and standard deviation of the number of adopted e-business technologies per firm over time (k)

	Minimum	**Maximum**	**Mean**	**Standard Deviation**
Time period				
v = 1 (1994)	0	5	.0089	.11904
v = 2	0	6	.0258	.19398
v = 3	0	7	.0486	.26550
v = 4	0	7	.0885	.36915
v = 5	0	7	.1619	.48780
v = 6	0	7	.2581	.61031
v = 7	0	7	.4287	.78360
v = 8	0	7	.6167	.91899
v = 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 zero of the seven technologies; one percent of the firms have adopted one technology. As time proceeds, the fraction of firms that have adopted no new technologies decreases continuously and the distribution spreads out, leading to higher mean values and a greater disparity in technological endowment in the early periods of the diffusion process. 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 increased continuously from 1994 to 2002.

Figure 1 - Distribution of the number of adopted e-business technologies per firm over time (k)



Source: E-Business Market W@tch survey Nov/Dec 2003. N=5,615.
All firms included have computers and Internet access and use the WWW and email.

6 Discussion

Section 2 discussed different factors that can lead to the acceleration mechanism we observe in the data. However, the empirical results presented above do not allow us to make inferences about which of the different reasons prevailed in causing the observed acceleration effect. Although it is not the purpose of this paper to differentiate between these potential causes, it is clearly of interest to know whether profit-maximizing adoption decisions or behavioral phenomena such as the escalation of commitment prevail in the observed acceleration effect. The latter would imply that firms keep investing into unprofitable e-business technologies, accumulating performance disadvantages compared to competing firms that have invested less in e-business technologies. Empirical evidence suggests that this is not the case. On the contrary, numerous studies provide evidence for a positive effect of IT investments on firm-level productivity, usually conditional on complementary investments in organizational change and human capital (Bertschek and Kaiser, 2004; Black and Lynch, 2004; Brynjolfsson and Hitt, 1996, 2000, 2003). Thus, although non-profit-maximizing reasons for adoption cannot be ruled out, evidence suggests that profit-maximizing causes prevail.

Another issue of interest is the question of whether and when the trend of the growing digital divide we showed in Section 6 will cease (and eventually disappear). Future empirical evidence will be required to answer this question. In our model, a reversal of the divergence trend is inevitable as long as (1) the number of technologies K remains constant, and (2) technologically more advanced firms do not drive their competitors out of the market. Technological convergence in the long run is only guaranteed under these strict conditions. Given that technological progress keeps expanding the e-business trajectory and real economic consequences of IT investments are plausible, we find it reasonable to expect that technological heterogeneity will be long lasting.

Our results imply that investment in technologies belonging to a particular paradigm can result in a technological lock-in of firms. Such a lock-in may not necessarily be desirable if other, potentially better paradigms exist or may come into existence in the future. If no superior alternative to a given technological paradigm exists, early investment into a new technological trajectory should yield competitive advantages if there are no dramatic improvements in technology over time and the cost of adoption does not rapidly decline. Such advantages could be long lasting if there is free entry and exit in the market and if firms are not ex ante identical. This would be the case if there are positive returns to scale, learning-by-doing effects, scarce complementary resources to the new technology, market reputation effects, and/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 late movers to adopt any of the new technologies. In addition, some firms might adopt preemptively in order to ensure strategic advantages (Fudenberg and Tirole, 1985; Ireland and Stoneman, 1985). This implies that an acceleration mechanism of technological change will have important consequences for the strategic timing of investment decisions and the resulting competitive dynamics. Again, in such a dynamic world of increasing returns, we are unlikely to find homogenous firms with identical technologies.

Our results also have macroeconomic relevance. Bernard and Jones (1996a) pointed out that a lack of technological convergence across countries will affect growth convergence. They showed cross-country divergence in total technological productivity and labor productivity in the manufacturing sectors from 1980-1988 (Bernard and Jones, 1996b). Our study provides microeconomic rationale and empirical evidence for the potential causes of such technological divergence. In our framework, technological divergence among countries happens any time a new technological frontier arises and countries are not ex ante identical, e.g., with respect to their sectoral composition or given level of technological development. We argued that such ex ante differences could lead to technological divergence that persists for at least some time. This implies that technological divergence is possible even if all countries and firms were to have equal access to the same technologies, i.e., if technology providers could sell to all countries without trade or capacity restrictions and managers around the globe had perfect information about the new technologies. As pointed out by Bernard and Jones (1996a), such technological divergence would negatively influence the rate of convergence in GDP per capita across nations and lead to lower convergence rates than those forecast by the neoclassical growth model, which assumes constant levels of technology across countries (Barro and Sala-i-Martin, 1992).

7 Conclusion

Our study shows how, and under what conditions, history can matter for the technological development of a firm. We conclude that the decision to adopt a technology today can affect the expected value of any other related technology in the future under fairly general circumstances. Hence, technological development can be viewed as a path-dependent process in which current choices with respect to technologies become the link through which prevailing economic conditions influence the future dimensions of technology, knowledge, and economic opportunities (Ruttan, 1997). In particular, we show that the more advanced a firm is in using a particular set of technologies, the more likely it will adopt additional related technologies. Our results imply that the standard assumption of constant production technologies across firms or countries is hard to reconcile with the empirical evidence and microeconomic logic behind dynamic adoption decisions.

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Appendix A – Data

Table A1 – Country-sector coverage of e-Business W@tch survey Nov/Dec 2003

	Sector									
Country	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**	**10**
A				68			132		100	
B		101				100				100
DK						67	67		66	
FIN										
F	100				101				100	100
D	100				100				100	100
GR	84		76	89	75		75			
IRL		70					70	71		
I	100				100				100	101
NL	100							101	102	
P				104		100				100
E	101				108				101	100
FIN	75		75					76		
S		80	75	79						80
UK	100				100				100	100
CY						64				
CZ		60		60			60	60	60	
EST	50	50	50	21	65	50	50	50	50	50
H			80	80						80
LT						57				
LV	51	49				51				
M							51			
PL	80	80	80	80	80	80	80	80	80	80
SLO			56				51	53	55	58
SK	50		50			50				60
N	30					70				

Note: Table shows numbers of successfully completed interviews, country names abbreviated by their international license plate codes

Table A2 – Size-class coverage of e-Business W@tch survey Nov/Dec 2003

	Sector									
Size class by number of employees	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**	**10**
1-9	372	164	196	193	440	249	207	170	374	345
10-49	283	130	154	166	289	194	199	141	291	268
50-249	285	143	144	151		170	178	139	326	288
>250	81	53	48	71		76	52	41	118	113

Note: Table shows numbers of successfully completed interviews, sector definitions are provided in Table A3.

Table A3 - Sector definition of e-Business W@tch survey Nov/Dec 2003

	Sector short name	NACE Rev. 1 Codes
01	Textile	17 – Manufacture of textile and textile products 18.1 – Manufacture of leather clothes 18.2 – Manufacture of other wearing apparel and accessories 19.3 Manufacture of footwear
02	Chemicals	24 – Manufacture of chemicals, chemical products and man-made fibers 25 – Manufacture of rubber and plastic products
03	Electronics	30 – Manufacture of office machinery and equipment 31.1 – Manufacture of electric motors, generators and transformers 31.2 – Manufacture of electricity distribution and control apparatus 32 – Manufacture of radio, television and communication equipment and apparatus
04	Transport Equipment	34 – Manufacture of motor vehicles, trailers and semi-trailers 35 – Manufacture of other transport equipment
05	Crafts & trade	17 – Manufacture of textiles and textile products 18.1-2 – Manufacture of wearing apparel and dressing 19.3 – Manufacture of leather and leather products (footwear only) 30 – Manufacture of office machinery and computers 31.1-2 – Manufacture of electrical machinery and apparatus 32 – Manufacture of radio, television and communication equipment and apparatus 34 – Manufacture of motor vehicles, trailers and semi-trailers 35 – Manufacture of other transport equipment 20 – Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials 36.1 – Manufacture of furniture 45.2-4 – Construction (Building of complete constructions, building installation and completion)
06	Retail	52.11 – Retail sale in non-specialized stores with food, beverages or tobacco predominating 52.12 – Other retail sales in non-specialized stores 52.4 – Other retail sale of new goods in specialized stores, except of motor vehicles and motorcycles
07	Tourism	*55* – Hotels and restaurants 62.1 – Scheduled air transport 63.3 – Activities of travel agencies and tour operators; tourist assistance activities n.e.c. 92.33 – Fair and amusement park activities 92.52 – Museum activities and preservation of historical sites and buildings 92.53 – Botanical and zoological gardens and nature reserve activities
08	ICT Services	64.2 - Telecommunications 72 – Computer-related activities
09	Business Services	74.1 – Legal, accounting, book-keeping and auditing activities; tax consultancy; market research and public opinion polling, business and management consultancy; holdings 74.2 – Architectural and engineering activities and related technical consultancy

		74.3 – Technical testing and analysis 74.4 – Advertising 74.5 – Labor recruitment and provision of personnel 74.6 – Investigation and security activities 74.7 – Industrial cleaning 74.8 – Miscellaneous
10	Health Services	85.1 – Health activities 85.3 – Social work activities

Appendix B – Robustness checks

Following Bandiera and Rasul (2006), who use a linear probability model with market fixed effects to analyze the adoption of sunflower crops among African farmers, a linear hazard rate model that controls for firm-specific fixed effects in our time-varying data can be specified. Retaining our notation from above, the linear hazard rate model in discrete time with the piecewise constant baseline hazard is

(A1) $$\lambda_{ijv} = \overline{\beta'_j x_{ijv}} + u_{ij} + \varepsilon_{ijv}$$

where $\overline{x_{ijv}} = k_{i,j,v-1}, k_{i,market,v-1}, \theta_{ij}$ and θ_{ij} is a vector of dummy period dummies, as in (9). The variables u_{ij} and ε_{ijv} are error terms with $E(u_{ij}) = 0$, $E(\varepsilon_{ijv}) = 0$ and strict exogeneity of the idiosyncratic error, $E(\varepsilon_{ijv} \mid \overline{x_{ijv}}, u_{ij}) = 0$.[8] The usual within-transformation leads to the fixed effects estimator

(A2) $$\ddot{\lambda}_{ijv} = \overline{\ddot{x}_{ijv}} \beta_j + \ddot{\varepsilon}_{ij}$$

where $\ddot{\lambda}_{ijv} \equiv \lambda_{ijv} - V^{-1} \sum_{v=1}^{V} \lambda_{ijv}$, $\overline{\ddot{x}_{ijv}} \equiv \overline{x_{ijv}} - V^{-1} \sum_{v=1}^{V} \overline{x_{ijv}}$ and $\ddot{\varepsilon}_{ij} \equiv \ddot{\varepsilon}_{ijv} - V^{-1} \sum_{v=1}^{V} \varepsilon_{ijv}$. The time de-meaning removes all firm-specific effects, including explanatory variables that do not vary over time. This procedure allows us to estimate β_j, even if $E(u_{ij} \mid \overline{x_{ijv}}) \neq 0$; see Ch. 10 in Wooldridge

[8] Essentially, we maintain our original specification of a linear index function of Equation (8) and allow for unobserved heterogeneity that might correlate with x_{ijv}. To relax the random effects assumption on u_{ij} and ε_{ijv}, we must give up the logistic link function, which maps the index values into the (0,1) space in Equation (8). To the best of our knowledge, no fixed effects estimator yet exists for any link function in a hazard rate context.

(2002) for the proof. The obvious disadvantage of the linear model (A1) is that it can predict values for the hazard rate that are outside the unit interval. However, we are not interested in prediction. Instead, the purpose of this robustness check is to see if the results reported in Tables 2 and 3 can be qualitatively confirmed in a setup that allows unobserved firm heterogeneity to be correlated with our variables of interest $k_{i,j,v-1}$. This approach is feasible because we are only interested in the direction and size of the estimated coefficients relative to each other, and these are unaffected by dropping the assumption of the canonical logistic link function. Tables A4 and A5 report the estimation results of (A2).

Table A4 – Linear probability model regressions for 3 e-business technologies with firm-specific fixed effects

Co-variables	**Online sales**		**Online purchasing**		**CRM**	
Other technologies used by firm:						
$k_{i,-j,v-1}=1$	0.015**	(0.003)	0.051**	(0.007)	0.013**	(0.002)
$k_{i,-j,v-1}=2$	0.021**	(0.006)	0.118**	(0.016)	0.049**	(0.004)
$k_{i,-j,v-1}=3$	0.051**	(0.012)	0.170**	(0.028)	0.143**	(0.010)
$k_{i,-j,v-1}=4$	-0.008	(0.021)	0.034	(0.056)	0.284**	(0.020)
$k_{i,-j,v-1}=5$	0.058	(0.057)	0.977**	(0.304)	0.267**	(0.043)
$k_{1,-j,v-1}=6$	1.017**	(0.165)	-	-	-	-
Technology usage in market :						
$k_{i,market,v-1}$	0.088	(0.006)	0.158**	(0.010)	0.057**	(0.004)
Constant	-0.006**	(0.002)	-0.015**	(0.003)	-0.003**	(0.001)
Model diagnostics						
N obs	44,545		42,310		45,257	
N groups	5,116		5,116		5,116	
Prob > F	0.000		0.000		0.000	
Rho	0.225		0.197		0.257	
F test for rho=0	0.000		0.000		0.000	

Standard errors of estimated coefficients are reported in ( ).
** denotes significance at the 95% confidence level, * denotes significance with 90% confidence.
Time dummies were included and time-constant variables were eliminated in all regressions.
Reference category: $k_{i,-j,v-1}=0$.
All firms included have computers, Internet access, and use the WWW and email.

Table A5 - Linear probability model regressions for 4 e-business technologies with firm-specific fixed effects

Co-variables	E-learning		ERP		KM		SCM	
Other technologies used by firm:								
$k_{i,-j,v-1} = 1$	0.016**	(0.002)	0.007**	(0.002)	0.004**	(0.002)	0.005**	(0.001)
$k_{i,-j,v-1} = 2$	0.052**	(0.004)	0.033**	(0.005)	0.023**	(0.003)	0.013**	(0.002)
$k_{i,-j,v-1} = 3$	0.09**	(0.008)	0.039**	(0.010)	0.088**	(0.006)	0.040**	(0.004)
$k_{i,-j,v-1} = 4$	0.047**	(0.015)	0.112**	(0.029)	0.144**	(0.014)	0.032**	(0.009)
$k_{i,-j,v-1} = 5$	0.155**	(0.031)	-	-	0.060**	(0.026)	0.055**	(0.018)
Technology usage in market :	0.00	(0.004)	0.009**	(0.004)	0.018**	(0.003)	-0.008**	(0.002)
$k_{i,market,v-1}$	-0.002	(0.001)	-0.005	(0.001)	-0.002**	(0.001)	0.00	(0.001)
Model diagnostics								
N obs	45,561		44,889		45,504		45,798	
N groups	5,116		5,116		5,116		5,116	
Prob > F	0.000		0.000		0.000		0.000	
Rho	0.180		0.403		0.322		0.241	
F test for rho=0	0.000		0.000		0.000		0.000	

Standard errors of estimated coefficients are reported in ( ).
** denotes significance at the 95% confidence level, * denotes significance with 90% confidence.
Time dummies were included and time-constant variables were eliminated in all regressions.
Reference category: $k_{i,-j,v-1} = 0$.
All firms included have computers, Internet access, and use the WWW and email.

In the regressions above, all significant coefficients of $k_{i,j,v-1}$ are positive. The general trend is that coefficients increase as $k_{i,j,v-1}$ gets larger, which is consistent with our main hypothesis of an endogenous acceleration of technology adoption. Similar to Tables 2 and 3, we find some deviations from this general trend for values of $k_{i,j,v-1} > 3$. As explained above, this is due to the very small number of observations with $k_{i,j,v-1} > 3$, even in the last observed period in the sample. An examination of the standard errors reveals that none of the estimated coefficients falling out of the general trend allows us to reject the hypothesis because the 95% confidence intervals of coefficients always overlap between neighboring values of $k_{i,j,v-1}$. Additional regressions that specified $k_{i,j,v-1}$ as an ordinal variable showed exclusively positive and highly significant coefficients. Thus, the fixed effects estimation results also support an endogenous acceleration mechanism.

Not surprisingly, firm-specific unobserved effects are highly significant in all models and account for up to 42% of the variance in λ_{ijv} . The market-specific effects of $k_{i,market,v-1}$, however, deviate to some extent from the random effects results reported in Tables 2 and 3. For example, the market coefficients for online sales and e-learning are significant under random effects, but insignificant under fixed effects. This indicates that unobserved market-specific factors, such as differences in the "suitability" of e-business technologies for particular sectors, are behind the positive coefficients of $k_{i,market,v-1}$ under random effects, rather than the actual level of e-business technology usage among firm's competitors. Exactly the opposite seems to be true for ERP adoption: while the market effect is insignificant under random effects, it becomes significantly positive under fixed effects. This suggests that a high level of e-business usage among competitors in the same industry does indeed have a positive direct influence on the adoption of ERP. These results indicate that strategic adoption motives among firms competing in the same market (Reinganum, 1981a,b; Götz, 1999) can be found for some technologies, but not for others.