The Influence of Installed Technologies on Future Adoption Decisions: Empirical Evidence from E-Business

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ABSTRACT AND KEYWORDS	
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The influence of installed technologies on future adoption decisions: Empirical evidence from e-business

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Abstract

This paper studies the adoption times of various e-business technologies in a large sample of firms from 10 different industry sectors and 25 European countries between 1994 and 2002. The results show that the probability of adoption increases with the number of previously adopted e-business technologies. Hence, the more advanced a firm is in using e-business technologies, the more likely it is to adopt additional e-business technologies, provided technologies do not substitute each other in their functionalities. This result is relevant for the marketing of new technologies, strategic planning and, from an economic perspective, for the convergence of growth across regions.

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JEL Codes: O33, O14

1 Introduction

Our article deals with the question: What determines the process by which e-business technologies spread among enterprises over time? This question essentially concerns the topic of technological change and progress. Understanding the diffusion of new technologies means understanding an essential part of technological change because the invention of a new technology is only a necessary, not a sufficient condition yet for technical advance. New technologies need to be adopted and used by firms to reach their full economic impact. However, many new production methods and technologies often find no commercial application. Also, even potentially beneficial technologies are usually not adopted by everyone instantaneously. Instead, diffusion of new technologies is a dynamic process that features pioneer users, followers, and typically also a number of non-adopters (Stoneman 2002).

Certainly, the scope of technological change can vary substantially for different kinds of technologies. Some new technologies may only have minor impact on production processes and competition, or have limited areas of applications. Other technologies may be applicable in many areas and may have considerable influence. Such general purpose technologies include steam power, electricity, computers, or the Internet. The focus in this paper is on e-business technologies, which constitute a number of related information and communication technologies (ICT) that are jointly based on the Internet. The purpose of these technologies is to support business processes, both within a company or between a company and its environment (e-Business Market W@tch 2003). Related technologies like e-business applications rarely stand alone (Dosi 1982, Stoneman and Kwon 1994, Stonman and Toivanen 1997, Colombo and Mosconi 1995). This makes the analysis of the diffusion of e-business technologies particularly interesting, because some of these technologies might be complements or constitute a pre-requisite for the adoption of another application. Also, firms that have already collected experience with one or more of these technologies might have learning effects that make the adoption of another related technology more attractive. If such effects prevail, what will be the consequences for technological development? Which diffusion patterns can we expect to find?

The empirical results we present below suggest that we can expect to see an acceleration of technology adoption and a growing “digital divide” between early adopters and late adopters for long time periods, which has important implications. For instance, it has been shown that the adoption of ICT and e-business technologies can positively affect firm performance (Bertschek and Kaiser 2004, Brynjolfsson and Hitt 1996, 2000, 2003, Koellinger 2008). As a result, these micro level effects could also influence the development of market structures and market shares of firms at the meso level, and eventually economic growth at the macro level (Jorgenson 2001, Oliner and Sichel 2000). In addition, the patterns we identify in our data have implications for the management and marketing of new technologies.

Our study uses firm-level data on the adoption of e-business technologies from a large representative enterprise survey conducted in Nov/Dec 2003 among firms from 10 industry sectors and 25 European countries. Our key results are that (1) the hazard rate of adopting an e-business technology increases with the number of previously adopted e-business technologies, and (2) there is a growing "digital divide" among firms in our sample for the period from 1994-2002.

Our data and our econometric approach allow us to control for unobserved heterogeneity among firms and potentially spurious state dependence. By doing so, we eliminate potential biases from omitted variables or market-specific trends, providing us with confidence in the conclusion that the observed acceleration of e-business technology adoption arises as the result of previous adoption decisions.

2 Theoretical background

The economics and management literature has identified various factors that influence the diffusion of new technologies among firms. Stoneman (2002) and Koellinger (2006) provide comprehensive overviews of this topic. In particular, the most prominent factors discussed are:

- The distribution of information among agents, including learning and dissemination of information
- The cost of acquiring new technology and changes therein over time
- The performance of new technology and changes therein over time

- Number and characteristics of technologies (only one new technology, two or more competing technologies, two or more complementary technologies)
- Existence of network externalities
- Level of competition among agents (none, duopoly, oligopoly, monopolistic competition, perfect competition)
- Firm characteristics and their distribution
- Discount factors
- Risk and ambiguity aversion of agents
- The extent of first mover advantages
- The extent to which realized profits generate new investment

These factors are not independent. Instead, different combinations of these factors can lead to very different diffusion dynamics. The various theories of technology diffusion among firms that are found in the economic literature can be subsumed as belonging to either the epidemic, rank, stock, or order effect type of models (Stoneman 2002, Karshenas and Stoneman 1993, Stoneman 1995).

In our empirical specification below, we include these factors either directly if our data allow us to do so or indirectly by controlling for unobserved heterogeneity in a random- and a fixed-effects specification of our econometric model. Of particular interest in our study are the consequences of technological interdependencies on adoption decisions since e-business technologies can serve different purposes within firms, but are all members of the group of ICT's that use the Internet as a communication platform. Thus, they belong to the same technological paradigm in the sense of Dosi (1982). Consequently, firms are not only faced with the option to invest into any one of the technologies belonging to this paradigm, but with the option to invest into progress upon the technological trajectory that is defined by the attributes and possibilities of the numerous technologies that belong to this paradigm. Dosi (1982) noted in his original paper that "'progress' upon a technological trajectory is likely to retain some cumulative features: the probability of future advances is in this case related also to the position that one (a firm or a country) already occupies vis-à-vis the existing technological frontier". Below, we discuss the conditions and mechanisms under which progress upon a technological trajectory can be subject to an acceleration mechanism, i.e. the more advanced a firm is, the more likely it is to make further progress on the frontier.

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. In addition to these profit-maximizing mechanisms, there are also behavioral reasons that can create a similar effect, but which may not always be desirable from a profit-maximizing perspective.

Under profit maximization, the probability of adopting a new technology increases 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:

1. **Technological complementarity**: If technologies are compatible and complementary in their functions instead of substitutes, the payoff from installing these technologies together is greater than the sum of the benefits gained when each technology is installed alone (Milgrom and Roberts 1990, Stoneman 2000). In this case, the technology choice decision of the firm in time t will depend upon its previous investments. For example, if A and B are technological complements, it might be profitable for a firm that has previously installed A to install B in t; whereas for some other firm that has not previously installed A it might not be profitable to install B.
2. **Joint inputs**: Complementarity between technologies can also arise if they require similar joint inputs to function properly. A well recognized joint input to computer technology in firms is skilled labor (Acemoglu 2002, Brynjolfsson and Hitt 2002,

Greenwood 1997, Krueger 1993). It is argued that investments into ICT lead to a higher demand for skilled labor and that ICT investments have been shown to profit from complementary investments into the re-organization of processes and organizational structures (Brynjolfsson and Hitt 2003, Black and Lynch 2004). Therefore, skilled labor, investments in training, education, process re-engineering and organizational change can be viewed as complements to investments in e-business technologies. Thus, these complementary investments can be expected to increase the payoff flow from each e-business technology. In addition, a firm that has previously made investments into human capital, adequate processes and organizational structures, will expect a higher return from any additional e-business technology than a firm that is still lacking these complementary inputs.

3. **Learning-by-doing**: Learning-by-doing may be another factor that endogenously influences a firms' ability and costs of making further progress upon a technological trajectory. As pointed out by Arrow (1962a), learning is a product of experience. Thus, the more experienced a firm is in using a particular technology, the more likely will it be able to improve the use of that technology and to make progress on the trajectory. The knowledge and experience a firm has accumulated will be reflected in the technology it currently uses, but also in its expected payoffs from any additional related technology. In Arrow's (1962a) model, the accumulation and continuous investment into knowledge is reflected in a downward drift in cost curves over time. In the same spirit, it can be argued that a firm that has already gained substantial knowledge in a given technological paradigm will have advantages in making further progress on the associated trajectory. Sheshinski (1967) provided a similar argument, pointing out that learning-by-doing dynamics are "irreversible", providing advantages to those firms that have an early start in competition. Thus, firms that are on a higher position on a technological trajectory have collected more experience with that technology, and therefore have cost advantages in "making the next step". Again, this reasoning results in a positive relationship between the position upon a trajectory and the momentum of progress.

4. **Financial slack**: Another reason why firms that are already advanced on a trajectory might have advantages in making further progress are imperfections in the capital market and financial slack. If progress upon a trajectory leads to higher profits, firms that are

more advanced on the trajectory can be expected to have more internal finances available for investing in further progress, ceteris paribus. In addition, information asymmetries between financial intermediaries and firms seeking external funding for investment projects could exist, favoring the financing conditions of those firms that have been successful in the past. If the net worth of a firm improves, lenders will become more willing to lend, and additional investments can be financed. This accelerator mechanism has for example been demonstrated in studies by Abel and Blanchard (1986), Hubbard (1990), and Hubbard and Kashyap (1992).

Two caveats are worthy of mention. First, the expected benefits from a technology will also depend on other relevant attributes of the firm, as mentioned at the beginning of this section. For example, a Knowledge Management solution may yield benefits for a large firm with many employees but be 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 e-business technologies.

Second, the above arguments do 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).

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 as results of behavioral biases 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 a positive 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 exercise 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 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 that earlier adoption decisions influence future ones.

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

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

$$(1) \qquad \lambda(t) = \lim_{dt \to 0} \frac{\Pr ob(t \leq T < t + dt \mid T \geq t)}{dt}.$$

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 vth interval so that it satisfies $t_{v-1} \leq t < t_v$ for $v = 1,...,V$. In the last observable interval, firm i's spell ($i = 1,...,N$) for technology $j = 1,...,K$ is either complete or right censored.

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 effect of previously installed technologies on future decisions to adopt related technologies. For notation, 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. 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 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. To allow for unobserved heterogeneity, a firm-specific error term, u_{ij}, with the following properties is introduced:

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

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:

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

for all $v = 2,...,V$, choosing $v = 1$ as the reference category for estimation[1] 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

[1] hence maintaining an intercept term

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 (3) 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

$$(4) \qquad \lambda_{ijv} = \frac{1}{1 + \exp(-\alpha_{jv}\theta_{jv} - \beta_j^{'}\overline{x_{ijv}} - u_{ij})}.$$

Because (4) depends on unobserved firm-specific effects u_{ij}, it cannot be used directly to construct the likelihood function. However, recalling (2), 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 (2), the likelihood contribution of each uncensored observation can be expressed as

$$(5) \qquad L = \int_{-\infty}^{\infty} \left[\prod_{v=1}^{V} g(y_{ijv}) \right] (1/\sigma_u)\,\phi(u_j/\sigma_u)du,$$

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). In other words, this model is equivalent to a standard random effects logit model applied to an appropriately arranged dataset (Jenkins 2004, pp. 82-84). This allows us to estimate the model conveniently using the *xtlogit* command in *Stata*.

4 Data

Equation (5) 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.[2] 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:

$$(6)\ k_{i,market,v} = \frac{\sum_{i}^{N_{market}} k_{i,j,v}}{N_{market}} \text{ with } i = 1,\ldots,N_{market}.$$

$k_{i,market,v}$ 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. Hence, $k_{i,market,v}$ captures strategic adoption motives for firms in the same industry as well as changes in how attractive it is

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[2] 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.

generally to conduct e-business in a particular industry over time. The market-specific variable $k_{i,market,v}$ is positively correlated with the individual-level variable $k_{i,j,v}$ 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. Furthermore, this assumption is only necessary for the random effects model (5). It is not required for the fixed effects estimation reported in the appendix, which yields qualitatively similar results.[3]

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 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

[3] The empirical assumption of the random effects model that market share and size class are exogenous is to some extent at odds with our theoretical reasoning that financial slack is one of the possible mechanisms that leads to an interdependence of adoption decisions over time. Hence, relaxing this empirical assumption is an important reason for the robustness check using the fixed effects specification in the appendix.

[4] 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.

pattern. The very small number of firms with values of $k_{i,-j,v-1}$ greater than 4 is responsible for these insignificant coefficients.[5] 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 adopting online sales is smaller for firms with $k_{i,-j,v-1} = 4$ than for firms with $k_{i,-j,v-1} = 3$.[6] 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.

[5] 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).

[6] 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 that more advanced e-business users are more likely to adopt additional e-business technologies. Theoretical arguments suggest that this acceleration effect can be the 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 fully support the claim that earlier e-business adoption decisions influence future adoption decisions in a strictly positive way.

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 ICT adoption and high skilled labor are complementary (Brynjolfsson and Hitt, 2002; Dewar and Dutton, 1986).

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 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.

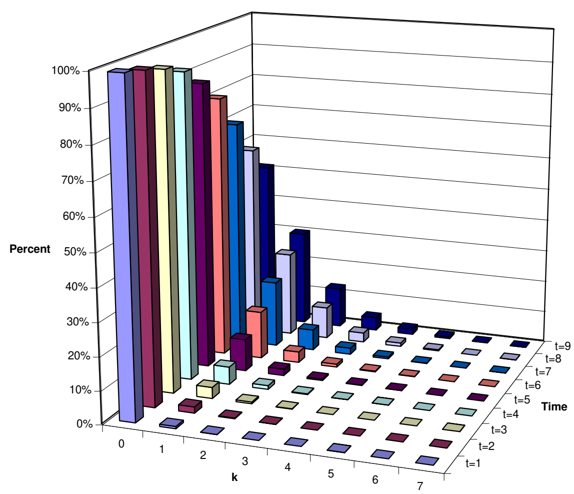
Table 4 - Mean value and standard deviation of the number of adopted e-business technologies per firm over time (k)

	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. Theoretically, 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. Under these strict conditions, technological convergence would occur in the long run. However, 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.

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. 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,b, Götz 1999). 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 firms following, it might be less profitable for later movers to adopt 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 adoption decisions 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 copy these resources perfectly 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 in the competition (Christensen 2003). 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. It also implies that the decision to invest into 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 the 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, it has some benefits to wait and 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. 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 most beneficial, especially if an acceleration effect can be expected.

Arguably, these are tough questions to answer and choosing the correct development path and the optimal time to invest are clearly decisions with far reaching consequences that require a very profound knowledge of the 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 independent industry experts and consultants to choose their path of action.

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 into related technologies can expect lower implementation costs and / or higher benefits of adopting additional technologies that belong to the same technological paradigm. Thus, they are more likely to make additional investments into 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 potentials 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.

Our results also have macroeconomic implications. 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 results show that current investment decisions are not independent from past investment decisions. In particular, we show that the more advanced a firm is in using e-business technologies, the more likely it will adopt additional e-business technologies. 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. This is consistent with the view that technological development is 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).

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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, $E(\varepsilon_{ijv} \mid \overline{x_{ijv}}, u_{ij}) = 0$.[7] 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

[7] 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.

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