D I S S E R T A T I O N

Technological change: An analysis of the diffusion and implications of e-business technologies

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Zusammenfassung

Die vorliegende Dissertation beschäftigt sich hauptsächlich mit zwei Fragen: Erstens, welche Faktoren beeinflussen den Prozess, durch den sich neue Technologien unter Firmen verbreiten? Zweitens, welche Konsequenzen ergeben sich aus der Verbreitung neuer Technologien? Beide Fragen beschäftigen sich mit der Dynamik des technologischen Wandels. Die Analyse wird am konkreten Beispiel von e-Business Technologien durchgeführt.

Dabei werden insbesondere die Konsequenzen von interdependenten Technologien untersucht. Es wird gezeigt, dass es zu steigenden Erträgen der Adoption kommen kann, wenn verwandte Technologien sich nicht in ihren Funktionalitäten substituieren. Dies kann zu einer endogenen Beschleunigung der technologischen Entwicklung führen. Dies bedeutet, dass die Wahrscheinlichkeit der Adoption einer Technologie mit der Anzahl der zuvor adoptierten, verwandten Technologien ansteigt. Diese Theorie wird empirisch getestet und in vier verschiedenen Untersuchungen mit zwei verschiedenen, großen Datensätzen bestätigt. Die Existenz einer wachsenden digitalen Kluft in der e-Business Technologie-Ausstattung der Unternehmen wird für den Zeitraum von 1994-2002 nachgewiesen.

Außerdem wird argumentiert, dass die Adoption neuer Technologien in Firmen strategische Bedeutung hat da sich daraus Möglichkeiten zur Durchführung von Innovationen ergeben. Diese können sich entweder durch reduzierte Produktionkosten für bestehende Produkte, neue Produkte und Dienstleistungen, oder neue Distributionskanäle manifestieren. Empirische Evidenz zeigt, dass e-Business Technologien derzeit wichtige Enabler von Innovationen sind und dass innovative Firmen mit höherer Wahrscheinlichkeit wachsen. Außerdem wird gezeigt, dass durch e-Business Technologien induzierte Innovationen gegenüber anderen Innovationsarten nicht inferior sind in Bezug auf deren gleichzeitiges Auftreten mit finanziellen Leistungsindikatoren.

Die Arbeit diskutiert die Implikationen dieser Ergebnisse aus volks- und betriebswirtschaftlicher Perspektive.

Schlagworte: Technologischer Wandel, Innovation, Diffusion, Adoption, verwandte Technologien, endogene Beschleunigung, e-business, IKT, Wettbewerbsfähigkeit, Performanz

Abstract

This dissertation primarily deals with two questions: First, what determines the process by which new technologies spread among enterprises over time? Second, what are the consequences of the spread of new technologies? Both questions concern the dynamics of technological change. They are analyzed considering the diffusion and implications of e-business technologies as a concrete example.

Particular attention is given to technological interdependencies. It is shown that increasing returns to adoption can arise if related technologies do not substitute each other in their functionalities. This can lead to an endogenous acceleration of technological development. Hence, the probability to adopt any technology is an increasing function of previously adopted, related technologies. The theory is empirically tested and supported in four independent inquiries, using two different exceptionally large datasets and different econometric methods. The existence of a growing digital divide among companies is demonstrated for the period between 1994 and 2002.

In addition, it is argued that the adoption of new e-business technologies by firms has strategic relevance because this creates opportunities to conduct innovation, either to reduce production costs for a given output, to create a new product or service, or to deliver products to customers in a way that is new to the enterprise. Empirical evidence is presented showing that e-business technologies are currently an important enabler of innovations. It is found that innovative firms are more likely to grow. Also, e-business related innovations are not found to be inferior to traditional kinds of innovations in terms of simultaneous occurrence with superior financial performance of enterprises.

Implications of these findings are discussed both for economists and management researchers.

Keywords: Technological change, innovation, diffusion, adoption, related technologies, endogenous acceleration, e-business, ICT, firm performance, competitive advantage

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Abbreviations

CAD	Computer aided design
CART	Classification and regression trees
CATI	Computer-aided telephone interviews
cdf	Cumulative distribution function
CIS	Community innovation survey
CMS	Content management system
CRM	Customer relationship management
EDI	Electronic data interchange
ERP	Enterprise resource planning system
GDP	Gross domestic product
HRM	Human resource management system
ICT	Information and communication technology
IT	Information technology
IO	Industrial organizations
KMS	Knowledge management system
MES	Minimum efficient scale
pdf	Probability density function
ROI	Return on investment
SCM	Supply chain management

PART I

1. Introduction

1.1. Purpose

The research results presented here primarily deal with two questions. The first question is the fundamental question in diffusion research: What determines the process by which new technologies spread among enterprises over time? The second question arises directly from the first: What are the consequences of the spread of new technologies?

Both questions essentially concern the topic of technological change and progress. Understanding the diffusion of new technologies and their consequences means understanding an essential part of technological change. This topic has intrigued economists and business scientists likewise for a long time. It hardly seems necessary to point out its importance. We look to technological progress to rescue us from the consequences of exhausting natural resources, to cure lethal diseases, to outsmart our competitors by exploiting new opportunities, to increase our wealth by making better use of the resources we have, to improve quality of life by saving time from things we do not like to do, to provide us with new forms of entertainment, and many other things. Technological progress has brought to us a wealth of tools and utilities that have effectively changed the way we live and work, among them engines, machinery, electricity, airplanes, telephones, computers, and the Internet.

However, the invention of a new technology is only a necessary, not a sufficient condition yet for technical advance. Many new methods and products often find no immediate 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. To understand these processes, one needs to concern issues that are among the more challenging to analyze: Diffusion is dynamic and hence time-dependent, uncertainty is inherent, heterogeneity of enterprises and markets plays a role, specific technological characteristics have to be considered, and imperfections are omnipresent. It is an important and exciting research field, both for economists and business scientists. Because of this, one of the purposes of this text is to look at technological change from both perspectives, trying to bridge the gap between the economics and the management literature on various occasions and drawing conclusions for both audiences.

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 text 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. Related technologies rarely stand alone. 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?

Ever since the end of the "dot.com bubble", there has been a very lively debate about the relevance and the impact of ICT and e-business technologies among economists, business scientists, managers, and in the public media. Therefore, another relevant question in this context is: Does IT matter, and if so, how?

The aim of this work is to make a contribution towards our understanding of these issues.

1.2. Contributions

This thesis contributes to the existing literature in a number of aspects. On the theoretical side, an underpinning of the effects of related technologies is offered. Specifically, it is argued that various factors, such as technological complementarities, learning effects, absorptive capacity and imperfections of financial markets, can lead to increasing returns to adoption. Hence, the probability to adopt any e-business technology is hypothesized to be a strictly increasing function of the number of other e-business technologies that a firm has already installed. As a result, a growing "digital divide" can be expected up to the point where the most advanced firms find no more additional related technologies that promise positive returns on investment. A mathematical framework is offered that makes these thoughts explicit and empirically testable.

On the empirical side, various innovative approaches are employed. To analyze the adoption and diffusion of e-business, a parametric model is always used in the first step to test the mathematically derived hypothesis explicitly. In addition, chapter 5 complements the parametric results with a non-parametric analysis that allows to gain additional insights about the data and provides an indirect robustness check for the parametric model. This non-parametric techniques in chapter 5 is used for the first time to analyze technology diffusion data. The parametric models in chapter 6 and 7 also feature some innovative elements. The discrete time hazard-rate model which is used in chapter 6 allows to control for unobserved heterogeneity of firms. In addition, the model has a semi-parametric specification of the baseline hazard which allows estimation without making the assumption that eventually all firms will adopt each technology as time goes to infinity – a weakness of standard continuous time hazard-rate models for analyzing technology diffusion data. Chapter 7 uses a fixed-effects error component model to estimate firm performance conditional on the market that a firm operates in, thus controlling for unobserved market specific effects. All analyses are based on large-scale survey data that were collected for the *e-Business Market W@tch,* a research project sponsored by the European Commission that had the objective to monitor the uptake and impact of e-business in various sectors of the enlarged European union. The datasets contain very detailed information at the individual firm level and represent population samples from numerous sectors and countries, covering a large part of economic activity in Europe in the years 2002 and 2003.

The results of these studies are also novel and important in their own right. The empirical results support the hypothesis of increasing momentum of development upon a given technological trajectory. Also, the existence of a growing digital divide is shown and its extent is quantified. In addition, in chapter 7 we learn that a substantial amount of innovation is currently related to Internet-based technologies. Also, it is shown that innovations based on ICT are at the very least not inferior to other kinds of innovations. The results suggest that innovative firms and firms that are more advanced in technology usage are more likely to grow. Also, it is found that not all types of innovation are related to profitability. Reasons for this are discussed. Finally, implications of all results are discussed both from an economic and a management perspective.

The original research presented in chapters 5 to 7 is accompanied by two chapters that give an up-to-date overview of the existing literature. All together, I hope that these chapters will be accessible, interesting, and convincing to the reader and possibly contribute to the debate and further research on the nature and the consequences of technological change.

1.3. Outline

The text is organized in three main parts. The first part describes the research topic in detail and provides an overview of what we currently know about technological change by means of an extensive literature review. This first part of the text comprises of chapters 1, 2 and 3. Part two contains chapters 4 through 7. These chapters present the novel research that was conducted for this thesis. Part three concludes the text by summarizing the most important new insights and by providing directions for further research.

The remainder of this first chapter continues with the discussion of the most relevant terminology that will be used throughout the rest of the book. This is necessary to pin down an understanding about the terms innovation, adoption, diffusion, technological progress, and e-business that is appropriate for the purpose of this study.

Chapter 2 gives a literature overview about the consequences of technological diffusion. Starting from a very general perspective, it discusses how technology determines the operating range of an enterprise and possible problems to appropriate returns from investments into new technologies. Then, the interplay between market structure and technology investment is considered. The potential of technology to spur productivity and economic growth is discussed. Closely related but not identical to the concept of productivity is firm performance, which might be measured on various criteria such as profitability, growth, market share, or stock value. Consequently, the relationship between technology investments and firm performance is also treated. Furthermore, the consequences of technological change for labor demand are surveyed. The chapter concludes with a number of implications and hypothesis regarding e-business diffusion.

Chapter 3 gives an overview of various streams of literatures that explain the nature of the diffusion process of technologies, considering findings from micro-economic theory, empirical IO, corporate finance and the management literature. Although technology diffusion is a topic of inquiry in all these fields, we find surprisingly little spill-over of insights between the disciplines. The chapter tries to identify main contributions and overlapping themes of the different streams. It specifies some hypothesis about which factors influence the decision of firms to adopt e-business technologies. In addition, the relationships between technology diffusion and the impact of new technologies are emphasized by showing numerous parallels and connections between the theories discussed in chapters 3 and 4. It is argued that both the diffusion and the impact of new technologies are closely related and that they together comprise an elementary part of technological progress and change. This concludes Part I.

Part II, which presents the original research, starts with Chapter 4 which describes the *e-Business Market W@tch* datasets that were used for the empirical analysis in the following chapters.

Chapter 5 presents a static analyses of e-business adoption. Particular attention is paid to the presence and consequences of related technologies. A theoretical model based on investment-theoretic considerations is introduced which leads to the hypothesis that, under specific circumstances, firms are more likely to adopt if they are already advanced users of e-business technologies. The hypothesis is tested with logistic regressions and in a simultaneous equation model. In addition, classification and regression trees are used to explore technological complementarities and usage patterns in more detail. The three empirical methods that are used in this chapter each provide unique insights into the adoption patterns of related technologies.

Chapter 6 extends the analysis to a dynamic scenario using pseudo-panel data. It tests the same hypothesis as chapter 5 but within a dynamic hazard-rate modeling framework. The results of chapter 5 are supported throughout although the analysis is based on a different dataset collected with other enterprises more than one year later. A formal definition of the growing digital divide is presented and empirical evidence for it is presented.

Chapter 7 tackles the question about the relevance of e-business technologies as a source of sustainable competitive advantage for firms. It is argued that e-business tools enable both product and process innovations. A model of firm performance is developed that controls for unobserved market-specific effects and estimates for the effect of e-business enabled innovations on turnover development, profitability, and employment development are presented and discussed.

Finally, Part III concludes the text with chapters 8 and 9. Chapter 8 summarizes the main findings and contributions. Chapter 9 discusses economic and managerial implications of the findings and suggests directions for future research.

1.4. Terminology

1.4.1. Innovation

The term innovation is widely used in various contexts. However, there is no unique and universally applicable definition for it. Practically, this means that instead of a universally "correct" definition, we must suffice with an understanding of the term that fits the purpose of the analysis. Here, we will need a definition that is broad enough to point out the link between innovation and technological progress, but also explicit enough to distinguish between innovation and related terms, as for example newness.

In common speech, innovation means "the introduction of something new" or "a new idea, method, or device" (Merriam-Webster Dictionary 2003). The precise meaning is usually clarified in the specific context it is used in. For instance, a quite different meaning can be attached to the term in a sociological or a legal context. Compare, for example, the understanding of the sociologist Hagen (1971, pp. 351-361) who views innovation as a factor that allows elites to build up power potentials, or the understanding of the German patent office (Deutsches Patentamt, 2004) about what constitutes an innovative activity.

For the purpose of this study, it is an obvious choice to use a well-known definition from the economics or business science literature. For an extensive discussion of the term innovation from the managerial perspective, see Hauschildt (1997, pp. 1-25). A popular example from the business literature is Rogers (2003) who defines innovation as an "idea, practice, or object perceived as new by the individual or other unit of adoption". The emphasis of this definition is clearly on the demand side of the market. In Rogers view, it is the perception of the customer that decides whether something is an innovation or not. This definition is especially popular for marketing purposes.

Another popular definition often cited in the managerial literature is by Tushman and Moore (1982, p. 132), who define innovation "as the synthesis of a market need with the means to achieve and produce a product that meet that need". This definition is broader than the one suggested by Rogers in the sense that it includes the supply side of the market. However, the focus is entirely on the commercial transaction – the purchase of a new product. The definition does not account for the possibility that an innovation may also occur on the users side as a consequence or a prerequisite of the usage of the new product.[1]

In contrast to many definitions of innovation that focus primarily on the perspective of the seller of a new product, idea, or practice, a more comprehensive definition is needed for the context of this work that allows to identify the relevance of innovations beyond the immediate sales interest of the inventor. An obvious candidate is the broad and popular definition by Schumpeter (1934, p. 66). He describes innovation as the "carrying out of new combinations". Schumpeter restricts this definition to those "new combinations" which are discontinuous, and not simply a small, continuous enhancement of an old combination. He identifies five possible cases:

1. "The introduction of a new good…
2. The introduction of a new method of production…
3. The opening of a new market…
4. The opening of a new source of supply…
5. The carrying out of the new organization of any industry, like the creation or breach of a monopoly position."

Schumpeter's definition is especially valuable because it outlines different dimensions of innovation in the economic and managerial sense. First of all, he does not restrict innovation to one specific functional dimension (e.g. marketing) but recognizes that innovations can occur in practically all spheres of the firm. In fact, his definition of innovation as "carrying out new combinations" is not even limited to the firm environment. They may also occur among individuals or non-profit institutions, although Schumpeter's interest was primarily on production.

Second, his definition includes the subjective dimension of innovation. The judgment of how and in which way the new and the old combinations of means and ends are different, is essentially tied to a subject and her perspective. This is implied in the "five possible cases", which could all relate to one and the same innovation (e.g. the gasoline-operated engine), but depending on the perspective of different subjects, this innovation could be a new good (e.g. the engine from the perspective of Carl Benz), a new market (e.g. from the perspective of all those who see the commercial potential of Benz' innovation), a new source of supply (e.g. for the established manufacturers of coaches), the introduction of a new method of production (e.g. for carters who switch from horse coaches to automobiles as a means of transporting their loads), or the carrying out of the new organization of an industry (e.g. from the ex-post perspective of an outside observer of the coach industry). Consequently, this definition of innovation implies that the question if something is an innovation cannot be answered without asking "new for who". In this way, Schumpeter's definition of innovation generalizes Rogers definition.

Third, Schumpeter raises the issue of different degrees of innovativeness. By limiting his definition to discontinuous new combinations, he clarifies that not everything which is somehow new already qualifies to be an innovation. For example, the invention of the gasoline engine and the development of a new taste variety of a

[1] Other definition from the managerial perspective can be found in Barnett (1953, p. 7), Becker and Whisler (1967, p. 463), Damanpour (1991, p. 556), Knight (1967, p. 478), Rickards (1985, p. 10, 28), Roberts (1987, p. 3), or Schmookler (1966, p. 2).

candy bar can hardly be measured on one scale. It is the discontinuity that distinguishes the one from the other. The gasoline engine actually replaces the horse, the new taste variety only diversifies the spectrum of candy bars. This has led to numerous attempts in the literature to classify different degrees of innovativeness. We find characterizations like “major” versus “minor”, “radical” versus “incremental”, or “basic” versus “improvement”. See for example Green et. al . (1995), who constructed four factors and 17 items to measure the degree of innovativeness.

Fourth, Schumpeter clearly distinguishes between invention and innovation. Invention is a necessary, but not yet a sufficient condition for innovation. Innovation does include the process of invention, but also the introduction of the invention in a market or process. Schumpeter’s five examples of innovativeness all include the notion of a practical use of the invention. The “carrying out of new combinations” requires an actual utilization of a new mean or the achievement of a new end. Thus, what distinguishes innovation from invention is that the former requires a practical use of the latter – an invention must be adopted to become an innovation (instead of just an idea or a prototype).

This broad definition of innovation by Schumpeter allows to take different perspectives on the subject. It seems suitable for our purposes and will be used henceforth.

1.4.2. Adoption and diffusion

Innovation can be viewed as a process (Becker and Whisler 1967, Hauschildt 1997, pp. 19-22) that typically involves stages like

1. first idea
2. discovery/observation
3. research
4. development
5. invention
6. introduction
7. ongoing usage

We can view stages one to five as a breakdown of the invention process, whereas innovation includes stages one to six. Stage seven – the ongoing usage - is a consequence of the innovation, but not part of the innovation itself. The terms adoption and diffusion of innovation refer to stage six of this process – the introduction of a new product or process among members of a social system (a firm, a market, a country etc.). Adoption refers to the individual decision to use a new product or process for the first time. This usually involves some kind of commercial transaction, contract or purchase.

The adoption decisions of different members of a social system are usually distributed over time. Diffusion means the aggregated spread of an innovation in a social system, which is the result of the distribution of individual adoption decisions (Litfin 2000, pp. 19-23). Adoption theory studies the determinants of individual adoption decisions. Diffusion theory expands the analysis to an aggregated, time-dynamic perspective that does not necessarily model the individual decision of each member of a social system. Ideally, however, adoption theory should be the fundament of diffusion theory to have a micro-foundation of the aggregate analysis. It should be noted that the diffusion of a new product or process is an imitation of the behavior of other members of the social system. However, for each individual, the adoption of the new product or process could be an innovation in the sense that it changes her way of doing things or doing a new thing for the first time (subjective dimension of innovation – “new for who”).

1.4.3. Technological progress

For the purposes of this study, the comprehensive definition proposed by Stoneman (2002) is adopted: Technology means the goods and services produced and the means by which they are produced in a firm, industry, or economy. Technological changes mean changes in the goods or services produced and the means by which they are produced. The terms technological change, technological advance, and technological progress are used interchangeably in this text, blinding out the slightly different ethical overtones of these terms. When speaking of technological progress or advance in this text, it is not necessarily implied that this progress or advance will be superior to the previous state in all regards – it simply means change in the economic sense specified above. Technological changes in the nature and types of goods and services produced are called product innovation. Technological changes in the techniques used in production are called process innovation (which includes e.g. changes in machinery, organizational changes, changes in the flow of goods or information, or managerial changes). However, as pointed out above, whether something is considered to be a product or a process innovation is often a question of perspective.

The attention to technology-related phenomena has spread in the last few decades to become an important concern for quite mainstream economic theories, e.g. “patent races”, “new trade theory”, “new growth theory” and even “real business cycle” macro models (Dosi 1997), but also in the managerial community with the emergence of research and teaching fields like “technology management”, “innovation management”, and “R&D management”. The study of technological progress is making steps “inside the black box” (Rosenberg, 1982). We begin to understand technological progress not as an exogenous shock that randomly shifts the supply curve, but as an explicit part of economic dynamics and business management.

The interest of economists to study technological progress was inspired by Schumpeter (1934) who viewed major technological innovations (“the carrying out of new combinations”) as the main source of long-term economic development. He advocated the view that economic development must be driven by forces that exist within the economy itself, and not just by external influences that the economy reacts to (Schumpeter 1934, p. 63): “Should it turn out that there are no such changes arising in the economic sphere itself, and that the phenomenon that we call economic development is in practice simply founded upon the fact that the data change and that the economy continuously adapts itself to them, then we should say that there is no economic development.” In other words, economic development in this sense does not mean history or culture or other influences that are exogenous to the economy. Neither does it simply mean the growth of population or income as a continuous process over time.

“Development in our sense is a distinct phenomenon, entirely foreign to what may be observed in the circular flow or in the tendency towards equilibrium. It is spontaneous and discontinuous change in the channels of the flow, disturbance of equilibrium, which forever alters and displaces the equilibrium state previously existing (p. 64)… These spontaneous and discontinuous changes in the channel of the circular flow and these disturbances of the centre of equilibrium appear in the sphere of industrial and commercial life, not in the sphere of the wants of the consumers of final products (p. 65)... The carrying out of new combinations means, therefore, simply the different employment of the economic system’s existing supplies of productive means – which might provide a second definition of development in our sense (p. 68)“.

From this perspective, the emergence and diffusion of new technologies among firms – thus technological change - is seen as a motor of economic development. This concept of economic development has gained new popularity recently through the very influential endogenous growth literature (see for example Jones 1998 and Romer 1990).

At the micro-economic level, the emergence of new technologies often bring about a myriad of changes that do not end with the adoption of one new technology, but include the adoption of various complementary technologies, accompanied by organizational changes, changes in products and services being offered, prices, quality levels, production processes and changing supplier relationships. The influential theoretical work by Milgrom and Roberts (1990) and Milgrom, Qian, and Roberts (1991) has demonstrated that it is no coincidence that these changes occur together. The key idea is that complementarities exist between technology variables and other key variables of the firm’s strategy, such as organizational design, production and order processes, inventory management, quality and delay of delivery. The firm’s decision to adopt any or all of the possible changes is marked by important non-convexities. Thus, it may be unprofitable for a firm to purchase a technology without adopting a changed marketing strategy or organizational structure, but it might be highly profitable to do all together. One key conclusion from these models is that under the presence of complementarities all sign-adjusted decision variables rise over time within a firm. Another conclusion is that it is plausible to expect coordinated and radical changes in various decision variables simultaneously. Once the adoption is well underway, it should proceed rapidly, with increasing momentum. It can also be shown that innovations in the manufacture of technological inputs both arise as a response to a growing market for those inputs and simultaneously encourage that growth (Milgrom, Qian and Roberts 1991). Complementarities among a group of core activities and processes can lead to a persistent, path-dependent pattern of change. Once the system begins along a path of growth of core variables, it will continue forever along that path, or until external forces disturb the system.

Another interesting and often cited stream of thought is the literature on technological paradigms and trajectories (Dosi 1982), which provide a concept for the direction of development. Dosi suggests that in broad analogy to the Kuhnian definition of a scientific paradigm (Kuhn 1962), technological paradigms can be defined. A technological paradigm is a model or a pattern of solution of selected technological problems, based on selected principles derived from natural science and on selected material technologies. A cluster of related concrete technological solutions can be associated with each technological paradigm, such as nuclear technologies, biotechnologies, or Internet technologies. Dosi calls the pattern and direction of progress based on a technological paradigm a trajectory. Technology, in this view, includes a perception of a limited set of possible technological alternatives and of notional future developments. We can think of the outer limits of a trajectory as the optimal combination of all relevant technological and economic variables, so to speak the production possibility frontier with respect to a given technological paradigm. The emergence of a new trajectory corresponds to the emergence of a cluster of related technological innovations in the Schumpeterian sense. The movement of a firm or an entire economy upon a trajectory can be described by the diffusion of technologies from the cluster within a firm or economy. The economic and managerial relevance of a new trajectory will depend on the scope and the "disruptiveness" of the associated technologies.

Numerous technological trajectories can exist in parallel. Also, trajectories can be more or less general and more or less powerful. In addition, there might be complementarities among trajectories because they require complementary forms of knowledge, experience, skills etc. When speaking of trajectories or technological paradigms in this text, the above given definition of these terms by Dosi (1982) is implied.

1.4.4. E-business

Before we proceed, it must be made clear what we mean by e-business and how it fits into the general framework.

The emergence of the Internet as a new mass medium in the late 1990's combined with a lively public debate about its merits has created a variety of terms to describe Internet-related technologies and activities. Policymakers, industry, and the media used different terms for the same concepts, and also often attached different meanings to the same terms. As a consequence of the initial confusion, there were numerous efforts lead by various statistical authorities and international organizations (e.g. OECD, European Commission, U.S. Bureau of the Census, Statistics Canada) to come up with a clear and consistent definition of terms as a first step for developing useful statistics to measure the "digital economy" (Mesenbourg 2001, p. 3; OECD 1999, pp. 7-9; EITO 1999, pp. 169-170; Atrostic et. al. 2001).

The existing definitions can be seen as differing in three key elements that they usually cover (OECD 1999, p. 10):

1. activities/transactions,
2. applications,
3. communication networks.

These three key elements are identical to the different dimensions that e-business comprises: A technological communication infrastructure, one or more (software) applications that run on this infrastructure, and the actual usage of the applications. The earlier definitions of e-business and e-commerce varied for example with the activity (e.g. retailing or delivery occurring electronically), the application (e.g. fully integrated online shop or an online catalogue with a simple email form), or the communication network they referred to (e.g. Internet or EDI). In addition, there has been a debate about the scope and the relationship of the terms e-business and e-commerce.

For the purposes of this text, it is useful to stick to the definition given by the European e-Business Market W@tch (2003), because the survey data for the empirical analysis in chapters 5 till 8 stems from this research project. The definition of the e-Business W@tch project is officially used by the European Commission (who initiated the project) and closely relates to the definitions suggested by the OECD and the U.S. Bureau of the Census. This ensures a wide acceptance in countries that follow OECD standards. Also, with this back-up by official authorities, the definition used here seems to become increasingly accepted in research and business practice as well.

The e-Business Market W@tch defines e-business as any business process that an enterprise conducts over non-proprietary computer networks, which relates both to external and to company internal processes. The understanding of the term e-business is such that is does not only describe external communication and transaction functions, but also relates to the flow of information within the company, i.e., between employees, departments, subsidiaries and branches. As distinct from this, e-commerce is taken to cover external transactions only, and it therefore might be conceived as a subgroup of e-business activities (see Figure 1).

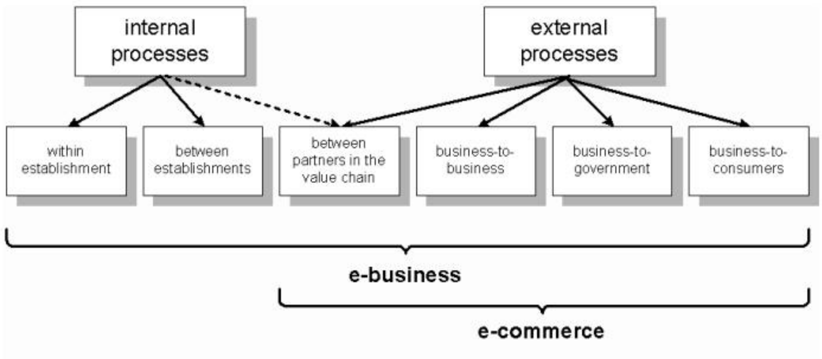


Figure 1 - Basic concept of “e-business” and “e-commerce”

The definition given above limits the scope of the terms e-business and e-commerce to the usage of non-proprietary networks (i.e. the Internet) for conducting transactions. The distinction was maintained by the e-Business W@tch team to be able to investigate the specific consequences of non-proprietary networks, which can be very different from using proprietary networks such as EDI (Cohen et. al. 2001).

The related term “information and communication technology” (ICT) refers in this context to the technological infrastructure or the tools of e-business, rather than to the processes associated with their usage. ICT can also be proprietary technologies (e.g. networks, computers, software, or proprietary CAD technologies). The use of ICT in business processes leads to e-business, if non-proprietary networks are used.

Other than the restriction to non-proprietary network technologies, the e-business definition used here is very broad by including any kind of business process that occurs within an enterprise or between an enterprise and external parties. The meaning of the term is explicitly not restricted to commercial transactions in the legal sense, but also includes other means of exchanging information in a commercially relevant way, for example for the purpose of optimizing logistics, sharing knowledge, or employee training. This broad definition has the advantage that for the purpose of analyzing the impacts of e-business, the attention of the investigator is not hastily restricted to a limited set of Internet-supported activities or applications that might ex post not turn out to be the most relevant.

How does e-business fit into the framework outlined above? Is it an innovation? If so, how “major” or “disruptive” is it? Is it part of technological progress in the sense of Schumpeter, Milgrom and Roberts, or Dosi?

An innovation in the Schumpeterian sense as “carrying out of new combinations” requires the utilization of a new mean, the achievement of a new end, or both. When a firm adopts an e-business solution it usually transfers parts of an existing process into a new process that is supported by the new Internet-technology. It changes the way of doing things. For example, when a firm adopts an e-learning solution, a part of the training activities could be shifted from the seminar room to the computer desktop of the employees. In our terminology this is the utilization of a new mean – a process innovation. Such a process innovation naturally requires more than simply the purchase of a particular software. In practice, the purchase of a specific e-business tool is only the first step in a longer implementation process that usually comprises

- customization of the software,
- implementation into the existing communication network,
- definition and implementation of interfaces of the new software with legacy software systems and data,
- development and integration of suitable content,
- re-engineering of business processes,
- and various training measures for employees to familiarize them with the new tools and routines.

A process innovation only occurs if the implementation succeeds, the routines are changed, and the new system is actually utilized.

The adoption of an e-business solution may also lead to the achievement of a new end, for example if the usage of the technology is the prerequisite for a new product or service offer that can be successfully introduced to the market (e.g. Internet auction platforms like Ebay – in this case the service innovation occurred simultaneously with the emergence of a new enterprise and a new market). Online banking is an example where the utilization of a new mean and a new end happened simultaneously. It is a product or service innovation to the customer that allows her to access her banking account and conduct financial transaction 24 hours a day from any Internet-terminal in the world, independent from bank branches and opening hours. To the bank, it is a process innovation because it automates the processing of customer transactions.

From these examples it becomes clear that e-business fits into the definition of innovation as the “carrying out of new combinations”, given that the implementation and utilization of the technology-supported new processes or the introduction of the technology-supported new product or service to the market actually succeed.

Further considering the functional dimension, one can find e-business solutions for practically all spheres of the firm (see Table 1). This illustrates that e-business offers a wide range of innovation potentials, again corresponding with the broad Schumpeterian definition that did not restrict the innovation term to a specific function of the firm.

Table 1 - Examples of e-business solutions for various functions of the firm[2]

E-business solution	Typically corresponding function of the firm
Online sales	Marketing / sales
E-procurement	Purchasing
Supply chain management (SCM)	Purchasing / logistic / production
E-marketplaces	Purchasing / sales
Customer relationship management (CRM)	Marketing / customer service
Knowledge management (KM)	Human resource management / R&D
Enterprise resource planning (ERP)	Accounting / controlling / logistics / purchasing / sales
E-learning	Human resource management
Group ware	General management / R&D

[2] The examples listed in the table only refer to those solutions which run on the Internet, i.e. fulfill our definition of e-business that is restricted to non-proprietary network technologies.

For the sake of completeness, different subjective dimensions of e-business innovation can be identified. Let's consider the example of e-learning, which is the usage of online, Internet-based technologies to support employee training (E-business W@tch 2003, Köllinger 2002, pp. 15-19).

E-learning can be a *new good* for the producer of a learning software platform (e.g. Saba, Docent) or a *new service* for an education content provider, who switches to this new distribution channel (e.g. globalenglisch.com, University of Phoenix). It can be a *new market* for all those who see the commercial potential of e-learning (e.g. SAP – a late mover into the market for e-learning software platforms, or NETg – an e-learning firm with origin in the United States who expanded into Europe as a new market). E-Learning can also be viewed as a *new source of supply* by those companies that add e-learning modules to their employee training curricula (e.g. Daimler-Chrysler corporate university). It may also be considered as a *new method* of knowledge generation, both from the perspective of the individual learner and the perspective of the firm that organises and conducts trainings. Finally, it may also be seen as a source for the *new organization of an industry* – the market for professional training services has seen quite a restructuring since the emergence of e-learning. Market shares have shifted from traditional training methods to e-learning and to new industry players, while incumbents reacted with different strategies to the new possibilities and threats (Köllinger 2001, pp. 63-72; IDC 2000).

One could easily formulate similar cases for other e-business technologies. It becomes obvious again that the question if something is an innovation cannot be answered without asking "new for who". In addition, it also shows that whether one views e-business as a product or a process innovation is essentially a matter of perspective.

The previous discussion leads to the following understanding of e-business:

An e-business technology may be viewed as

- a product innovation or a new market from the perspective of the suppliers, if their technological inventions are successfully introduced to the market;
- an enabler of process innovation from the perspective of the adopter, if the implementation of the e-business technology succeeds, the routines are changed, and the new system is actually utilized; or
- an enabler of product or service innovation from the perspective of the adopter, if the e-business technology is successfully used to offer a new service or deliver products to customers in a way that is new to the enterprise.

Note that in all three cases the definition of e-business as an innovation is conditional on certain restrictions. This is especially important for the perspective of the adopter. For the adopting firm, the technological solution is only a tool to enable innovation, the purchase of the tool itself does not constitute an innovation yet. Thus, the question if and to what extent e-business technologies are actually used to conduct innovations on the side of the adopters is already an empirical one.

This leads to the question how "disruptive" or "major" e-business-enabled innovations might be. From the previous discussion we know that e-business offers a wide range of innovation potentials, spanning over many functional areas of each firm. In addition, many of these e-business solutions can be applied in various sectors of the economy, so the scope of the innovation potentials for the economy is also very broad. However, whether we observe major changes occurring due to the adoption of e-business technologies essentially depends on how each individual firm deals with the available technologies. The e-business induced changes that are possible in each firm can be quite radical, but they may also be incremental. In the worst case, an e-business investment may also turn out to lead to no changes or to no desired changes (i.e. a writing off). In practice, we find that some firms rely very heavily on Internet-supported processes (e.g. Dell, E-bay), whereas others don't. Thus, the question whether e-business is a "disruptive" innovation in the Schumpeterian sense that acts as a driver of economic development is actually also an empirical one. Chapter 7 will discuss this issue in more detail, based on empirical results.

Interestingly, many aspects of e-business seem to comply with the assumptions in the model of Milgrom and Roberts (1990). We are faced with a number of new technologies that can serve different purposes within firms, but are all members of the group of ICT's that use the Internet as a communication platform. We may expect that some of these technologies will be complementary to each other and to other decision variables of the firm, such as flexible production schemes, automated supply chain management, quicker engineering and production times or customized marketing activities. This would mean that it is plausible to expect path-dependent developments and increasing momentum once the adoption of some core variables is under way.

Finally, how does e-business relate to Dosi's concept of technological paradigms and trajectories? Recall that Dosi (1982) defines a technological paradigm as a model or pattern of a solution of selected technological problems, based on selected principles derived from the natural sciences and on selected material technologies. Following this conceptual framework, we could define e-business as a cluster of related technological innovations that are jointly based on the Internet. The technological problem that all e-business solutions try to solve is to optimize the exchange of commercially relevant information, which is essential for running and controlling any business. They do so by providing specific software solutions that run on non-proprietary computer communication networks with a universally standardized protocol (TCP/IP). In this sense, e-business is a technological paradigm with a very general scope, because it's "normal problem solving tools" are applicable in various regions, sectors, firms, and functional areas. The normal course of development along the e-business trajectory starts with the non-availability of any technology from the e-business cluster within a firm or country, progresses with the adoption of various technologies, and possibly ends with adopting all available e-business tools. Note that this is not a deterministic process. Not all firms need necessarily adopt all technologies that are associated with a given paradigm. However, the rate of progress upon a trajectory can be related to the position of a firm upon the trajectory because of complementarities, learning effects, rebates and financial consequences of earlier investments. Chapters 5 and 6 will discuss this in detail.

2. Consequences of technological diffusion

An extensive amount of research has been conducted on the consequences of the emergence of new technologies (for an overview, see for example Stoneman 1995). The purpose of this chapter is not to give a complete treatment of all relevant contributions to this topic, such an endeavor would be clearly beyond the scope of this text. Instead, the purpose is to point out some important topics that have been demonstrated to be directly related to technological change in general in order to identify possible consequences of e-business technologies. Some of the emerging issues can be addressed in later chapters, while most will necessarily remain subject to further research.

2.1. Technology and the supply function

The technological environment is fundamental to each firm and the entire economy because it determines the available operating range of each individual enterprise. In micro-economic theory, firms are endowed with production-possibility sets, which are determined by the available technology. Producers maximize their profits over these technological possibilities, giving rise to supply functions (Arrow and Debreu 1954, Mas-Colell et. al. 1995, ch. 5, Tirole 1988, Varian 1992, ch. 1). From this general starting point, it is obvious that the technological environment influences all areas of economic activity. Technology determines the types of products and services being produced in an economy and the optimal combination of machinery and labor to produce these outputs. It also influences market structures. For example, whether a technology is convex or not will have an influence on the expected market structure and competitive dynamics of an industry. Technology also influences the equilibrium conditions in each market, and thereby market prices, aggregate output and the distribution of social welfare. This implies that not only the profits of the firms operating in a given market depend on the technology used, but also consumer welfare. Hence, technology is a crucial element for the living standards in an economy.

The largest part of economic theory takes technology as exogenous and derives equilibrium conditions given a particular technology (i.e. cost function). It is implicitly understood by economists that technology is a fundamental aspect of economic activity, but it is mostly treated as a "black box". However, there is also a substantial part of the literature that considers the incentives and consequences of technological change explicitly. Examples are the research on R&D incentives, patents, licensing, technology diffusion, new growth theory and real business cycle theory (Geroski 1995, Beath et. al. 1995, Romer 1996, ch. 3 & 4, Stoneman 2002).

Technological change always comprises of several parts. The first part is the emergence of a new technology, which is a product innovation from the point of view of the firm producing the technology. A new technology can either emerge as a consequence of a deliberate research and development effort, but it can also emerge as a by-product of some other activity or by pure chance. The second part is the introduction of the new technology among other firms. By adopting and implementing the new technology, user firms try to change their way of production, which constitutes a process innovation. Alternatively, user firms can also adopt the new technology to create a new product or service for their customers, which constitutes a product innovation. Finally, both product and process innovations can occur simultaneously on the side of the technology-adopting firm if the implementation succeeds.

In micro-economic terms, a product innovation corresponds to the generation of a new production function (Kamien and Schwartz 1982, p.2), or alternatively leads to product differentiation (Beath et. al. 1987, Shaked and Sutton 1986, Vickers 1986), depending on how new the product is.

A process innovation, on the other hand, can be viewed as an outward shift of an existing supply function, which is normally modeled by assuming that the new technology will lead to lower variable costs in the production of an existing good or service (Beath et. al. 1995, Dasgupta and Stiglitz 1980, Reinganum 1981 a,b).

The possible consequences of a successful product or process innovation that are induced by a successful implementation of new technologies create market adjustments that can yield competitive advantages for the innovative firm. The prospect of these advantages triggers the investment into new technologies and the associated diffusion process. The nature of these closely interdependent incentives, decisions and market adjustments is further discussed in chapters 2.3, 2.4, 2.5 and 3.

2.2. Appropriability problems

A relevant and non-trivial question is who will benefit most from an innovation. Apart from the literature that emphasizes the actual products and processes used in an economy when talking about innovation and technological change, it is also not uncommon to think of technology as generic knowledge or information that is generated by investing into R&D (Stoneman 2002, 4-6, Geroski 1995). Typically, the terms knowledge, information, invention, innovation and technology are inexactly treated as synonyms in such contexts. Although this is not the approach that is followed throughout this text, it does have some merits because it points out potential problems for incentives to invest into technology and the ability of innovators to benefit from their investment.

The main argument is that knowledge and information have to a large degree attributes of a public good. Information may be non-rivalrous in the sense that its use by one firm does not automatically preclude the use by another. It may also be non-excludable if the producer of the new knowledge is unable to effectively prevent non-payers from using it. Patents are one way to assign property rights to knowledge. However, not all commercially valuable knowledge complies to the legal standards required for getting patent protection. Thus, a successful inventor may involuntarily create a positive externality for the market without being able to get a private benefit from the R&D investment. Hence, the production and dissemination of new knowledge or information might be subject to market failure and create problems for the inventors.

If the use of information by one firm does not preclude the use of the same information by another firm, the sale or involuntary transfer of the new information by the inventor instantly destroys her monopoly (Geroski 1995). Also, a potential buyer of the information will have difficulties in judging the value of the information before it is revealed. However, at the moment the information is revealed there is usually no additional value in purchasing it. Thus, the inventor is unlikely to recoup her investments into generating the new information, which creates a disincentive to invest. This constitutes a potential for market failure because everyone might be better off with the new information than without it, but the incentives to invest are small if social returns exceed private returns on investment.

In addition, market failure might arise because the creation of knowledge often involves substantial fixed costs which lead to increasing returns to scale. Also, knowledge and information are inherently discrete, which usually prevents marginal pricing and also implies economies of scale even if the information can be perfectly codified and protected with a patent. Finally, investments into the generation of new knowledge is risky in two ways. First, the inventor has ‘technological’ uncertainty about how to make something work. Second, there is the additional uncertainty about how to sell the new idea on a market (i.e. how to turn the invention into an innovation). This double uncertainty might be another cause of market failure for the investment into new technology (Arrow 1963, Geroski 1995, p. 91)

Thus, there are numerous potential problems for an inventor to appropriate returns from her investment into new knowledge. On the other hand, according to Geroski (1995, p. 93) there are two reasons why these problems may not be so severe in practice:

First, the appropriability problem depends on the extent that the transmission of knowledge is costless. As soon as the acquisition of knowledge becomes a cost factor for whatever reason, knowledge loses the non-excludability attribute and increases the chance of the inventor to yield a private return. The second reason why information and knowledge are often not public goods is because many new ideas can be embodied in an output sold as a new product or service. Naturally, it is much easier to claim property rights over and charge for things or services than for ideas or concepts.

The costs of transmitting a new technology (voluntarily or involuntarily) are rarely actually zero. It seems clear that the costs of transmission depend on the nature of the technology. They tend to increase with complexity, the rate of change, and the degree to which the technology relates to other complementary or specialized assets of firms and their degree of experience (Geroski 1995, p. 117). Also, the ease of transmitting knowledge tends to decrease if the nature of the knowledge is more tacit than explicit, and hence cannot be easily codified.

However, even if the public goods characteristics of an invention can be effectively circumvented by whatever means, this does not yet guarantee that the inventor will be able to appropriate private returns. MacDonald and Ryall (2004) have shown in a formal analysis based on coalition games that even if a technology or innovation takes the form of a valuable, rare, and imperfectly imitable firm-specific asset, this does not guarantee private returns of the owner of the technology. They show that a non-imitable resource is neither a necessary nor a sufficient condition for profitability because the ability of a firm to appropriate private returns also depends on how consumers value the product of the firm and whether there is competition for the product on the consumers side. In other words, the firm must also be able to effectively restrict its supply such that some consumers who would value the product are not served. On the other extreme, even if the technology would be perfectly imitable, this does not rule out that firms might appropriate excess returns in case they have another scarce resource, such as production capacity (i.e. if all firms together cannot serve all customers although the technology is common knowledge). Only if there is perfect imitation and no scarcity of supply, no firm will be able to gain profits irrespective of their bargaining skills and customers will appropriate all value. The point is – even if a successful innovator is perfectly able to circumvent the public goods problem of his invention, this does not automatically solve his appropriability problem.

In the case of e-business technologies, technology suppliers have found many ways to circumvent the public goods problem. The new "knowledge" about how to run certain business processes based on Internet technologies is usually embedded in products (hardware and software) and consulting services (customization, implementation, migration, training, and supervision), which can be sold. This does, however, not imply that all technology suppliers can be profitable, but at least they are not unprofitable because of a disability to exclude customers from the usage of their innovations.

Whether the users of the new technology are able to appropriate private returns from their investments into the new technologies and the corresponding process innovations is even less clear. Let's assume some industry is characterized by all firms originally using the same (old) technology. Each of these firms might originally be profitable or not. Now a new technology arrives that makes production more efficient and could in principle be bought by any firm in the industry (hence it is non-exclusive and represents some generic new knowledge, such as a standardized enterprise software solution that contains a set of proven best practice business processes). The question is if adoption of the new technology will allow a firm to benefit from the investment, i.e. to yield private returns exceeding the original returns. The answer to this question depends on the timing of adoption decisions. For example, it can be shown that under monopolistic competition, firms that successfully introduced a new production process are only able to get private returns from their investment as long as their competitors have not also adopted the same process (Götz 1999). If all firms adopt immediately, no firm will get excess returns and all benefits will be passed on to consumers. Firms that do not adopt, however, will lose market share and will eventually be driven out of business.

The story changes, however, if firms are not completely homogeneous ex ante and if the new technology closely relates to complementary or specialized scarce assets, such as managerial competence, the presence of rare technical experts, or a high level of technological experience among employees. In such a case, only firms that posses the necessary complementary scarce resources will be able to benefit from the new technology. Or, in other words, the value of the new technology is not identical to each firm in the market. It could also be that the technology is not generic, but can be customized to suit individual needs of companies, thus making it more difficult for rivals to imitate. This opens up the possibility to create a scarce resource that cannot be easily copied by rivals, thus increasing the chance to appropriate private excess returns, provided that there is some degree of competition for the product on the consumers' side.

The bottom line for the users' side thus is: adopting generic "best practice" e-business solutions will at best generate temporary excess returns, as long as competitors did not successfully copy the same practice. Sustainable advantages that are due to e-business technology can only be achieved in two ways: (1) if the technology can be customized, complementing some other scarce resource of the firm, thus limiting imitation; or (2) if the technology can be used to innovate a new product or service offer that is valuable to customers and cannot be perfectly copied by competitors.

A number of empirical studies have dealt with different methods of appropriability and their effectiveness. Levin et. al. (1987) find that for new processes lead time (early adoption) and learning curve advantages were most effective in securing private returns, followed by secrecy about the new process and marketing related advantages. Patents were found to be least effective for appropriating returns from new processes. For new products, patents turned out to be more important, but still not as effective as lead time, learning curve and marketing advantages. Taylor and Silberstone (1973) found that the influence of various measures also varied from sector to sector. For example, patents seem to work better in the pharmaceutical industry and the manufacturing of other chemical products than in other sectors.

Another relevant issue in this context is the imitation time that firms need to copy the action of the first innovator. Mansfield (1985) found that rivals learned about decisions made to develop new products or processes some 12-18 months after the decision has been made. Considering the average development process, which takes about 2-3 years to complete, there is a very good chance that the news will leak out before the project is finished (Geroski 1995, p. 107). If, however, the innovation is readily codified and can be purchased as a technology from some provider (as in the case of many e-business technologies), the imitation time might be considerably lower and thus the diffusion process of the technology faster than in the study by Mansfield (1985).

Summing up, the research on appropriability problems has pointed out that investments into technology might be subject to market failure for various reasons. One important reason is that the inventor could be unable to exclude non-payers from copying the invention. In this case, the social returns to the invention might exceed the private returns and hence create no incentive for the potential inventor to invest. This incentive problem wears off if the inventor is able to embed its new idea in a new product or service that is valuable and scarce for customers, or in case of a new process ceases with the complexity of the technology and its relation to other complementary and scare inputs, such as specialized labor. To profit, the innovating firm must at least gain a temporary monopoly position which will be destroyed once competitors are able to perfectly copy the innovation and serve all customers in the market. Hence, lead time, learning curve advantages, secrecy, patents, capacity constraints, marketing related advantages, and other scarce complementary resources of a firm can contribute towards securing private returns on investment and overcoming the appropriability problem.

2.3. Market structure

The relationship between technology, innovative activities and market structure is complex and has been subject of extensive research in the industrial organizations literature. The results of these ongoing research activities are relevant both for policy makers (for defining competition policies that ensure dynamic efficiency) and business managers (for choosing optimal innovation strategies to gain profitability and to survive in the market).

Technology influences cost structures and, thus, plays an important role for determining market structure. This is a one-directional relationship. However, the relationship between technology and innovation on the one hand, and market structure and innovation on the other is a two-directional relationship. While the present state of technology influences the range of possible future technological development by means of successful innovation, the occurrence of successful innovation changes the technological environment. Furthermore, a given market structure influences firms' incentives to invest into innovative activities. Successful innovations, in turn, might initiate changes in market structure by stimulating the growth of the successful innovator at the expense of its rivals or changing the minimum efficient plant size for operation in a market, hence leading to a rise or fall in industry concentration. Thus, technology, market structure and innovative activity are all endogenous variables in dynamic models of market development (Scherer 1980, p. 5).

Market structure is determined by the size of the market, the number of firms in the market, and their size class distribution. The optimal size of firms in a market is given by the shape of their cost function, which depends on the presence of economies of scale and scope. The size of the market is related to the position of the demand function, which might be subject to network externalities. The interaction of the aggregate supply and demand function pose limits on the feasible number and size distribution of firms in equilibrium. Thus, they shape the boundaries of the industry market structure.

According to Panzar (1989), an industry configuration is a number of firms, *m*, and related output vectors $y^1, y^2, ..., y^m$ such that $\sum y^i = Q(p)$, where *p* is the vector of market prices and $Q(p)$ is the system of market demand equations. Thus, supply equals demand. An industry structure which is sustainable in a long-run equilibrium must guarantee that firms in the industry make at least zero profits. Thus, if an industry structure is to be feasible, the market demand curve must not lie to the extreme left of the firm's average costs curves. Formally, a market structure is feasible if $p \times y^i \geq C(y^i) \; \forall i$, i.e. no firm in the market makes negative profits.

However, not all feasible industry structures will be sustainable. In fact, for some markets, industry configurations with one, two, or a thousand firms might all be feasible. In order to be sustainable, an industry structure also needs to be efficient. Efficiency of an industry can be defined as

$$(2.1) \quad \sum_{j=1}^{m} C(y^j) = \min_{m, y^1, ..., y^m} \sum_{j=1}^{m} C(y^j) \equiv \sum C^I(y^I),$$

where $y^I \equiv \sum y^j$ is the total industry output and $C^I(y^I)$ is the industry cost function. Therefore, according to Panzar (1989, pp. 34-35) an industry configuration is efficient and sustainable if and only if it is made up of a number of firms and a division of output that yield the lowest possible total industry costs of production. However, as the technological environment changes, the cost functions and / or the output vectors of firms begin to change and an industry structure that was feasible and efficient in the past might not be sustainable anymore. This could lead to exit of enterprises from the market and greater concentration or encouraging new entry and higher competition.

To reiterate, the feasibility and efficiency of a market structure at any given point in time is given by the shape of the cost function of firms and the demand function of the market. The dynamic structure of a market, however, is influenced by the interplay of firms' incentives to invest into innovation, their ability to appropriate returns from their investments, and possible shifts in the demand function of a market.

To elaborate on these issues in more detail, the following two sections will look at economies of scale and scope as factors that influence the shape of the cost function. The section after that looks at network externalities as a factor that influences the shape of the demand function. Thereafter, the interplay of market structure and innovation are discussed in more detail in two sections.[3] A special section is the one on technology competition, which takes a game-theoretic approach to analyze firms' strategic incentives to invest in R&D and analyses the market outcomes of such games. The following section mentions additional factors that can influence the dynamic relationship of innovation, technology, and market structure. Finally, the last section summarizes the main results and relates them to the diffusion of e-business technologies.

2.3.1. Economies of scale

The limits of perfectly competitive market structures have frequently been attributed to technological constraints and cost structures resulting from them. It is argued that costs determine prices and, thus, influence industry structure (Hay and Morris 1991, p. 27). The notions of economies of scale and scope are important in this regard because they imply that the size and the product range of a firm influence their cost structure.

According to the standard definition, economies of scale are present in a single product environment when an increase in all input levels is followed by a more than proportional increase in output (Panzar, 1989). Economies

[3] Nepelski (2003) discusses some of the literature mentioned in sections 2.2.2. to 2.2.5 to analyze whether the diffusion of e-business technologies in the automotive industry relates to an increase in industry concentration.

of scale can be measured as the ratio of average costs to marginal costs. If total the cost of aggregate output *Y* at factor price *w* is represented by a simple cost function $C(Y,w)$, then average costs are defined as $AC = C(Y,w)/Y$ and marginal costs as $MC = dC/dY$. The degree of economies of scale is given by $S(Y,w) \equiv AC/MC = \{C(Y,w)/dC/dY\}$. If $S(Y,w)$ is greater than, equal to or smaller than 1, the firm faces increasing, constant or decreasing returns to scale (Bailey and Friedlaender 1982).

Economies of scale might occur for various reasons. For example, product-specific economies occur if a higher production volume of a product leads to a better utilization of available resources, like facilities, managerial staff, or R&D. They also occur if the marginal costs of an additional unit are close to zero, but the production of the first unit involves substantial fixed costs. This is typically the case in all content industries (music, newspapers, magazines, radio, television) where the production of the content is very costly, but the distribution of the content to an additional customer has costs close to zero. Economies of scale might also be plant-specific, where the construction of a big plant might be less expensive relative to its output than the production of a small plant. Finally, economies of scale might also be present when multiple plants are operated by a single firm where some organizational elements (management, personnel, R&D or technology adoption) might be utilized by more than one plant, hence leading to a cost reduction in output size.

Note that economies of scale depend on the available technology. Hence, a change of the technological environment might lead to changes in the degree of scale economies.

Economies of scale exist in many industries (Scherer 1980). Yet, in most production or distribution activities a firm reaches a point at which further cost reductions arising from size or production increase are exhausted. Any further expansion beyond this point would result in diseconomies of scale (Scherer and Ross 1990, p. 102). The point at which the average cost attains its minimum represents the industry minimum efficient scale (MES), which plays a key role in determining industry structure (Schmalensee 1988, p. 653). The MES determines the optimum firm size that, together with the total industry size, determines the optimum number of firms in a market (Curry and George 1983, p. 217).

The presence of strong economies of scale in an industry creates significant entry barriers (Bain 1956, p. 55) and leads to high market concentration or even monopoly outcome. However, as Panzar (1989, pp. 24-29) pointed out, economies of scale are neither necessary nor sufficient conditions for sustaining natural monopoly. The perquisite for a natural monopoly is a cost function that is strictly subadditive over the entire range of outputs. Formally, a cost function is said to be subadditive if $C(\sum Y^i) < \sum C(Y^i)$, where each proportion of Y^i may range over all levels of output up to $\sum Y^i$. An industry is a natural monopoly through the output level Y if $C(Y')$ is strictly subadditive at all $Y' \leq Y$, i.e. if up to output level Y it is cheapest if only one company produces everything.

The theoretical importance of economies of scale as a determinant of industry structure has been supported by empirical research. For example, in the meta-study by Curry and George (1983) it was found that all surveys confirmed a significant relationship between economies of scale and industry concentration. Technological factors also seem to explain the observed similarity across analyzed countries in the ranking of industries by concentration level.

2.3.2. Economies of scope

Cost savings cannot only arise from the size of an enterprise, but also from its scope of activity. Whenever the costs of providing the services of the sharable input to two or more product lines are subadditive, the multiproduct cost function exhibits economies of scope (Panzar and Willig 1981). For the two product case, this can be formally expressed by $C(Y_1, Y_2) < C(Y_1, 0) + C(0, Y_2)$ where Y_1 and Y_2 stand for the outputs of product 1 and 2 respectively. The measure of the degree of scope economies is simply a proportion of the total production cost that is saved by joint production to total costs $S_c = \{C(Y_1,0) + C(0,Y_2) - C(Y_1,Y_2)\}/C(Y_1,Y_2)$. Economies of scope are present if S_c is greater than 0. If economies of scope exist, firms with a diversified product mix enjoy lower total costs than total costs of firms specializing in single products (Bailey and Friedlaender 1982).

There are various reasons why economies of scope might occur. First, it might be that some production factors are not scarce and hence can be used for the production of various goods or services. For example, a reputable brand name might give rise to economies of scope. Second, it could be that different products share the same scarce inputs, and cost advantages arise from producing more than one kind of product if spare capacities of the joint input exist. For example, this could be managerial competence or a good communication infrastructure of a company. Third, it could be that there are cost complementarities between different outputs, i.e. when the marginal cost of producing one good falls as the production of the other good increases. Examples for this can be found in the chemical industries when one product is the byproduct of another.

Again, the presence of economies of scope is influenced by the technological environment and changes in technology might change the level of economies of scope. Since most firms offer more than one product, the concept of economies of scope seems to be of great significance. However, in contrast to economies of scale, there is little empirical evidence for the presence of economies of scope. One reason for this are measurement problems. Baumol et. al. (1982) have pointed out conditions for correct measurement. But for a few exceptions, there have been little attempts to implement them in empirical research and the available evidence is inconclusive (Hay and Morris 1991, p. 37).

2.3.3. Network externalities

The presence of network externalities is yet another factor that can influence market structures. It relates to the shape and the position of the demand function for a new network-based technology. Generally, an externality is said to be present whenever the well-being of a consumer or the production possibilities of a firm are directly affected by the actions of another agent in the economy (Mas-Colell et. al. 1995, p. 352). Externalities can be positive or negative. Networks exhibit positive consumption and production externalities (Economides 1996a). Network externalities are a concept that is directly related to technology, in particular technological infrastructures that are organized as networks, i.e. components which are physically or virtually linked like railways, telephone lines, or the Internet. A network externality occurs if the components of a network are compatible, hence if linking the components gives rise to complementarities (Economides 1996a). The value of such a network depends on the number of components that are connected to it. For example, in a telephone network each owner of a telephone is a component in the network and the value of the network to each user is the greater the more other users have a telephone. If such a network has *n* users, then there are $n(n-1)$ potential components, i.e. people one could call if the components are compatible. Thus, the value of the network is proportional to $n(n-1) = n^2 - n$, hence it increases exponentially in the number of users. The willingness of each potential user to join the network and her willingness to pay for it consequently depend on the expected number of other users (Shapiro and Varian 1999, p. 184, Economides 1996a).

When a new network technology is introduced to the market, the eventual market outcome depends on customers' predictions about how the network will evolve. Consequently, there will be feedback loops and numerous equilibria are possible, i.e. either a zero size network or a large network size might emerge (Katz and Shapiro 1985, 1992, Economides 1996b). If two or more alternative network technologies are introduced to a market, the market outcome might be characterized by a "winner takes all" scenario and a lock-in by historical events (Arthur 1989, Church and Gandal 1993, David 1985, Katz and Shapiro 1986). An interesting question in this regard is whether the producers of competing technologies should risk a standards war or opt for compatibility of their systems (Besen and Farrell 1994, Farrell and Saloner 1986, 1992, Katz and Shapiro 1985, 1994). The research on this topic has shown that although network externalities occur on the demand side of a market (sometimes they are also referred to as demand side economies of scale), the presence of these effects has far reaching implications for the market structure on the supply side, strategic behavior of technology suppliers, and the efficiency and desirability of the market outcome.

Furthermore, positive externalities might not only occur among consumers, but also among firms in vertically or horizontally related industries. This could be a possible source of increasing returns to scale. To see this, consider the following example by Mas-Colell et. al. (1995, pp. 374-375):

Consider a bilateral externality situation involving two firms. Firm 1 may engage in an externality-generating activity that affects firm 2's production. For example, this could be a specific output, knowledge, or the utilization of a communication technology that firm 2 also uses (whereby firm 1 provides additional value to the communication network). The level of the externality generated by firm 1 is denoted by *h*, and firm *j*'s profits conditional on the production of the externality level *h* are $\pi_j(h)$ for $j = 1, 2$. It is standard to assume that $\pi_1(\cdot)$ is concave, hence that firm 1 is subject to decreasing returns to scale. However, this may not automatically be true for firm 2 also.

Suppose that firm 2 produces an output at price 1, using an input at price 1 also. Firm 2's production function is $q = h^{\beta} z^{\alpha}$, with $\alpha, \beta \in [0,1]$. Thus, *h* is a positive externality. Given *h,* the maximized profits of firm 2 can be calculated as $\pi_2(h) = \gamma h^{\beta/(1-\alpha)}$, where $\gamma > 0$ is a constant. If $\beta > 1-\alpha$, than firm 2's profit function is *not* concave in *h* and firm 2 exhibits increasing returns to scale because $\alpha + \beta > 1$. Thus, if firm 1 increases the production of the positive externality *h*, it is profit maximizing for firm 2 to increase its scale rather than just substituting *h* for *z*.

The above discussion allows to formulate some possible implications for the diffusion of e-business technologies. First of all, e-business technologies are likely to be subject to network externalities because they are communication tools that are jointly based on the Internet. The Internet itself clearly features network externalities: The more individuals and firms use the Internet, the more valuable it becomes. The same is true for each e-business technology that is installed in a firm. The value of these technologies usually increases the more individuals make use of them. For example, the value of a knowledge management system, an online marketplace, or an e-procurement system clearly increase with the number of users. Furthermore, as far as systems are compatible between firms, positive externalities generated by an additional user within a firm or a new firm joining the network spill over to other firms. This has three implications: First, the more firms jump on the "e-business wagon", the more valuable it becomes for other firms to join in too. Second, large firms with many employees will benefit more from e-business technologies that are primarily used in-house than small firms can. This is because a large number of in-house users implies a higher value of the communication network. Third, as far as systems are compatible and linked across companies, they could possibly be a source of increasing returns to scale given the reasoning from above. This could shift up the minimum efficient scale of firms in an industry and hence increase concentration levels if demand remains constant. However, this last point might be counteracted by new business opportunities that open up in an industry due to the emergence of the new technologies, e.g. new possibilities to differentiate products. Hence, there might also be new firms entering the industry and exploiting these opportunities. In addition, the continuously falling prices of progressively more powerful computer equipment and software tools lower the investment barriers into ICT for small firms and give them access to resources that were formerly privilege of large enterprises. Thus, the net-effect of ICT and e-business diffusion for market structures could be mixed.

2.3.4. Market structure and innovation incentives

Present industry structures might influence firm's incentives and abilities to invest in innovation and new technologies. Research interest has focused on the question which market structure best promotes innovation and technological advance. The debate largely focuses on the two Schumpeterian (1942) hypothesis that (1) there is a positive relationship between innovation and monopoly power with the concomitant of above normal profits; and (2) that large firms are more than proportionately innovative than small firms. Both Schumpeterian hypotheses are related to the rank effects literature that explains differences among firms in their timing to invest into new technologies (chapter 3.2.2). It is argued that large firms and firms with some price-setting power are more likely to be early adopters of new technologies.

The relationship between monopoly power and innovation has been subject to lively debates in the economic literature. There are two ways in which monopoly can affect innovative activities (Scherer 1980, p. 423). First, the anticipation of extraordinary profits is of course an incentive for developing an innovation. It is necessary to have some monopoly power for a while to realize an extraordinary profit. This monopoly power is the ability to prevent or at least to retard imitation (Kamien and Schwartz 1982, p. 27). Even in a competitive industry a firm might secure a monopoly position stemming from a successful innovation by means of patent protection or sufficient lead time to build up capacity to realize economies of scale or strategic know-how. This line of reasoning is consensus. Second, the possession of monopoly power could precipitate firms' innovative activities. However, this issue is subject to controversy.

Arguments in favor of the first Schumpeterian hypothesis claim that monopolistic profits can serve as an investment pool for further research. Also, monopolists can have advantages in being able to finance an innovative activity internally, which includes advantages in controlling the flow of information about the innovative activity, thus making it more probable to appropriate returns from the investment (Kamien and Schwartz 1982, p. 29). Contrariwise, a monopolist might be subject to lethargy and more bureaucracy, which could hinder the ability to innovate. Furthermore, a monopolist's attention might focus more on protecting current profits rather than seeking new profit opportunities. Kenneth Arrow (1964) has formally shown the possibility that a newcomer to an industry might have greater incentives to invest into a cost-reducing process-innovation than the monopolistic incumbent. He showed that both for drastic and non-drastic innovation, the newcomer's incentive to invest exceed the incentive of the monopolist because the incumbent calculates the incentive as the difference between expected future profits and current profits, whereas the newcomer sees the profits from the innovation as a pure gain. Segerstrom and Zolnierek (1999) have shown that this assumption is not always true. According to their findings, whether industry leaders or industry followers are most innovative depends on the R&D cost advantages with respect to market power. The incentives of the follower to innovate are the greater relative to the incumbents incentives, the smaller the cost advantage of the incumbent to innovate. However, if the cost advantage of the incumbent is substantial, then the incentives to innovate will be greater for the incumbent.

The empirical investigation of the first Schumpeterian hypothesis is extremely challenging because of the difficulties to measure monopoly power in empirical studies. Still, there are numerous papers that address this issue empirically. One stylized fact that emerges from this work is an inverse U-shaped relation between concentration ratio and innovative activity (Scherer 1967, Mansfield 1977, Comanor 1967). A slight amount of concentration seems to promote invention and innovation. But beyond a moderate amount of concentration, further increases in concentration do not seem to be associated with more rapid rates of technological advance (Baldwin and Scott 1987, p. 90). In addition, Paul Geroski (1994) has pointed out an important source of biased estimation results: technological opportunities (the availability of potential investment projects) may not be evenly distributed across all industry sectors. Geroski (1994) showed that industries with high technological opportunity are characterized by high concentration ratios, considerable market share, and higher profitability. The technological opportunity variable explained about 60% of the innovativeness variance and thus turned out to be very important. Hence, estimation results that do not control for technological opportunity might over-estimate the positive effect of monopoly power on innovation incentives.

The second Schumpeterian hypothesis, that large firms are more than proportionately innovative than small firms, is also subject to debate. Arguments in favor of the hypothesis include economies of scale and scope. Positive scale and scope effects my be present on the input side as well as the output side of innovative projects (Kamien and Schwartz 1982, p. 32). Large firms have advantages in attracting highly specialized staff which is needed for innovative projects. Because of the indivisibility of labor it might only be viable for large firms to hire such personnel. Also, large firms might have large research laboratories with different specialists who can benefit from each others work. In addition, large firms have advantages to utilize specialized equipment and they may benefit from well-established marketing and distribution channels to exploit the benefits of innovative activities (Nelson 1959, p. 303). Furthermore, innovative activities involve risks and large firms have advantages in managing these risk, given that innovative activities are usually not divisible: According to portfolio theory, the variance of a portfolio can be decreased by diversifying investments into various risky projects that are not perfectly correlated. Hence, large firms can diversify their portfolio of investment projects and thereby limit their overall risk whereas small firms often put their entire existence on stake if they undertake one big, risky project.

On the other hand, bureaucracy and communication problems might limit the positive effects of large size on innovative activities. In a large organization, ideas and findings may be more likely to get lost than in a small firms. Also, researchers may also be less motivated in a large firm than in a small firm because in the latter, their compensation may be more directly related to their performance. Some evidence for this can be found in researchers leaving large companies to found their own enterprise to exploit ideas that their former employer would not sponsor (Kamien and Schwartz, p. 33).

The empirical evidence on the relationship between firm size and innovative activity is also subject to various measurement problems. For example, many studies of firm size and innovative behavior take R&D spending as the dependent variable to indicate innovative activity. However, R&D spending is a measure of input, and not a measure of output of innovative activity. The evidence on the relationship between firm size and innovation is mixed. Some studies examine a positive relationship (Comanor 1967, Acs and Audretsch 1987, Blundell et. al. 1999), while others did not find a significant relationship (Mansfield 1964, Cohen et. al. 1987). Scherer (1967) found evidence for an inverse U-shaped interaction between size and firms' R&D intensity. The results also vary with the industry that is being analyzed, for example whether the industry is capital intensive, mature or emerging seems to play a role for what type of innovations are being observed and what type of enterprises bring them to the market (Acs and Audretsch 1987, Cohen and Klepper 1996).

Comprising, there is evidence for an inverse U-shaped relationships between innovative activity and monopoly power, as well as innovative activity and firm size. Even though small innovative enterprises exist, it appears that small firms are less likely to be leaders in technological competition. Large firms and market leaders have, up to some boundary, advantages in carrying out risky and innovative projects. Nevertheless, it appears that neither a large size nor monopoly power are prerequisites for high performance in innovative activities. Furthermore, no industry structure seems to be absolutely superior in terms of incentives for technological development. The relationships are rather complex and tend to vary from industry to industry.

2.3.5. Innovation and market structure

As pointed out above, technology and changes in the technological environment that are induced by successful innovation have a direct impact on market structures. First, technology determines economies of scale of production and thus the minimum efficient size of a firm in an industry. Thus, if the emergence of a new technology increases the minimum efficient plant size while demand remains constant, the industry is likely to become more concentrated. Second, successful innovations create entry barriers and may give the innovator a sustainable advantage. For example, the innovator may hold a patent, or use her lead time to build up capacities to realize economies of scale, gain advantages from learning and experience, build up reputation, or exploit possible network effects on the demand side of the market.

The importance of technology as determining the cost structure of an industry and thus its concentration level is well recognized since the early works of Bain (1956) and Blair (1972). The faith in technological determinism of market structure has been reinforced by the evidence of cross-country similarities in industry concentration ratios (Caves 1989).

Recently, this line of research has been refined by making a distinction between exogenous and endogenous sunk costs (Sutton 1991). Exogenous sunk costs are those that are given by the technology, for example the costs for setting up a single production unit of minimum efficient size. These exogenous sunk costs are equal for all entrants in an industry. Endogenous sunk costs, on the other hand, are those that are incurred by each firm to increase consumers' willingness to pay for a company's product. This includes R&D expenditures and advertising, which are obviously also sunk, but in contrast to the exogenous sunk costs, these variables are part of each firms' choice set and thus endogenous.

The industry concentration ratio is determined by the size of the market and entry costs. Thus, according to Sutton (1991), an increase in market demand or a decrease in exogenous sunk costs will result in a lower concentration level and a higher number of enterprises in the market, ceteris paribus. However, in Sutton's (1991) model the analysis of industries with significant endogenous sunk costs is more complex because R&D and advertising influence market demand. However, an increase in market size alone does not result in the reduction of concentration ratios because the competitive reaction of other firm's in the market will raise the equilibrium level of endogenous sunk costs in the industry. Thus, instead of more firms joining the industry, entry barriers will be raised and the incumbent firms will grow.

According to Sutton (2001), the only plausible way to raise margins and recovering sunk costs in an industry with intensive innovations is through the change of market structure. This can be achieved by consolidation or via exit of firms. Thus, industries in which competition is centered on technological progress can be expected to be more concentrated than it would be implied given the minimum efficient size alone.

The vulnerability of a given market structure depends on whether an aggressive newcomer who outspends all incumbent firms in R&D can cover his expenses on innovation. The question is whether such an escalation strategy pays off. According to Sutton (2001), the answer to this question depends on the industry. In particular, it depends on two characteristics. First, if R&D is effective in raising consumers' willingness to pay for products belonging to the relevant group of products on which R&D is spent, than escalation becomes more profitable. Ineffective R&D will consequently not benefit an escalation strategy. Second, if the scope of R&D activities is broad and benefits various product groups, and if these product groups are close substitutes, then the escalation strategy is more viable. Therefore, in industries in which products are close substitutes high concentration levels can be expected. In such an industry it is profitable to follow the escalation strategy because any technologically aggressive firm is able to capture sales from smaller rivals operating both its own product range and that of rivals.

Sutton's theory predicts that in industries in which innovative efforts are insignificant, the lower bound to the concentration level is zero no matter how homogenous submarkets are. That is, if the escalation strategy is ineffective the market can accommodate an undefined number of firms with a small market share each. On the other hand, in an industry in which R&D investments are both high and effective, the lower bound to the concentration level should increase together with the degree of product substitutability. Empirical support for this theory was found by Sutton (1991, 2001) and Robinson and Chiang (1996).

Further empirical evidence on innovation as a determinant of market structure development has been collected by numerous authors. Phillips (1966) found that successfully innovating firms tend to grow at the cost of others, leading to a rise of concentration level (Kamien and Schwartz 1982, p. 72). Mansfield (1983) investigated whether the introduction of innovations has influenced the MES in the chemical, drug, and petroleum industries and concluded that most process innovations led to an increase in MES that resulted in an increase in industry concentration. He also found evidence that successful innovators grow faster than their competitors (Baldwin and Scott 1987, p. 99). Hannan and McDowell (1990) examine the process of technology adoption in the banking sector and its impact on concentration level. Their findings suggest that the adoption of new technology enabled innovative firms to enlarge their market shares, which resulted in either an increase or decrease in the market concentration ratio. If large firms were first to adopt the new technology, the concentration level rose. Otherwise, if small firms were first to adopt, concentration levels decreased.

Thus, a complex relationship exists between market structure and innovation. While existing market structures influence firm's incentives to invest in innovation, successful innovative activities will change the existing market structure to the disadvantage of the non-innovators. The evolution of industry structures is largely influenced by technological change and firms' incentives and ability to innovate. Hence, technology, innovative activities, and market structure should all be viewed as endogenous variables in models of industry evolution.

2.3.6. Technological competition

A part of the theoretical literature that explicitly adheres to this view is the game-theoretic approach to analyze technological competition. This stream of research has improved our understanding of strategic aspects of technological competition and their immediate consequences for the development of industry structures. For an excellent overview, see Beath et. al. 1995. According to the game-theoretic approach, firms invest into innovative activities for two reasons (Beath et. al. 1995): They seek profitable investment opportunities (profit incentive) and they seek to give themselves a strategic advantage over their rivals (competitive threat). A strategic advantage may occur because a better process or a better product can enhance a firm's market share. If a firm knows that its rivals are engaging in innovative activities, it will see its own competitive position as being under threat. This creates an incentive to also invest in innovation in order not to lose out to rivals. The incentive to invest depends on the difference between the pay-off if the firms wins the technological competition and its pay-off if it loses, in which case the successful rival takes over part or all of its market share.

In general, the models found in this literature abstract from economies of scale effects and assume constant returns to scale. However, some of the models allow a heterogeneous starting position of firms in terms of differences in their cost function, as a probable result of past technological competition.

The literature can be divided into non-tournament models and tournament models. In non-tournament models, potentially many firms can obtain an equivalent improvement in their cost function by spending an equivalent amount on R&D. Usually Cournot competition is assumed in the product market, and products are assumed to be substitutes. There is only one stage to the game in which all firms simultaneously choose their output and R&D expenditure levels. The results depend on the elasticity of substitution between the product commodities and the effectiveness of R&D spending to reduce marginal costs of production (Dasgupta and Stiglitz 1980, Beath et. al. 1982). It can be shown that social optima only occur under very special circumstances, otherwise there will be market failures in the amount of R&D activity and in the number of firms in the market. While this type of models is well-suited to address questions of social optima, it does not explain the stylized fact of technological competition that "success breeds success" (Beath et. al. 1995, Dasgupta 1986). The "success breeds success" story implies that there are only a limited number of successful innovators (maybe only one) which are able to carry their advantage on over time. This issue is addressed in tournament models (also known as "patent races").

In these models, technological competition takes the form of a tournament in which there is only one winner and a race to be the first to make the discovery. Obviously, the central question in these models is whether in the process of dynamic competition *persistent dominance* of one firm emerges, or whether advantages of any technological leader in the industry will be short-lived and competition will be characterized by a persistent pattern of *action/reaction*, and a constant switch in who is leading the competition.

The factors that influence the outcome of such games are very complex, and as noted by Beath et. al. (1995, p. 142), the results can be quite confusing because different models yield conflicting predictions about the expected outcome. The reason is that these models are typically built on different assumptions, and these assumptions are responsible for different predictions. One of the lessons that can be learnt is that results tend to vary dramatically between the static and the dynamic analysis. To illustrate, consider the following two examples.

First, in models that concern the tournament of two firms for a single innovation, the outcome depends crucially on the type of competition that is assumed. If Cournot competition is assumed, than depending on how drastic the innovation is, there are scenarios where *action/reaction* will be the outcome. However, if the assumption of Cournot competition is replaced with the assumption of Bertrand competition, *persistent dominance* will be the outcome in all cases (Beath et. al. 1995, p. 146, Vickers 1986). Thus, while Bertrand usually leads to more competitive outcomes in the static case, it can give less competitive outcomes in the dynamic case.

Second, there are almost reverse predictions for models that analyze a race for just one innovation, and models that analyze a continuous race for a sequence of innovations. Vickers (1986) has shown that only some of the strongest conditions for *dominance* or *action/reaction* carry over to sequences. Furthermore, conditions that are sufficient for *dominance* or *action/reaction* in single-innovation models can lead to exactly opposite outcomes in sequential models (Beath et. al., p. 148).

In summary, the game-theoretic literature demonstrates that the market outcome of technological competition is highly sensitive to numerous factors:

1. Certainty vs. uncertainty: whether the success of an R&D investment can be taken for granted or not
2. Mode of competition: Whether firms are in a mode of price (Bertrand) or quantity competition (Cournot-Nash)
3. Type of innovation: Whether firms compete for a new product or a new process innovation
4. Drastic vs. non-drastic innovation: The extent to which the innovation enables cost savings or differentiates product offers
5. Rate of progress: How fast new technologies become available
6. Leap-frogging vs. catch-up: Whether technology becomes common knowledge after a while and thus enables firms to *leap-frog* certain technological developments, or whether the technology can be effectively protected from imitation by the innovator, in which case rivals would have to spend more to *catch-up*.

Variations in one or more of these parameters and assumptions can lead to drastically different market outcomes and strategic incentives of firms to invest in new technologies. Empirical evidence with field data for these types of models is naturally hard to come by. However, the normative and positive predictions of these models point out important factors to guide empirical research on these issues and inform managers and policy makers about circumstances to look out for to guide their decisions.

2.3.7. Other dynamic factors

Other then the strategic incentives of firms to invest into technology that are identified in the game-theoretic literature, there are three additional dynamic factors that influence the sequence of technological competition and its market outcome. All three dynamic factors contribute to our understanding of the "success breeds success" story.

First, learning by doing may endogenously influence the ability and costs of making further technological progress. Kenneth Arrow (1962a) deserves credit for recognizing learning by doing as an important factor of economic activity. He pointed out two widely accepted generalizations about the process of learning. First, learning is a product of experience. And second, learning from repetition is subject to sharply decreasing returns, hence the learning stimulus must be evolving to continuously increase knowledge. Based on these initial facts, Arrow (1962a) advanced the hypothesis that "technical change in general can be ascribed to experience, that it is the very activity of production which gives rise to problems for which favorable responses are selected over time." In his model, the cumulative production of capital goods acts as an index of experience. Furthermore, he assumes that all learning is incorporated in the new capital goods and that no additional learning takes place on the side of the user. Furthermore, he views learning as a pure by-product of production, ignoring factors such as schooling or research. The accumulation and continuous investment into knowledge is reflected in a downward drift in cost curves over time. As pointed out by Sheshinski (1967), such economies of scale are dynamic by nature and thus "irreversible", which benefits those firms that have an early start in competition. Parente (1994) and Chari and Hopenhayn (1991) have pointed out that learning by doing may cause constant long-term growth paths. Lieberman (1984), Hatch and Mowery (1998) and others have demonstrated the empirical relevance of learning by doing effects, while Spence (1981) and Lieberman (1984) pointed out the importance of learning by doing for the evolution of market structures. Surprisingly though, the presence of strong learning by doing effects must not automatically lead to *persistent dominance* in a dynamic market. Jovanovich and Nyarko (1996) showed that an agent may be so skilled at some technology that he will never switch again to a newer, better technology, so he will experience no long-run growth from a certain point in time on. A less skilled agent might switch to a newer and better technology, however, and overtake the more skilled agent. Thus, *action/reaction* can also occur when learning from experience is important.

Second, R&D has a dual role: It does not only create new technologies and knowledge, it also enables a firm to develop and maintain their broader capabilities to assimilate and exploit externally available innovation. Hence, conducting its own R&D helps a firm to learn and to benefit from R&D conducted elsewhere. This dual role of R&D has been pointed by Cohen and Levinthal (1989). Other scholars of technological change have also observed that firms invest in own R&D partially to be able to utilize information which is available externally (Allen 1977, Mowery 1983, Tilton 1971). Thus, learning through R&D helps a firm to absorb extramural knowledge. This "absorptive capacity" of firms represents an important part of their ability to create new knowledge. Absorptive capacity is different from learning-by-doing in that the latter refers to the automatic process by which firms become more practiced, and, hence, more efficient at doing what they are already doing. In contrast, with absorptive capacity a firm may acquire outside knowledge that will permit it to do something quite different (Cohen and Levinthal 1989). This observations sheds a different light on R&D. For example, it implies that firms might conduct R&D even if they are not able to prevent the new knowledge to spill out into the public domain. Specifically, they might conduct R&D in order to gain first-mover advantages from technological knowledge generated in universities or governmental laboratories. Or they might invest in R&D to be able to act as fast second mover in the face of spillovers from a competitor's innovation. Thus, firms that are active in R&D might have competitive advantages even if they are not able to perfectly appropriate returns from their investment (e.g. if they conduct pure basic research that is not readily embedded in some product, service, or process innovation).

Third and finally, a "success-breeds-success" story might emerge because of imperfections in the capital market. In the real world, information asymmetries exist between financial intermediaries and firms that seek external funding for investment projects. This might lead to varying financing conditions for firms that intend to invest into the same investment project, depending on their past financial performance. Because of information asymmetries, the creditor will not only look at the nature of the investment project but also at the past performance of an enterprise to evaluate the risk associated with the credit. Consider for example the influential role of credit ratings by Standard and Poor's or others on firms' ability to get external financing. If current access to capital depends on past performance, then firms that successfully innovated in the past might have an advantage today to finance investment projects that could yield them superior returns in the future. Or, in other words, when borrowers' net worth improves, lenders become more willing to lend, and additional investment can be financed. Thus, imperfections in the capital market might lead to a "success-breeds-success" story because they over-proportionately benefit the winner of a technological competition. The finance literature has analyzed this effect in detail and found strong evidence for this accelerator mechanism (Abel and Blanchard 1986, Hubbard 1990, Hubbard and Kashyap 1992). Against this backdrop, Köllinger (2003) analyzed the dynamics of turnover and e-business development, finding that firms that invested into e-business technologies in the past are more likely to experience increasing turnover today and also are more likely to increase their e-business investments in the future. Although the findings are only suggestive because the analysis was based on a cross-sectional dataset and not on a panel, they indicate that a "success-breeds-success" story could also occur in the deployment of e-business technologies.

These dynamic aspects of technological competition have important implications for the diffusion of new technologies. They suggest that if learning-by-doing occurs, or if firms can increase their "absorptive capacity" by investing into R&D or other innovative activities, or if financial markets over-proportionately benefit the winners of past technological competition, the decision to adopt a new technology will not be independent from past investment decisions. Hence, path-dependent developments and a “success-breeds-success” story could emerge. Chapter 3.5 further elaborates on these issues. In addition, these theories suggest that the performance and the success of an enterprise is closely linked to its ability to keep up in technological competition. Thus, investments into new technologies have explicit strategic implications and should be treated as such. Chapter 7 further investigates on this issue.

2.4. Productivity and growth

One of the most widely accepted insights from economics is the recognition of technical change as a major driver of long run economic growth. Scholars of economic growth attribute the development of wealth and the differences in wealth across nations to a large degree towards technological advance. Already Schumpeter (1934) suggested that the diffusion of major innovations is the driving force behind the business cycle, in particular the long run Kondratieff cycle. Economists’ attention to the role of technological progress in improving wealth has been reinforced by Solow’s (1957) discovery that only a small fraction of per-capita growth was associated with an increase in the ratio of capital to labor. The famous Solow residual in the growth accounting framework turned out to trace seven-eighth of total GDP growth, while increased capital per man hour made up for only one-eighth. Studies of economic historians have also delivered direct evidence for the role of industrial innovation as the engine of growth (Grossman and Helpman 1994). For example, Fogel (1964) estimated that railroads as a single innovation added 5% to U.S. GNP by 1890. Other studies by Rosenberg (1972) and Landes (1969) have also emphasized the role of new technologies to spur industrial development and the purposive and profit-driven nature of technological progress. The role of technological progress as a driver of economic growth also becomes intuitively clear if one tries to imagine what last century’s growth performance would have been like without the innovations in generating and using electricity, the emergence of the automobile industry, airplanes and air traffic, the transistor and integrated circuits, computers, radio, television, mobile telephony and others.

In a seminal paper, Solow (1956) advanced a neoclassical model of long run macroeconomic growth that became the standard reference for the following decades. Solow assumed a production function with capital and labor as inputs, constant returns to scale, an exogenously given growth rate of labor (fertility) and technology (inventions and their assimilation in the production process) and an endogenously determined rate of savings. One of the results of this model is that the steady-state rate of growth of income per person depends only on the rate of technological progress and not on the rates of saving and population growth. Furthermore, in the steady state, the marginal product of capital is constant, whereas the marginal product of labor grows at the rate of technological progress. If technology would be constant over time, the only rise in per capita income would come from the accumulation of physical capital. An economy with an initially low capital-labor ratio will have a high marginal product of capital. Over time, capital per worker will rise, which will generate a decline in the marginal product of capital. At this point, savings will also decline to the rate were new capital will only be purchased to replace worn out capital. At this point, the economy would reach a steady state with an unchanged standard of living (Grossman and Helpman 1994). However, if technological advance takes place (which Solow assumed to be exogenous or “falling from the sky”), the marginal product of capital need not decline as capital per worker increased. Instead, technology makes workers more productive and the accumulation of capital would continue to keep pace with the effective labor force, even with a constant population.

Thus, technological progress leads to higher wealth because it makes labor more productive. To illustrate this result in a simplistic way, one can think of a farmer plowing a field with a horse or with a tractor – the tractor will enable the farmer the plow a much larger field in one day, the increase in productivity will be due to technical progress and the purchase of the tractor. As long as technological innovations come up that enable farmers to plow more land in one day, an additional accumulation of capital in the form of new machines will occur to take advantage of the possibility of achieving higher labor productivity. This mechanism leads to higher production and a higher income per capita.

However, this neoclassical framework also turned out to have some weaknesses. Notably, one of the key variables in the model (technological advance) was treated as exogenous and hence the theory said nothing about whether technological advance and hence sustained long term growth are plausible and realistic assumptions. Also, the model turned out to have some weakness when put to the test against real world data. For example, the independence of growth and cross-country saving rates that was suggested by the Solow model could not be found. Instead, it turned out that savings and growth are strongly positively correlated (Mankiw et. al. 1995). Furthermore, the model has weaknesses to explain the large magnitudes of international differences in per capita income. Also, it predicts a much faster rate of convergence between countries as empirical studies suggest. In addition, it predicts much higher returns to capital in poorer countries than what is actually observable.

Consequently, later research has focused on solving these limitations by proposing various extensions and changes to the original framework. Most noticeable, the endogenous growth literature has made contributions by making technological progress endogenous. This helps to explain the existence of technological progress and offers a more realistic description of R&D (Mankiw et. al. 1995). In particular, the influential model by Romer (1990) sees economic growth as driven by the generation of new technologies in a research and development sector that are then used in the sector that produces final goods and services.[4] Grossman and Helpman (1991) show that by making R&D endogenous and allowing firms to appropriate private returns to their R&D investments leads to a macro model with sustained growth in per capita output, even if population size is constant and the economy has no physical capital. Other scholars have also included the theory of monopolistic competition into growth theory to account for the fact that successfully innovating firms are likely to gain at least temporarily monopoly positions (Romer 1990, Aghion and Howitt 1992), giving rise to models that predict sustainable growth as plausible outcomes.

Other approaches have suggested a broader definition of capital investments than proposed in the original neoclassical framework. Romer (1986, 1987) argued that capital investments create an externality that may not only benefit the owner, but also others in society. Furthermore, the role of human capital and knowledge has been emphasized. The argument is that agents do not only forgo consumption to accumulate physical capital, but also human capital (skills) by investing into schooling and training. Because human capital and physical capital are complementary inputs in the production process, both are needed to generate sustained growth (Lloyd-Ellis and Roberts 2002). Rosenberg (1982) and Young (1993) stressed the inherent uncertainties associated with innovative activities and the fact that producers using new technologies rarely achieve commercial viability until after they experience a prolonged period of learning-by-doing. In particular, Young (1993) has integrated both innovation incentives for R&D and bounded learning-by-doing in a growth model.

Recent advances in growth theory have also explicitly considered the diffusion process of new technologies, hence recognizing the fact that newly invented technologies do not gain immediate full usage (Barro and Sala-I-Martin 1997, Grossman and Helpman 1991, chp 9 and 11, Rivera-Batiz and Romer 1991). For example, Barro and Sala-I-Martin (1997) point out that imitation is usually cheaper than invention, advancing a theoretic argument that explains why some countries become technological leaders and some followers. They show that the ability and the costs of imitation have a substantial effect on the expected rate of convergence between countries. In an empirical paper, Parente and Prescott (1994) find that technology adoption barriers can account for a substantial part of income disparity across countries, emphasizing the role of technology diffusion as an important driver of economic growth.

From a policy perspective, the findings from the growth literature emphasize the role of technological progress and capital accumulation as the most important factors that determine the wealth of nations in the long run. In particular, this implies that the abilities of a country to innovate (to do R&D), to assimilate knowledge and new technologies, and to accumulate high levels of human capital through education and training are the key variables to promote long run economic growth and wealth. This is good news because the provision of R&D and technology centers, universities, schools, as well as incentives to utilize these resources are all variables that governments can favorably influence.

ICT, productivity and growth

Given the recognized importance of technological change as a driver of productivity and GDP growth, it is not surprising that the joint emergence of a productivity growth resurgence in the US in the 1990's and the simultaneous massive diffusion of new ICT's has stimulated a debate about a "new economy", where ongoing productivity improvements in ICT were believed to lead to a sustainable and higher rate of total factor produc-

[4] This model, however, assumes instant transfer from the R&D to the producing sector and thus abstracts from the complications of technology diffusion.

tivity growth. Numerous studies have since dealt with two major questions in this context: (1) How much productivity growth is due to ICT, and (2) will ICT be an additional and sustainable source of growth?

Numerous authors stressed that ICT may be characterized as a typical general purpose technology that, like earlier technological breakthroughs, has a wide range of applications and a large impact on economic activity (Breshnahan and Trajtenberg 1995, Helpman 1998). At the aggregate level, Jorgenson (2001) and Jorgenson and Stiroh (2000) argue that the resurgence of growth in the US is mainly founded on the development and deployment of semiconductors that continuously exhibit a price decline and increasing performance, following Moore's law (Moore 1965, Ruttan 2001 pp. 317-365). Other authors have also demonstrated an increasingly productive use of ICT in the user-sectors, and not only a productivity growth in the ICT producing sector itself (Oliner and Sichel 2000, Baily and Lawrence 2001). Gordon (2000) raised doubts about this productivity growth acceleration story and attributed most of the observed changes in US-productivity to price-measurement problems and cyclical factors. Although measurement problems and a debate about the sustainability of ICT-enabled growth remain, there is wide consensus that ICT does have positive effects on productivity growth (for an international overview article, see van Ark 2002).

However, the ICT-induced productivity effects vary significantly between sectors (Nordhaus 2002). The largest productivity growth effect occurs in the ICT-producing sectors themselves, and only smaller (but still measurable) effects in the well-measured non-farming business sectors. In the US, the largest positive effects of ICT-enabled growth in the ICT using sectors occurred in retail, wholesale, and security trading. Interestingly, the same industries in Europe experienced much slower productivity growth although they also invested heavily in ICT, but were not able to recoup growth effects due to mostly structural factors (van Ark 2002, Nordhaus 2002). In fact, the growth differences in these three industries explain much of the total observed productivity growth gap between the US and Europe at that time (Gordon 2002).

Some authors have also analyzed the impact of ICT on firm-level productivity. It is usually stressed that ICT investments must be combined with complementary investments in work practices, human capital, and firm restructuring to have an impact on performance (Brynjolfsson and Hitt 2000, David 1990, Greenwood and Jovanovic 1998, Malone and Rockart 1991). Brynjolfsson and Hitt (2003) find that computers make a positive and significant contribution to output growth at the firm level. The implied returns increase if longer time differences are taken into account, which suggests that time-intensive complementary investments into organizational restructuring have to be undertaken. In a similar spirit, Hempell (2002) argues that firms with innovative experience are particularly well prepared to make productive use of ICT by introducing appropriate complementary innovations. Bertschek and Kaiser (2004) show that ICT has indirect effects on productivity by enabling workplace reorganization and organizational change, stressing strong complementarities between these investments.

Summarizing, ICT is indeed a relevant part of current technological change processes and an important factor that contributes towards growth. However, the magnitude of impact varies significantly between sectors and can either be hampered or promoted by structural factors. Most of the productivity gains occur in the ICT-producing sectors themselves. At the level of individual firms, ICT investments lead to productivity gains if they are combined with complementary investments into innovative activities like workplace reorganization, organizational change, or process restructuring. Hence, ICT does currently play an important role both for economic development and for the efficiency of individual firms. Whether ICT induced growth effects will remain sustainable as some of the scholars suggest, will, however, only be seen in the long run.

2.5. Firm performance

The management and organization science literature looks at innovation primarily from the perspective of the individual business unit, viewing innovation as a possible source of competitive advantage and superior performance of firms. Thus, this stream of research focuses on the question if and under which conditions companies are able to appropriate private returns from an innovative activity. Firm performance is related to productivity, but is much more broadly defined. Firm performance includes productivity as one possible measure of performance, but is not limited to it. Numerous concepts and variables are used to measure performance. For example, March and Sutton (1997) mention profits, sales, market share, productivity, debt ratios, and stock prices. Ittner et. al. (1997) differentiate between financial and non-financial measures of performance. Financial measures include operating income before tax, cash flow, net income, earnings-per-share, sales, economic value added, return on invested capital / assets / sales, stock price return and cost reduction. Non-financial measures are, for example, customer satisfaction, employee satisfaction, product or service quality, employee safety, market share, non-financial strategic objectives, innovation and employee training. Evidently, these different measures of performance are correlated. Which of the measures is given priority is essentially a matter of perspective - management, employees, and stake holders will most likely emphasize different performance measures as most relevant to them. In empirical studies, the choice of the performance measure is often limited by the availability of data.

It is obvious that numerous factors influence the performance of an enterprise, for example its market of operation, the presence of economies of scale and the size of the firm, market structure and market share of an enterprise, as well as firm-internal structures and resources (like technology, organizational structure, human resources, or managerial competence). Lenz (1981) provides an interdisciplinary summary of numerous "determinants" of organizational performance.

Among all factors, how does innovation affect performance? Scholars of firm performance have made numerous contributions to this topic. However, a fundamental problem is the identification of causality in such studies. As March and Sutton (1997) noted: "Most studies of organizational performance are incapable of identifying the true causal relations among performance variables and other variables correlated with them through the data and methods they normally use. Although there are studies that mitigate these shortcomings, the emperor of organizational performance studies is for the most part rather naked." With respect to the relationship of innovation and performance, the principal question that is so hard to answer is whether firms' perform well *because* they are innovative, or if they are able to innovate *because* they perform well. The two-way interdependence of innovation and performance has also been discussed in theoretical papers. For example, the game-theoretic literature on patent races has shown that innovation incentives, market share, turnover, and profitability are all endogenous variables with complex relationships.

Notwithstanding the principal limitation to identify cause and effect, there is some robust evidence that innovation and good performance are related, i.e. that innovative firms perform better and vice versa. For example, Mansfield (1968) reported that innovators in the steel and petroleum industries grew more rapidly than other firms in those industries during the years after an innovation. Armour and Teece (1978) showed that the adoption of administrative innovations in petroleum firms increased the rate of return on owners' equity. Lawless and Anderson (1996) tested the effects of innovation and market complexity on firm performance, using data from the US computer industry 1982-91. The dependent variable in their study is the difference between a firm's predicted market share in each year and its realized market share. They find that generational technological change fosters the emergence of product market niches and local rivalry. Firms that differentiate within a niche are rewarded, while changing niches bears a short-term penalty. Notably, strong performers adopt new technologies quickly, without changing niches. Easton and Jarrell (1998) conduct an empirical study about the performance effects of Total Quality Management (TQM), an organizational innovation. The findings indicate that performance, measured by both accounting variables and stock returns, is better for the firms adopting TQM (not implying a clear causality). Bolton (1993) showed that the propensity to innovate fluctuates with organizational performance, rather than stemming solely from a firm's inherent characteristics. The results emphasize the two-way relationship between innovation and performance.

An important aspect of innovation and performance is the "success breeds success" story that was mentioned earlier in chapter 2.3. The basic argument was that successful innovation in the past leads to superior performance today, which increases the chances of conducting successful innovation again, which will lead to superior performance in the future and so on, leading to a virtuous circle. If the success breeds success story is true, does this imply that failure also breeds failure? Masuch (1985) analyzed the possibility of the occurrence of vicious circles in organizations, concluding that many structural sub-optimalities of organizations, such as underperformance, stagnation, or decay, are caused by vicious circles. An interesting aspect of vicious circles is the behavior of decision makers in risky situations, such as the decision to invest into an innovative activity with uncertain outcome. Wiseman and Bromiley (1996) deliver empirical evidence that firms facing decline change their investment behavior in risky projects and fall into a trap of taking unprofitable risks that ultimately exacerbates their decline. The authors point out an interesting theoretical conflict surrounding the risk-taking behavior of firms in decline. Many scholars believe that declining firms reduce their risks and cut back on innovative investments, which leads to further decline because of foregone profit opportunities. Other scholars, who have a primary interest in risk per se, come to the opposite conclusion that low performing firms take more risks than other firms and such risks reduce their subsequent performance. According to Wiseman and Bromiley (1996), this argument is closely related to prospect theory (Kahneman and Tversky 1979), assuming that firms facing a loss context (where expected performance falls below performance targets) usually have project options that they frame as continued losses. Firms facing this situation may opt for projects of higher risk, where that higher risk translates into greater variance in project outcomes. If a project's outcome variance is large enough, the project may include a small probability of success. Firms that follow such reasoning will choose riskier projects, since lower risk projects guarantee failure to meet aspiration levels (Singh 1986). However, on average firms pursuing projects with unreasonable risk will experience loss, and that loss may exceed that of a lower risk project. Both mechanism could give rise to vicious circle dynamics, but for different reasons. The empirical results of Wiseman and Bromiley (1996) support the latter theory.

Although the causal relationship between innovation and performance is not unambiguous, it is clear that innovation and success are strongly correlated and therefore of high strategic importance for managers. This implies that Internet-based technologies should also be of high strategic importance, as far as they are used as enablers of process or product innovation rather than as mere infrastructural technologies. Recently, there has been a lively debate about the strategic importance of IT and the Internet (Porter 2001, Carr 2003). The dispute is about whether investments into IT and Internet-based technologies enable firms to gain sustainable advantages. Chapter 7 provides some new insights that contribute towards this debate.

2.6. Employment effects

Another highly relevant and much debated issue are the employment effects of innovation and technical change. The central question is if technological change creates or destroys jobs. The debate is as old as economics as a scientific discipline, with early contributions to the debate by Adam Smith, Karl Marx, and Ricardo (Vivarelli 1995). There is no unambiguous answer to it, and recent research has emphasized that employment effects vary with the level of analysis (firm, sector, national economy) and the type of innovation (product vs. process). A common belief is that because innovation is related to growth, rapid innovation and growth would solve the unemployment problem. However, an innovation might lead to productivity growth without leading to GDP growth. The employment effects can be very different for the two kinds of growth (Edquist et. al. 2001). Growth effects vary for miscellaneous types of innovation (Kuznets 1972). A common conceptual framework is to differentiate between product and process innovations. Product innovations can occur in goods or in services, while process innovations can be either technological or organizational, with varying implications for employment effects.

A product innovation corresponds to the creation of a new supply function. Given a sufficient demand for the new product, it will usually create additional demand for both capital and labor production factors by the innovating firm. This is often called the *compensation effect* (Pasinetti 1981). However, if the new product does not satisfy a completely new kind of demand or does not serve an entirely new function, i.e. if it only functionally replaces an old one, there will also be a *substitution effect*. The net employment effect of such an innovation could be either negative or positive, depending on (1) whether the new demand for satisfying the function changes when the new product replaces the old one and (2) the labor intensity of the production technology of the new product compared to the old one. However, in most cases product innovations are employment creating even if substitution effects are taken into account (Katsoulacos 1986, Kuznets 1972, Edquist et. al. 2001, p. 97).

Process innovations usually also have both a compensation and a substitution effect, however, their net effect is much less clear than for product innovations. Process innovations reduce the costs of production for a given unit of output, hence they increase productivity per unit of input. This corresponds to an outward shift of an existing supply function. Depending on the price elasticity of demand and the degree of competition in the industry, this outward shift of the supply function will lead to growth and lower equilibrium prices. This compensation effect is stronger for competitive industries and high price elasticity's of demand. However, an increase in productivity implies that a given level of output can be produced by less amount of input. Thus, if demand and output remain constant, a process innovation will lead to a reduction of labor, ceteris paribus. While the compensation effect can mitigate job losses, they can only promote net employment gains when growth in production and demand outstrips productivity growth. This usually only happens when the price elasticity of demand is greater than zero, which is only a rare case (Edquist et. al. 2001, p. 119).

Also, the effects depend on the specific kind of process innovation. Technological process innovations that replace labor by capital will have a stronger employment reducing effect than process innovations that lead to organizational changes. In fact, organizational process innovations might be either labor-saving or capital-saving, while technological process innovations are primarily labor-saving (Edquist et. al. 2001, p. 35-37). Organizational innovations are also special in the sense that they can be viewed as investments into human capital by the provision of new knowledge through education, training, and learning-by-doing (Becker 1975). This constitutes a special kind of investment because it is durable, generates continuing returns, and is embodied in "knowledge carriers" (Machlup 1980). Thus, if an employment reducing effect of organizational process innovations exists at all, it is likely to be much smaller than the employment reducing effect of technological process innovations.

In addition to this static firm-level view on different kinds of innovation, a dynamic macro-level view emphasizes that there are likely to be secondary effects of innovation because whether something is a process or a product innovation is essentially a matter of perspective (see chapter 1.4.1). Some product innovations in one sector can turn out to be process innovations in another sector leading to secondary employment effects. Edquist et. al. (2001, p. 100) differentiate the net-employment effect of product innovations according to three product categories:

- Consumer products
- Investment products
- Intermediate products

Only investment products can play the double role of employment generation in one sector and labor displacement in another. The net-employment effect of an investment product innovation hence depends both on the effect in the technology producing sector, and the effects in the using sectors. For consumer and intermediate goods innovation, there is usually only the primary (typically employment increasing) effect.

A double role of product innovation can also occur in the service sector if the new product is an organizational innovation that is commoditized and sold as a consulting service. The net employment effect of such an organizational innovation depends also on the size of the compensation and the substitution effect in the sectors adopting the innovation and in the sector that supplies the consulting service.

Thus, it is clear that the employment effects of innovations depend on the specific type of innovation. They can also vary significantly between aggregation levels (firm, industry, national economy). An employment increase in one (successfully innovating) firm might lead to employment losses at the industry level or at the national level, depending on whether output growth offsets productivity growth. Thus, the net impact of an innovation on employment remains essentially an empirical issue that cannot be unambiguously predicted ex ante.

Empirical evidence suggests that overall employment effects of innovation *at the firm level* tends to be positive. Firms that innovate in products, but also in processes, grow faster in their respective markets and are more likely to expand their employment than non-innovative firms, regardless of industry, size, or other characteristics (for an overview see Pianta 2004).

Studies on the *industry level* show that the employment impact is positive in industries characterized by high demand growth and orientation towards product (or service) innovations, while process innovation tends to lead to job losses. Recent sectoral evidence for Europe suggests a prevalence of labor-saving process innovations. Slow growth on the demand side and increasing international competition has pushed many firms towards restructuring and process innovations. This leads to the well-known phenomenon of jobless productivity growth which is currently being witnessed in many European countries. However, product innovation has confirmed its positive effects on output and jobs (Pianta 2000, 2001, Antonucci and Pianta 2002, Evangelista and Savona 2002, 2003).

The *overall effect* depends on the country and period being studied. The higher economic growth (total output and demand), the higher is the positive impact of innovation, while technical change in stagnating or closed economies tends to be associated with serious employment losses. According to Pianta (2004), empirical evidence suggests that institutional factors and macroeconomic conditions play an important role for the nature and the effect of technical change on employment at the macro level. The employment impact is generally more positive the higher is the ability to generate new products and to invest in new economic activities, and the stronger is the effect of price reduction, leading to increased demand. Aggregate studies generally point out the possibility of technological unemployment, which emerges when industries or countries see the prevalence of process innovations in contexts of weak demand. Firms innovating in both products and processes may be successful in expanding output and jobs regardless of economic context, but often at the expense of non-innovating firms.

In addition to the quantity impact of innovation on employment, there also exists a quality aspect. The question is what kind of jobs are created or destroyed by innovation? A large literature on skill biased technical change (Acemuglu 2002) finds that technical change is biased towards skilled workers as it replaces unskilled labor and increases wage inequality and polarization. Unskilled jobs have long been declining in absolute terms in Europe and growing only slowly in the US, while skilled jobs for educated workers are created at a faster pace in most countries (Pianta 2004). Analyzing the particular skill-biased effects of ICT-enabled innovation, Brynjolfsson and Hitt (2002) find that innovative firms that combine investments into ICT, complementary workplace reorganization, and innovations in products and services tend to use more skilled labor. In particular, the effects of ICT on labor demand are greater when IT is combined with organizational restructuring, highlighting the importance of IT-enabled innovation.

The employment effect of e-business technologies have yet to be analyzed. E-business will most probably generate new jobs in the hardware, software, and consulting industries because for these sectors e-business essentially is a product (or service) innovation that creates new supply functions. On the side of the technology using sectors and on the aggregate level, however, the net employment impact of e-business is less clear. While we can expect that firms that successfully conduct product or processes innovations using e-business technologies will grow faster than non-innovating firms, they will probably do so at the expense of non-innovating firms, especially considering the currently stagnating demand dynamics in many markets in Europe. Hence, a certainly plausible assumption would be that e-business technologies will just be another instrument for many firms to rationalize and restructure at the expense of total employment in a low GDP growth scenario. Also, we may expect that the diffusion of e-business technologies will have a skill-biased effect on labor demand, favoring well-educated workers with ICT skills.

2.7. Implications for e-business diffusion

The above discussion on the consequences of technological change has emphasized that technological development is *endogenous* to the development of productivity, growth, market structure, employment demand and firm performance.

Some implications and hypotheses for the diffusion of e-business technologies can be derived from the discussion which can be tested using firm-level data in later parts of this study. To the extent that e-business technologies turn out to be effective in either (1) enabling companies to conduct process innovation and reduce their marginal costs or (2) to come up with new product or service varieties, the following impacts can be expected:

First, it was discussed that the emergence of new technologies may lead to changes in market structure (chapter 2.3). Thus, not every company will benefit from the diffusion of e-business technologies, there will be winners and losers. The direction and the extent of these changes will, however, largely depend on past and current market structures. Also, the effects of e-business technology-induced process innovations in an industry will vary with the degree of price-elasticity of demand and the degree to which e-business related product or service innovations raises consumers' willingness to pay (Sutton 1991). Hence, the incentives to invest into e-business technologies and related innovations can be expected to vary from industry to industry, similar to earlier innovative activities (Sutton 2001, Acs and Audretsch 1987, Cohen and Klepper 1996). Also, following the argument of Geroski (1994), the technological opportunities of e-business might be very different across industries. This leads to **Hypothesis 1**:

Hypothesis 1 - Diffusion patterns of e-business technologies will vary across industries.

Sutton's (1991) theory also suggests a systematic relationship between industry concentration ratios and the intensity of technological competition: Industries with a high level of technological competition are more likely to be concentrated because this is the only way how firms in such industries can recover the sunk costs of fast technological progress. In addition, a generally high level of technological competition will increase firms' absorptive capacities for new technologies like e-business (Cohen and Levinthal 1989). To the extent that e-business provides sufficient industry-specific opportunities, the following hypothesis can be derived:

Hypothesis 2 - Industries with high levels of technological competition and high concentration ratios are likely to be leaders in e-business adoption.

Independent from industry membership, the discussion suggested a number of firm-specific factors that influence whether a firm will invest in e-business and whether it will be able to benefit from the investment. For example,
e-business technologies are likely to be subject to network externalities. Thus, as far as systems are compatible

between firms, the higher the number of firms that use e-business technologies, the more valuable it becomes for other firms to join in too. Once a critical mass of users is reached, Internet-based process technologies are likely to become a “new standard” of communicating within and across companies. In addition, large firms with many employees have more potential in-house users of communication technologies. In conjunction with the inside that large firms are, up to some threshold, more likely to invest in innovation (Acs and Audretsch 1987, Comanor 1967, Scherer 1967, Schumpeter 1942), this leads to:

Hypothesis 3 - Large firms are more likely to adopt e-business technologies that are primarily used in-house.

Also, a possible inverse U-shaped relationship between market power and innovative activity has been discussed (Comanor 1967, Scherer 1967, Mansfield 1977). Thus, we can also expect that there will also be an inverse U-shaped relationship between firms’ market power and their probability to adopt e-business technologies:

Hypothesis 4 – Firms with a medium degree of market power are more likely to adopt.

The game-theoretic literature has also pointed out who are likely to be the winners in technological competition (Beath et. al. 1995): Firms that are able to outpace their direct competitors in technological development will capture market shares from the rivals, possibly up to the degree that they the drive their competitors out of business and gain dominance in the market. Conditional on the assumption that the new technology of the early mover is indeed superior, this mechanism simply reflects that “time is money” and therefore being quick can yield competitive advantages:

Hypothesis 5 - Early movers in technological competition can enjoy excess returns as long as their competitors have not perfectly copied them.

However, once imitation was successful and an innovation has successfully diffused among market players, no single firm will be able to realize excess returns on the innovation anymore. Yet, the positive effects of the innovation will not be lost, they will simply be passed on to consumers in the form of greater product variety and lower prices. As a consequence, successful diffusion of an innovation will increase market size. Hence, independent from whether innovating firms will be able to appropriate private profits from their investments, successful innovation will lead to growth of the innovator, ceteris paribus (Hannan and McDowell 1990, Mansfield 1983, Phillips 1966, Sutton 1991, 2001):

Hypothesis 6 - Innovators are more likely to grow than their competing non-innovators, independent from their ability to achieve excess profits.

The discussion about the employment impacts of innovations and new technologies stated that the net impact depends on the relative strength of the substitution effect and the compensation effect. On the one hand, the substitution effect implies a reduction in the demand for labor because new technologies and more efficient processes partially replace low-skilled labor. On the other hand, the compensation effect implies a growing demand for labor due to an expansion of the innovative firm. The net employment effects of new technologies and innovations vary across different aggregation levels (firm, sector, national economy). Also, they vary for different kinds of innovations and new technologies (e.g. product vs. process innovations). Most e-business technologies promise efficiency gains because they enable to automate a variety of routine tasks. Thus, they can be expected to have a labor substituting effect after the implementation is completed and the routines have been effectively changed and optimized. Consequently, firms that are more advanced in using e-business technologies can be expected to reduce their staff due to the substitution effect, ceteris paribus.

Hypothesis 7: Firms that are more advanced in using e-business technologies are more likely to reduce employment than their less advanced competitors, ceteris paribus.

Yet, the compensation effect also suggests that process innovations lead to efficiency gains that allow the innovator to grow at the expense of non-innovating rivals. Also, product or service innovations are usually associated with growth because they enable a company to fulfill new needs and wants of customers. The growth of the innovating firm will be especially pronounced if direct competitors have not yet imitated the innovation. Thus, the compensation effect will be more pronounced in the short run than in the long run (after all rivals have copied the innovation). To the extent that e-business technologies are used to introduce innovations to a firm, they can be expected to have a compensation effect in the short run.

Hypothesis 8: Firms that recently used e-business technologies to innovate are more likely to increase employment than non-innovative firms, ceteris paribus.

Furthermore, the research on the dynamics of technological competition has demonstrated that a "success breeds success" story could emerge as a consequence of five distinct reasons – complementarity of technologies (Milgrom and Roberts 1990), strategic behavior of agents (Beath et. al. 1995), learning by doing (Arrow 1962a), increases in absorptive capacity (Cohen and Levinthal 1989), or imperfections in capital markets (Abel and Blanchard 1986). Provided that the early movers in technological competition are able to appropriate some private gains of their investments[5], it is likely that they will be successful in building a sustainable advantage over their rivals in the dynamic process of technological competition, possibly even up to degree that they achieve industry dominance, if one or more of these accelerating forces are at work. This will be discussed in more detail in section 3.5. Finally, two additional aspects have been mentioned in the above discussion that seem important. First, it was pointed out that changes in technology might influence the degree of economies of scope and the MES of an industry. These are additional ways of how new technologies can induced changes in industry structure (see page 18). However, the direction of the effect of e-business technologies is not unambiguously determinable because two contrary effects are at work. On the one hand, the network characteristics of Internet-based technologies imply economies of scale. On the other hand, Internet-based technologies also offer new business opportunities to start-ups and small firms that previously did not exists. The net effect will probably vary among industries. Given the data that was available for this study, it is not possible to track changes in market structure over time and relate these changes unambiguously to the diffusion of e-business technologies. Therefore, no particular hypothesis is formulated for this point. Second, on various occasions it was mentioned that investments into technology might be subject to market failure, which can result in either too much or too little investment in technology compared to the social optimum (e.g. page 12 and 21). This could occur because firms anticipate problems to protect their innovation from immediate imitation or because the competitive dynamics in an industry induce sub-optimal investment levels. However, it is also not clear a-priori which scenario is likely to occur, if market failure will occur at all, or what the social optimum would actually be in reality. Thus, no hypotheses are formulated for this aspect either because the direction of the relationship is ambiguous and the estimation of social optima are subject to severe difficulties in an empirical investigations.

[5] This assumption reflects the argument of **Hypothesis 5** that early movers can enjoy excess returns as long as their competitors have not perfectly copied their practices.

3. Theories of technological diffusion

Theories of innovation diffusion are concerned with the process by which new technologies, practices, products, or services spread across their potential market over time. Empirical studies of innovation diffusion identified a very robust stylized fact that seems to apply to all kinds of innovations, including new technologies, production processes, organizational innovations, or consumer products: Innovations spread in their potential market over time following an S-shaped aggregate curve, featuring early adopters, a majority of followers, late adopters and frequently also a substantial number of non-adopters (Bain 1964, Bass 1964, Griliches 1957, Mansfield 1968, Rogers 2003, Stoneman 2002). Frequently, years pass from the first introduction of an innovation to a market to the point where saturation levels are reached. At first sight, it is not intuitively clear why this process may take so long. If an innovation satisfies a new mean or achieves a given mean in a superior way, why do not all potential users adopt the innovation immediately? This is the fundamental question that theories of innovation diffusion address.

The study of innovation diffusion is interesting and relevant for various reasons. From an academic perspectives, it concerns questions that deal with decision dynamics of consumers or firms in situations that can involve incomplete information, risk, and ambiguity. Understanding the nature of these dynamics is an indispensable cornerstone to understand the nature of technological change and development. It also has important practical implications: For example, theories of innovation diffusion reveal insides into who will be the winners and the losers of innovation diffusion, when is the optimal time to adopt an innovation for a particular firm or individual, and they can help marketers of innovation to optimize marketing strategies and production plans. From a policy perspective, it is relevant to understand the optimal rate of diffusion, to identify possible market failures, and to understand which policy actions could be undertaken to reach the optimal rate of diffusion.

3.1. Different perspectives on innovation diffusion

A long tradition of research on the diffusion of innovations can be found both in the economics and the management literature. Both fields developed their own research agendas independently and surprisingly little cross-reference and acknowledgment of the contributions of the respective other side can be found, although numerous parallels and complementarities exist.

Fundamentally, there is one branch of work devoted to the diffusion of innovative consumer products, and a second branch that considers innovations among firms, including technological, process, and organizational types of innovation. Innovations for consumer markets or firm markets are very different and have thus lead to different streams of research: First, innovations for consumers or firms are often different in their nature and do not necessarily overlap. Some innovations that are relevant for firms (for example a new production technique) are irrelevant for consumers and vice versa. Second, the incentive to adopt an innovation is very different for consumers and firms. Consumers maximize their personal utility given their budget constraint (Becker 1965, Horsky 1990). For private individuals and households the purchase of a new good or service is a consumptive activity that yields immediate or ongoing utility gains from the time of purchase on, which is adjunctive to the time spent on consuming the new good or service. Firms, on the other hand, maximize their profits in a given market setting (Götz 1999, Fudenberg and Tirole 1985, Reinganum 1981a,b). Their payoff from an innovation does not only depend on the innovation itself, but on the amount they produce, the costs they bear, and the price they can charge for their product. For firms, the decision to adopt an innovation is an investment decision that involves costs in the expectation of future – rather than immediate - rewards which is based on efficiency gains in their production activities (Dixit and Pindyck 1996, Huisman 2001). Third, firms are usually in competitive situations[6] – their gains from an innovation depend on the behavior of their competitors and their costumers. Consumers do not compete against each other on output markets, their utility from purchasing an innovation is directly and exclusively determined by the new product or service itself and their own behavior.

Depending on the purpose of each particular study, scholars have emphasized different perspectives on the diffusion process and different levels of analysis were chosen. As a general trend, the economics literature has put more emphasis on the study of innovations for firms, while the marketing literature has focused more on consumer product innovations. The strategic management literature has numerous contributions for both types of innovations. The focus in the economics literature has recently been on the analysis of individual decisions and behavioral foundations of innovation diffusion, thus emphasizing a micro-level of analysis. On the other side, the marketing profession has put more emphasize on forecasting performance, introducing various extensions upon the seminal epidemic diffusion model of Bass (1969) (see Mahajan et. al. 1990). These epidemic type of models take an aggregate view of the diffusion process and abstract from individual-level decision making. The strategic management literature, once again, features contributions to both streams of research.

Yet another aspect in the study of innovation diffusion is the distinction between intra-firm diffusion and inter-firm diffusion (see for example Stoneman 2002, pp. 57-58). While intra-firm diffusion considers how new technologies, work practices or organizational changes gain acceptance within a given firm after management has decided to adopt the innovation, inter-firm analysis abstracts from inner-organizational dynamics and treats adoption as an investment decision and an all-or-nothing event. The level of use of the innovation within the firm after the adoption decision is not considered explicitly in inter-firm analysis. Obviously, studies on intra-firm diffusion focus on organizational aspects and human resources, while inter-firm studies have an emphasis on firm-heterogeneity and strategic, market-oriented aspects.

For the purpose of this study, the focus is henceforth on the diffusion of technological innovations among firms because e-business technologies clearly belong to this category (see chapter 1.4.4). Furthermore, the inter-firm perspective is taken. Hence, the interest is primarily on the market and inter-firm dynamics of the diffusion process. The primary objective of this approach is to explain differences in the adoption behavior among firms. Inner-firm processes (such as learning-by-doing) are considered as factors that contribute towards the heterogeneity of firms. However, consistent with the literature on inter-firm diffusion of innovations, the adoption of a new technology is treated as an investment decision and an all-or-nothing event, abstracting from the level of utilization of the new technology within each firm. The following sub-chapters will summarize important insights both from the management and the economics literature on the diffusion of technological innovations among firms. Selected work is cited that is most relevant to this study. A particular purpose of this literature review is to link important insights from the economics and the management literature as a preliminary to derive adoption criteria for e-business technologies in section 3.6. The chapter concludes with section 3.7 which points out parallels and connections between the diffusion of new technologies (chapter 3) and the consequences of the technological diffusion (chapter 2). In the subsequent empirical chapters (5 and 6), this study pursues a micro-level view emphasizing the adoption dynamics at the level of the individual firm, testing explicitly some of the hypothesis developed in chapters 2 and 3.

3.2. Economic theory of technology adoption

The economic literature has identified various factors that influence the diffusion of new technologies among firms. 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

[6] Not meaning competition to purchase a potentially scarce technology, but competition on a given output market.

- 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. This terminology and classification of economic diffusion models has been introduced by Paul Stoneman (Stoneman 2002, Karshenas and Stoneman 1993, Stoneman 1995). The basic arguments and conclusions of these different approaches to explain the diffusion of new technologies among firms are briefly outlined below, focusing on the diffusion of a stand-alone technology without network effects. For a comprehensive and in-depth overview, the book of Stoneman (2002) is a valuable resource.

3.2.1. Epidemic effects

Epidemic models of innovation diffusion take a macro-view of the diffusion process. As the term "epidemic" suggests, these models have a close analogy to the analysis of the spread of infectious diseases. The basic idea is that users and non-users of a new technology mix socially and make contact over time. When a user meets a non-users, she "contaminates" the non-user with the innovation, which eventually results in an adoption decision of the non-user. The process starts with a few original users who are "infected" by the new technology. As time proceeds, the share of "infected" agents in the population increases due to the social mixing. Thus, in the beginning of the processes the number of agents who adopt per period increases. While more and more agents have adopted, the share of non-users gets continuously smaller. Thus, after some point of inflection, the number of adopters per period decreases again towards the end of the process, eventually leading to a saturation level where all agents have adopted the innovation.

Mathematically, this idea can be simply expressed as a logistic function that gives rise to the empirically observable S-shaped diffusion curve. Let *N* be the number of potential adopters, and *M(t)* the number of adopters at time *t*. Assume that there is constant mixing within the population such that individuals will make contact with $\partial M(t)/N$ users of the technology. If *q* is the probability that contact will lead to adoption, the number of new users in period *t* can be expressed as

$$(3.1)\quad \frac{dM(t)}{dt} = \frac{\theta M(t)}{N}\{N - M(t)\}$$

where $\theta = \delta q$ is the probability of an infectious contact. This equation can be solved with respect to *M(t)* yielding

$$(3.2)\quad M(t) = \frac{N}{1 + \exp(-p - \theta t)}$$

which is the standard logistic function (Stoneman 2002, pp. 29-33). Here, *p* defines the starting date of the diffusion process (the intercept term), θ determines the speed and the shape of the diffusion curve, and *N* is the market potential of the innovation.

Examples of the epidemic approach in the economic literature are Griliches (1957), Bain (1964), Mansfield (1968), and more recently Gruber and Verboven (2001) and Beck et al. (2005). Although logistic type of models often provide good fit to historical diffusion data, the approach has been criticized on various grounds. First of all, the model is silent about what exactly happens when a user and a non-user meet, i.e. why such a contact should result in an adoption. A common interpretation is that social contact leads to a transfer of information between agents. Non-users may originally not know about the new technology or may not be convinced about its benefits. In this way, social contact may indeed spur the spread of an innovation. As such, the essence of epidemic models is that the dissemination of information is driving the diffusion process.

However, this interpretation also has clear limits. Social contact is clearly not the only source of information that real world agents have. In many ways, the epidemic model is lacking behavioral and economic content. For example, given that many innovations take years to reach their market potential, it is implausible to assume that the only reason why some agents have waited with the adoption was because they did not know about it. If they knew about the new technology and were not convinced about its benefits, it is not plausible why they should passively wait for an information to arrive and not actively search for it up to some optimal stopping point of the searching process. Furthermore, if uncertainty or ambiguity about the new technology are prevalent and deter agents from adopting, this should be modeled explicitly rather than being mixed together with ignorance of agents with respect to the innovation. In addition, the model takes the number of potential users N as exogenously given, being silent about what determines N. Also, there is no story involved about why and which new technologies should be chosen by a company. The model also assumes that the technology remains constant over time, both in terms of performance and costs of acquisition. However, changes in technology might influence both the diffusion speed as well as the number of potential users N.

Epidemic models of innovation diffusion are in essence disequilibrium models, as noted by Stoneman (2002). The equilibrium level of users of a technology is N, the model explains the adjustment process towards the equilibrium within a population, but until the end of the diffusion process the market is out of equilibrium. Furthermore, the epidemic model is a self-propagating, deterministic mechanism that cannot be stopped before all potential users have adopted.

In summary, epidemic models stress the role of information dissemination as a key factor that drives the diffusion process. This basic insight is useful. Also, the model often has good fit to historical diffusion data. However, beyond the information story, the behavioral and economic content of epidemic models is limited.

3.2.2. Rank effects

In contrast to epidemic models, the theory of rank effects takes a micro-perspective on the diffusion process leading to probit- or logit-type of models. Rank effect models assume perfect information and rational profit-maximizing behavior of firms. The diffusion process is not deterministic and does not occur endogenously. Instead, it is driven by exogenous factors, such as technological improvements over time or falling costs for acquiring the technology.

The basic idea is that firms differ from each other in at least one relevant dimension such that the net present value of a technological innovation is higher for some firms than for others. This makes it possible to rank firms in terms of the benefit to be obtained from the use of the new technology. Firms that rank higher are expected to adopt more rapidly. Important dimensions of heterogeneity are e.g. firm size, location, previous investments, availability of complementary inputs, R&D intensity, market factors, inner-organizational factors, different expectations, or different access to financial resources (David 1969, 1991, Davies 1979, Stoneman 2002). There are numerous parallels between the theory of rank effects and some of the literature on the consequences of technological change that was discussed in chapter 2. For example, large firms might be more likely to adopt a new technology because they have the necessary financial resources (see section 2.3.4 and the Schumpeterian hypotheses) or because the technology has increasing returns to scale (see section 2.3.1 and 2.3.3 on network externalities). Also, Sutton's (1991) theory predicts that innovative efforts will be higher for firms that act in markets where innovative activities successfully raise consumers' willingness to pay and where product groups are close substitutes (see section 2.3.5). Thus, the market on which a firm is active is one source of heterogeneity that contributes to different adoption dynamics among companies. In addition, section 2.3.7 pointed out that the history can matter for the dynamics of technological progress. In particular, past investment decisions of firms can lead to learning-by-doing effects, affect their ability to absorb new technologies, or influence their ability to finance new investment projects. Hence, past investment decisions of firms are one factor that contributes towards the heterogeneity of firms and possibly influences the adoption behavior of new technologies.

The theory of rank effects argues that the benefits of adoption have some kind of distribution within the population, usually following some bell shaped curve. Each firm considers the gross benefits and the cost of acquisition for its own situation and, in the absence of uncertainty, adopts if the former exceeds the latter.

Let their be *N* heterogeneous firms without strategic interaction. Define the costs of acquisition at time *t* as c(t) and the net present value of the technology at time *t* as G(t). The new technology is adopted if $G(t) \geq c(t)$. Because firms are allowed to be heterogeneous, only a fraction m(t) of the entire population will exhibit $G(t) \geq c(t)$ and adopt. Hence, the level of ownership of the technology at time *t* will be $M(t) = m(t)N$. $M(t)$ can change over time due to exogenous changes that either increase G(t) via technological improvements or decreases in c(t), giving rise to a diffusion curve. The shape of the diffusion curve depends on the distribution of m(t). Note that m(t) may remain smaller than unity even if $t \to \infty$. Thus, depending on the characteristics of the technology, the distribution of firm characteristics, and the costs of the technology there might be a significant number of non-adopters in the population even in the long run.

Rank effect models provide an economic explanation for the occurrence of diffusion processes even if agents behave perfectly rational and all information about the new technology are public knowledge. They emphasize heterogeneity of firms as the primary source of differences in adoption decisions. A particular strength of the rank effects approach is that it allows to incorporate any dimension of firm heterogeneity into the modeling approach that is related to the ability and the propensity of firms to innovate. Thus, it is a very general and flexible approach for empirical studies of innovation diffusion at the micro level. Also, in contrast to epidemic models, the market potential of a new technology must not be assumed exogenously, instead it depends on factors that are endogenous and can vary between different firm populations and technologies.

A limitation of the approach is that the empirically observable S-shaped pattern cannot be explained by rank effects in the absence of technological improvements or falling costs of the technology over time. Also, firms are assumed to be independent of each other. Thus, rank effect models are not informative about strategic aspects of technology adoption.

3.2.3. Stock effects

The strategic aspects of technology adoption are emphasized by stock effect models. They take a game-theoretic approach that focuses on the interdependencies of payoffs between firms that compete on the same output market. Important contributions in this spirit are Reinganum (1981a,b), Quirmbach (1986), and more recently Götz (1999) who integrates stock and rank effects in one model.

Similar to rank effect models, the game-theoretic approach to innovation diffusion assumes rational, profit-maximizing agents and perfect information. Also, the diffusion process does occur due to exogenous factors, such as technological improvements or falling costs of the new technology. However, in contrast to the rank effects approach, stock effects do not assume firms to be independent or heterogeneous. Instead, firms are assumed to be identical *ex ante* and they compete on some given output market. Then a new process technology arrives that has the potential to reduce production costs. The payoff of each firm depends on its costs of production, its output level, and the price it can charge. All three variables might be different before and after the adoption of a new technology. Also, the decision of one firm to adopt will affect the payoff level of all competitors. In this way, stock effect models have parallels to the game-theoretical models of technological competition that were discussed in section 2.3.6.

In stock effect models, the diffusion process also occurs as an equilibrium that changes its level over time due to exogenous changes. The basic idea is that as more and more firms adopt the cost-reducing process technology, industry output will be expanded and the equilibrium market price will fall. At any point in time, it is not profitable for all firms to adopt the innovation because this would pass on all excess gains directly to the consumer via higher output levels and lower prices. Excess returns from adopting can only be realized as long as not all competitors have also adopted. Thus, at any point in time there is a unique equilibrium number of firms that will use the new technology, depending on market conditions and the costs and benefits of the new technology vis-à-vis the old technology.

To illustrate the basic argument, consider the basic Reinganum (1981b) model which, in addition to all assumptions listed above, supposes myopic expectations of firms. The following notations are used:

$p(t)$ - equilibrium market price at time *t*

$M(t)$ - the number of users of the new technology at time *t*

c_0 - cost per unit of output of the old technology

c_1 - cost per unit of output of the new technology

$q_0(t)$ - output of the firm at time *t* using the old technology

$q_1(t)$ - output of the firm at time *t* using the new technology

$\Pi_0(t)$ - annual profit at time *t* using the old technology

$\Pi_1(t)$ - annual profit at time *t* using the new technology

$V_0(t,t)$ - present value of the profit streams of the old technology

$V_1(t,t)$ - present value of the profit streams of the new technology

r - the discount rate

$C(t)$ - costs for purchasing the new technology at time *t*

The annual profits of firms using the old or the new technology depend on the market, production costs, and quantities produced. Thus, they are respectively defined as

$$(3.3)\quad \begin{aligned} \Pi_0(t) &= (p(t)-c_0)q_0(t) \\ \Pi_1(t) &= (p(t)-c_1)q_1(t) \end{aligned}$$

If the new technology is superior to the old, $c_1 < c_0$ and $q_1 > q_0$. Therefore, firms using the new technology have a cost advantage and produce more. Hence, they exhibit excess returns compared to firms using the old technology:

$$(3.4)\quad \Pi_1(t)-\Pi_0(t) = (p(t)-c_1)q_1(t)-(p(t)-c_0)q_0(t) \geq 0$$

As the number of users of the new technology increases, aggregate output will be expanded and thus the equilibrium market price will fall. Because of this, profits of both old and new technology users will decline. Depending on the shape of the demand curve, profits of the new technology users usually decline faster than profits of the old technology users. Thus, the profit difference between old and new technology users also decline over time, but remains positive until all firms have adopted the new technology.

The decision to invest depends on the present value of all future profit gains. If the technology has an infinite life, the present value of the new and the old technology respectively can be written as

$$(3.5)\quad \begin{aligned} V_1(t,t) &= \int_{\tau=t}^{\infty} \Pi_1(\tau,t)\exp(-r\tau)d\tau \\ V_0(t,t) &= \int_{\tau=t}^{\infty} \Pi_0(\tau,t)\exp(-r\tau)d\tau \end{aligned}$$

Now consider that firms have myopic expectations, thus at time τ for all $\tau > t$, they expect the number of users $M(t)$ at that point in time to be the same as at time *t*. In such circumstances, the profits realized at $\tau > t$ will depend on the number of users at that time, firms will expect that for all $\tau > t$ the profits they generate will be the same. This simplistic approach can be extended to include more realistic assumptions without changing the basic message of the approach (Stoneman 2002, p. 45). Under myopic expectations, the profits for users and non-users can simply be written as

$$(3.6)\quad \begin{aligned} \Pi_1(\tau,t) &= \Pi_1(M(t)) \\ \Pi_0(\tau,t) &= \Pi_0(M(t)) \end{aligned}$$

and the difference in payoff streams between the two technologies is given by

$$(3.7)\quad V_1(t,t)-V_0(t,t) = \frac{(\Pi_1(M(t))-\Pi_0(M(t)))}{r}$$

which is decreasing in $M(t)$. Given (3.7) the decision rule to invest into the new technology is given by

$$(3.8)\quad V_1(t,t) - V_0(t,t) = \frac{(\Pi_1(M(t)) - \Pi_0(M(t)))}{r} \geq C(t)\,.$$

The equilibrium number of firms that should adopt at time *t,* $M(t)^*$, can be established (Reinganum 1981b) and depends on the costs of the technology at time *t*. As $C(t)$ declines over time, $M(t)^*$ will increase and a diffusion process will occur.

Note that in contrast to the rank effects model, here diffusion occurs although firms are *ex ante* identical. The only difference arises between users and non-users of the new technology. There is also no heterogeneity among adopters with respect to their annual profit flow depending on when they adopt. At all times, all non-users make the same profits and all users make the same (but higher) profits. Thus, over all periods, the early adopters do best in terms of excess returns they can earn. At the end of the process, all firms will have adopted the new technology – thus they will henceforth be identical again. In such a setting, excess returns from technology adoption are not sustainable in the long run and have only a temporary effect.

It is also interesting to observe that the basic stock effect model allows for the possibility of different diffusion dynamics in various industries. Because the incentives to invest do not only depend on the technology, but also on the slope and the position of both the aggregate demand and supply functions in which firms operate, a very rapid adoption could be an equilibrium outcome in one industry, while in another industry a much slower pace could also be an equilibrium. Thus, as long as aggregate supply and demand conditions are not equal across industries, we can expect different diffusion dynamics in different industry sectors.

Notice further that the basic stock effects model says nothing about which firms should adopt first. It only establishes an equilibrium number of new technology users that would maximize profits. It is silent about how firms should coordinate to reach this equilibrium by assuming that firms precommit themselves to an adoption date. In the model, the firm which is able to precommit itself to adopt first does best, yet any firm can adopt first in equilibrium. The model does not consider how firms would solve this dilemma. Hence, in the basic stock effects model, in addition to responding to external stimuli, firms are also in a coordination game which adds strategic uncertainty to their decisions. This has, to my best knowledge, not been explicitly considered yet. However, this additional strategic uncertainty might have a considerable influence on the diffusion process.

3.2.4. Order effects

Order effects models can be viewed as an extension of the stock effects approach. The basic stock effects model claims that the annual profits of all users of the new technology are the same, irrespective of when they have adopted and how many other firms have adopted at that time. Hence, firms are identical *ex ante* and *ex post* to their adoption decisions.

However, this must not be the case if some of the assumptions of the stock effect model are relaxed somewhat. This is the extension that is proposed by order effects models. If, for example, we allow free entry and exit in the market, positive returns to scale, learning-by-doing effects, scarce complementary resources to the new technology, market reputation effects, competition about the timing of adoption, or discount rates that are lower for previously more profitable companies, this can yield a story where firm size, market structure, and performance are endogenous to the diffusion model, i.e. where being an early adopter yields much higher returns which can be sustained even if other firms adopt later. The first adopter thus influences the adoption decision of followers in additional (strategic) ways and first mover rents may not be completely extinguished by other firms following. It might also make it less profitable for late movers to adopt at all. In this case, early adopters will be able to sustain an advantageous position even in the long run, as long as one abstracts from technological uncertainty or technological improvements over time. The relevance of these additional strategic elements of the timing of investment decisions has been discussed in section 2.3.7.

Interesting contributions to this line of reasoning are Fudenberg and Tirole (1985), who show that early (preemptive) adoption of one firm can impact on the preferred adoption date of other firms, with varying results for equilibrium adoption strategies for different market structures. Ireland and Stoneman (1985) argue that early adoption might allow the first mover to pre-empt certain scarce inputs, such as the best geographical location or scarce skilled labor.

The bottom-line is, an order effect is said to occur when early adoption yields sustainable excess returns that cannot be replicated or extinguished by later adoption decisions of other firms. If this is the case, firms might preemptively adopt a new technology although this would not be indicated by return on investment considerations alone. The timing of adoption decisions in such a setting becomes an explicitly strategic move.

3.2.5. Risk and uncertainty

Rank, stock, and order effect models all assume complete information and certainty with regard to the payoff from a technology investment. However, in reality the decision to invest in a new technology involves risk and uncertainty in a number of dimension. First, there is uncertainty about the performance of a technology, i.e. the potential of cost reduction due to the new process technology is usually not known precisely. Second, there is uncertainty about whether the firm can succeed in implementing the technology successfully, thus realizing the potential of the technology. Implementation could fail due to technological problems or a failure of the technology to diffuse successfully within the firm. Third, the firm's payoff obviously also depends on demand conditions on its output market. Fluctuation in demand will make the payoffs from technological investments uncertain. Fourth, the ability of a firm to appropriate private gains from a technology investment depends also on the behavior of its competitors, as emphasized in stock and order effect models. Thus, there is also strategic uncertainty about the expected payoffs from the investment.

The imitation effect in epidemic models (Mansfield 1968, Stoneman 2002, pp. 55-57) has been interpreted as a result of uncertainty reduction over time. As more and more firms use a technology, non-adopters learn about the true potential of the technology by observation and their level of uncertainty reduces, making adoption more probable. However, this approach can be criticized on various grounds. For example, one strange implication of this interpretation is that uncertainty is reduced over time (the variance of the expected payoff is reduced), however firms never change their initial expected value of the technology and only learn that their initial expectation was right as uncertainty reduces (Stoneman 2002, p. 56). This implies that a firm never learns that adoption could be unprofitable or that its initial estimate was wrong. Also, the epidemic approach does not allow for improvements of the technology over time and models diffusion as a deterministic process with a fixed (a priori determined) end level of use, which is by itself contradictory to the concept of uncertainty.

Two additional modeling approaches can be found in the literature that explicitly deal with uncertainty – the mean variance approach and the real options approach.

The mean variance approach (Stoneman 1980, 1981) assumes that firms simultaneously use a mix of old and new technologies. Each technology is characterized by an expected or mean return and the variance attached to the mean return. Firms try to optimize their portfolio of old and new technologies, trading off the expected returns and variances of the technologies following the standard optimal portfolio approach from the finance literature. The variance of the expected returns for each technology is comprised of two parts: A true variance (which is determined by the state of the world and the nature of the technology) and a second part that results from a lack of knowledge about the technology. This second part only exists for new technologies, not for old ones that the firm has already been using for some time. Also, the true mean of the returns of a new technology are not known to firms a priori, they have to be figured out by learning. Learning occurs according to Bayesian rules, leading to updates in the expected mean return of new technologies (the expected mean can either increase or decrease) and to reduction of that part of the variance which is due to lack of knowledge. Firms might differ in their characteristics, having a distribution of different levels of risk aversion, initially expected prior estimates of the mean returns of a new technology, or proportions of estimated variance which is due to a lack of knowledge. As time proceeds, firms learn about the new technology and the variance which is due to lack of knowledge is reduced, spurring additional usage (i.e. a restructuring of the technology portfolio towards the newer technologies given that prior estimates of mean returns had not to be corrected downwards; or a larger share of the population using the new technology).

The real options approach takes yet another perspective on risks, yielding some interesting insides into investment decisions that can also be incorporated into stock, order or rank effect type of models (see Huisman 2001 for some interesting examples of this). The basic idea of the real options approach is to view technology adoption as an investment decision that possesses three characteristics: irreversibility, uncertainty, and possibility of delay (Dixit and Pindyck 1996, ch. 3). In contrast to the net present value method, which suggests that firms should invest when the expected present value exceeds the expected present value of expenditures of the technology, the real options approach results in a different investment rule. While the net present value method assumes that an investment project is a now or never decision, the real options approach explicitly considers the possibility to delay the investment and specifies the value of the option to defer the investment decision.

The approach exploits an analogy between technology investments and financial call options. A financial call option gives the holder the right, but not the obligation, to buy a particular good (e.g. a stock, bond, or a ton of cement) for a specified price before or at a specified time. Similar, a new technology can be viewed as an investment opportunity that gives a firm the right, but not the obligation, to carry out the investment. Assuming that the technology will not disappear again, the opportunity to invest into the technology can be viewed as an infinitely lived call option on a dividend paying activity. The dividend of the activity is the expected benefit from the technology at each future point in time. Because the future payoffs of the technology are uncertain due to various possible changes in the environment, the possibility to delay the investment into the technology has a value vis-à-vis an immediate investment or the pre-commitment to invest at some specific time in the future. This value of waiting is expressed by the value of the call option. The resulting investment rule is that firms should only invest when the expected net present value of the technology exceed the option value of waiting (Huisman 2001). This investment rule can rationalize diffusion processes even in worlds with complete information, homogeneous agents, and no external continuous technological improvements or falling prices. Note that the option value of waiting is greater for higher levels of uncertainty of the payoffs.

A central result of these approaches is that the extent of uncertainty associated with the payoffs from a new technology will affect the preferred adoption date of a firm (Sarkar 2000, van den Goorbergh et. al. 2001, Thijssen et al. 2001a, b, Pawlina and Kort 2001). Delaying adoption is more attractive to firms for higher levels of uncertainty about the future price or future returns of the technology. Delay will also be more attractive if firms expect the mean acquisition costs of the technology to grow only slowly or negatively over time (falling prices).

Although recent theoretical advances about uncertainty in technology investment decisions have significantly improved our understanding of the role of uncertainty in particular decision environments, these insides have – to my best knowledge – not yet been combined with insights from the behavioral economics and psychological literature about the behavior of individuals in uncertain environments. The above cited economic literature makes only rough assumptions about the behavior of individuals in risky and ambiguous situations. For example, even for the rare case that risk aversion is assumed, it is usually ignored that people tend to have systematically distorted perceptions of risks and payoffs. However, the rapidly emerging field of behavioral economics provides manifold evidence that actual human behavior in risky and ambiguous situations is very complex and only badly described by the standard assumptions of risk aversion or expected utility theory (see for example Kahneman and Tversky, 1979; Thaler et. al., 1997; Fox and Tversky, 1995; Schade et al., 2002, Burmeister and Schade 2005, Schröder and Schade 2002). It has not yet been analyzed how these psychological phenomena influence the behavior of real decision makers in the specific context of technology investments in firms. Thus, we do not yet know how different information conditions and levels of uncertainty actually influence the spread of new technologies among firms in the real world where perceptions and risk attitudes of decision makers do matter. This could be subject to interesting future research.

3.3. Empirical results from the IO literature

Given the insights provided by the theoretical IO literature, the natural role of empirical studies should be to test theories and to indicate the relative importance of different factors that have been suggested to influence the diffusion process. However, many articles are either purely theoretical without an empirical test, or they engage in a rigorous econometric analysis, but without explicitly testing the theoretical models that are proposed elsewhere. One might speculate about the causes of the divide between theoretical and empirical studies in the IO literature, but two obvious reasons are the technical difficulties in transferring complex theoretical models into econometrically testable equations and the lack of appropriate data sources that incorporate all relevant variables (e.g. expectations of benefits, price changes, information asymmetries between firms, or differences in risk preference and premiums). Also, the different theoretical explanations of innovation diffusion are based on sometimes conflicting assumptions, which makes it difficult to integrate them in one all-embracing estimation equation. The few noticeable exceptions are the studies of Karshenas and Stoneman (1993) and Stoneman and Kwon (1994) that include rank, stock, order, and epidemic effects in their estimation framework.

The results from various empirical studies provide considerable evidence for both rank and epidemic effects, thus suggesting that different facets of firm heterogeneity and the spread of information over time are important drivers of the diffusion process. The evidence for strategic stock and order effects, however, is much weaker and also less frequently analyzed in empirical studies (Karshenas and Stoneman 1993, Stoneman and Kwon 1994, Zettelmeyer and Stoneman 1993, Stoneman 2002, p. 103).

Important dimensions of firm heterogeneity that have been identified to influence adoption decisions are firm size, market structure, market share and industry characteristics, consistent with the arguments presented in section 2.3. Most studies have found a positive relation between firm size and speed of adoption analyzing numerous different technologies, industry sectors, and geographical regions (for example Mansfield 1968, Romeo 1975, 1977, Davies 1979, David 1969, Hannan and McDowell 1984, Rose and Joskow 1990, Pennings and Hariato 1992, Thomas 1999). However, as an exception Oster (1982) finds negative size effects in a study of the diffusion of basic oxygen furnace and continuous casting in the US steel industry.

The evidence on the effects of market share and market structure are more inconclusive. Hannan and McDowell (1984) find a positive relation between market concentration and the diffusion of automatic teller machines in the US banking industry. A positive effect of market concentration on diffusion is also found in Romeo (1977). In contrast, Levin et. al. (1987) find a negative effect of both concentration ratio and market share in a study of optical scanner diffusion in retail grocery stores in the US. Karshenas and Stoneman (1993) find no significant effect of concentration ratios in their study of controlled machine tool diffusion in the UK engineering industry.

The costs of adopting a new technology have been shown to influence the speed of diffusion. The probability to adopt usually increases as the price of the technology falls or opportunity costs increase (e.g. the price of labor when a new labor-saving technology is available). Evidence for this is provided by Karshenas and Stoneman (1993), Stoneman and Kwon (1996), and Hannan and McDowell (1984).

Furthermore, empirical evidence suggests that technologies diffuse faster and reach higher market penetration levels the higher the expected benefits from adoption (Mansfield 1968, Griliches 1957, Davies 1979). However, the correct measurement of firms' expectations in empirical studies is still a critical issue and a potential field for future research (Karshenas and Stoneman 1995).

Some empirical studies have also analyzed the effect of government intervention in the diffusion process. Evidence suggests that governmental intervention rarely speeds up the diffusion process and government-controlled firms do not move faster than privately owned companies (Hannan and McDowell 1984, Oster and Quigley 1977, Rose and Joskow 1990).

There is also some evidence that cyclical effects influence firms' adoption decision with more technology investment taking place in periods of cyclical upswing and less in periods of a downturn (Romeo 1977, Davies 1979).

Some important questions regarding the dynamics of technology diffusion still remain open and present potential for future research. For example, a panel data analysis incorporating technology investment decisions *and* performance parameters (such as profits or market share) over time would provide valuable new insights into the dynamics of market structure development and technological change. Also, the strategic dynamics (as proposed by stock and order effect models) need a more rigorous empirical analysis. How do real decision makers behave in such situations of strategic uncertainty? Furthermore, the role of risk with regards to the properties of technologies need to be disentangled from the role of ambiguity and the process of information acquisition about the new technology. As theory suggests, these are different concepts with different impacts on the diffusion process. Empirical studies with real world data clearly have limitations to answer these questions. Instead, laboratory experiments might provide useful new insights because they allow to control and to manipulate risk, ambiguity, and information conditions in explicit ways.

3.4. Management literature on technology adoption

As pointed out above, the management literature also has a long tradition of studying innovation diffusion among firms. Surprisingly though, there is very little acknowledgment of contributions made outside the own profession and only scarce cross-reference between the IO literature and the management literature respectively. In the language of epidemic diffusion models, one might speculate that the various contributions have failed to "contaminate" research in the neighboring discipline due to a lack of social mixing and information exchange between scholars of both professions. This is unfortunate because the research agendas of both professions are highly complementary.

The studies concerning innovation diffusion in the management literature are more frequently of empirical nature and only a few papers make purely theoretical contributions. The theoretical papers are either optimization models in the tradition of operations research or micro-economic market equilibrium models. Numerous papers also make theoretical contributions by developing conceptual relationships based on taxonomies and testing their usefulness in empirical studies.

The management literature complements the IO literature in various ways. First, there is an extensive literature focusing on organizational heterogeneity as a determinant of differences in innovation adoption. Thus, there is compelling evidence for the existence of rank effects in the management literature. Also, the management literature provides a much richer view of different factors that contribute towards rank effects. Second, management research has put more emphasis on different attributes of the innovation itself as a determinant of its diffusion process. Third, the management literature features some interesting approaches that deal with information acquisition and uncertainty in more detail. On the other hand, the management literature lacks an overarching theoretical framework and a common terminology that unifies the manifold approaches to study innovation diffusion. The IO literature has such a framework, and most contributions from the management literature fit into the rank or epidemic type of models outlined above. As such, the IO framework helps to survey and to classify the various approaches found in management papers. Also, IO scholars have emphasized the strategic aspects of technology diffusion in their stock and order effect models – this perspective is almost entirely missing in the management literature. Thus, both research agendas together provide a much better understanding of what determines technology diffusion than either field alone.

As indicated above, the management literature has identified numerous relevant dimensions of firm heterogeneity that contribute to differences in adoption behavior and timing.

Souitaris (2002) and Pavitt (1984) stress the importance of sector membership as a driver of different innovation dynamics among firms. Pavitt (1984) identified different technological trajectories in four sectoral classes of industrial firms (supplier dominated firms, scale intensive firms, specialized suppliers and science-based firms). Souitaris (2002) tests Pavitt's taxonomy and concludes that it resolves the problem of various inconsistent results on the determinants of technological innovation by differentiating between the four sectoral classes.

DeCanio et. al. (2000) point out that organizational structure influences a firm's ability to adopt a new technology. Hence, different organizational forms can lead to rank effects among firms. They build a theoretical model of a firm-internal network structure of connected agents. The model examines the diffusion of a new technology throughout this network and how the network adjusts to exogenous changes. In the model, the profitability of the firm depends on the structure of the firm-internal network and its ability to adapt well to a new technology and exogenous changes. The authors argue that a failure to recognize the importance of organizational structure on the performance of firms will lead to bias in estimation of costs or benefits of a change in external circumstances, including the arrival of a new technology.

Hurley and Hult (1998) relate firms' culture to the capacity to adapt and to innovate. They find that market orientation and organizational cultures that emphasize learning, development, and participative decision making. In a similar spirit, Zmud (1982) investigates different factors influencing the in-house adoption of organizational innovation in an empirical study. The results stress the importance of different types of organizational innovation (technical vs. administrative) and their fit to the organization. Centralization and formalization of decision processes are identified as sources of heterogeneity among firms that lead to different adoption behavior.

Various studies have focused on the endowment of firms with different forms of human capital as a source of different adoption behavior. Dewar and Dutton (1986) empirically tests whether different models are needed to predict the adoption of technical process innovations that contain a high degree of new knowledge (radical innovations) and a low degree of new knowledge (incremental innovations). The results suggest that extensive knowledge depth – measured by the number of technical specialists in a firm – is important in the adoption of both types of innovations. Larger firms are likely to have more technical specialists and hence adopt more radical innovations. Their results fit into the complementary investments story proposed by Milgrom and Roberts (1990): Investment into human capital in the form of technical specialists appears to be a major facilitator of technical process innovation adoption. In a related spirit, Kelley and Brooks (1991) present an empirical study to explain why certain types of small firms have failed to adopt well-known improvements in process technology. They argue that three sets of factors explain which establishments are likely to have adopted programmable automation: 1) cost and profitability incentives, 2) internal resources and accumulated technical competencies of the firm including complementary IT applications, and 3) firm's linkages to external sources of expertise for learning competencies about the new technology's capabilities and limitations. The results suggest that technical competencies and the availability of complementary resources and technologies helps firms to learn faster about a new technology and thus increase the chance of adoption. Nilakanta and Scamell (1990) study how different information sources and communication channels influence the diffusion of database development tools. They also stress the importance of technical specialists, concluding that the nurturing of inhouse specialists who might take on the role of boundary spanning individuals or champions will be useful to educate the users of the innovations. Ahire and Ravichandran (2001) also emphasize the importance of complementary investments into skills and processes as a determinant of organizational innovation.

In a related spirit, Glynn (1996) develops the concept of organizational intelligence which is conceptualized as being functionally similar to individual intelligence (i.e. as purposeful information processing that enables adaptation to environmental demands). Organizational intelligence is viewed as a social outcome that relates to the individual intelligence of employees by mechanisms of aggregation, cross-level transference, and distribution. Differences in organizational intelligence are viewed as a source of firm heterogeneity and might lead to differences in innovation adoption.

Hauschildt (1999), Gemünden and Walter (1996), and Witte (1998) emphasize the importance of individuals who act as innovation promoters in organizations. The presence of such individuals might lead to different adoption dynamics among enterprises.

Ettlie and Vellenga (1979) identify the risk-taking climate of an organization as a factor that contributes to different innovation dynamics. Risk-taking organizations adopt innovation earlier, consider innovations with fewer concrete performance criteria, and see innovations as less complex.

Srinivasan et. al. (2002) find that firms' adoption decisions can be attributed to differences in "technological opportunism" among firms. Technological opportunism is a construct that captures sense-and-response capability of firms with respect to new technologies and is not identical to organizational innovativeness in general.

Papadakis and Bourantas (1998) and Tabak and Barr (1999) focus on different personality characteristics of managers and CEOs as a determinant of innovation decisions. Both papers find that different characteristics such as risk propensity, self-efficacy, demographic characteristics and individual perceptions of strategic decision makers are relevant and help to explain differences in adoption decisions among firms.

In summary, the management literature has identified the following relevant aspects that contribute towards rank effects:

- sector membership,
- organizational structure, - culture, and - intelligence,
- different endowments with human capital (including in-house specialists and innovation promoters) and
- the availability of other complementary inputs to a technological innovation (such as related technologies, accumulated experience, skills and adequate processes),
- the risk taking climate of a organization,
- the ability of the organization to perceive and pursue technological opportunities,
- different characteristics and personalities of strategic decision makers among firms.

The management literature also features some interesting extensions to epidemic diffusion models. One of the short-comings of the most basic forms of epidemic models that was mentioned above is that they interpret the epidemic effect as a result of the dissemination of information through social contact, however they do not explain what exactly happens when two agents meet or why agents might not actively search for information instead of passively waiting to "get infected" by it. Two papers by McCardle (1985) and Oliva (1991) overcome this limitation by building models of optimal information acquisition. McCardle (1985) analyzes the adoption decision of a firm for a new technology with original uncertainty about the profitability of the technology. A firm can wait to adopt in order to gather additional information about the technology via observation of other firms and Bayesian updating. Optimal stopping rules for the information acquisition are derived via dynamic programming. The model predicts that even managers who behave optimally will occasionally adopt unprofitable technologies and reject profitable ones. The study of Oliva (1991) combines a theoretical model with a numerical simulation. The model uses a response surface based on catastrophe theory to examine the interaction of information and profitability estimates on the firm's adoption of a new technology or innovation. Oliva's (1991) approach allows a positive estimate of the firm's decision process, against which the normative theoretical rules of McCardle (1985) can be compared. Note that both models take a micro-perspective and view information acquisition as an active search process with optimal stopping rules instead of a passive “contamination” of a firm with the “truth”.

Mamer and McCardle (1987) make an interesting contribution towards the modeling of uncertainty and combine it with strategic considerations. Their model considers both the uncertainty about the technology and the uncertainty about actions of competitors. While uncertainty about the technology can be reduced by gathering additional information (Bayesian updating), uncertainty about competitive reaction cannot be reduced. The paper combines game theory and dynamic programming to solve the optimization problem. The analysis shows that substitute competition induces the firm to use a less optimistic decision strategy and thus decreases the probability of adoption. Complementary competition, on the other hand, has the opposite effect. In addition, the model shows that occasionally unprofitable technologies might be adopted even if firms follow an optimal strategy. This is because of the costly sequential nature of information and uncertainty associated with the profitability of the new technology.

Various authors in the management literature have also stressed different attributes of the innovation itself as a determinant of its commercial success and speed of diffusion. For example, Gatignon et. al. (2002) provide a valid and reliable measurement instrument to differentiate between different kinds of technological innovations and show that the type of the innovation has an influence on its diffusion. The constructs they use are: new competence acquisition, competence enhancing / destroying, core / peripheral, incremental / radical, and architectural / generational. It turns out that the commercially most successful innovations are those that built on existing competencies in companies as well as acquiring new competencies from outside the firm. Radical innovations are more likely to be commercially successful than incremental ones. Innovations that relate to the core business of a firm seem to be considered as strategic and diffuse faster, while innovations that either destroy competencies or require the acquisition of new competencies diffuse slower.

Rogers (2003) specified five criteria that describe an innovation and relate to its commercial success and diffusion: relative advantage, compatibility, complexity, testability, and observability. According to Rogers, although these attributes are inherent to the innovation, it is not the objective value of these attributes but the perception of these attributes by customers that determines the success of the innovation. The potential for commercial success and a fast diffusion of an innovation is hypothesized to be positively related to high values of the perceived Roger’s criteria. The emphasize on the innovation-specific Rogers’ criteria is especially prominent in Marketing studies.

Other authors that have also compared different innovations, their attributes, and consequences for their speed of diffusion are Mansfield (1993), Meyer and Goes (1988), and Nault et. al. (1997), all confirming that innovation-inherent attributes are relevant for the diffusion process.

3.5. Multiple related technologies and development paths

Up to this point, the discussion has focused on the diffusion of stand-alone technologies which are adopted in isolation from other technologies. However, in reality technologies are rarely completely detached from each other. In particular, e-business technologies are characterized in the introduction as a number of technologies that 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. 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. This section addresses the main issues that arise when firms are not only confronted with the opportunity to invest in one particular technology, but with a set of investment opportunities into a number of related technologies.

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”. The following chapters contribute by making this relationship explicit. This is possible by showing that, under specific circumstances, progress upon a technological trajectory can be subject to increasing returns, which leads to an acceleration mechanism. This has, to my best knowledge, not been done yet. This section aims to link different theories that can rationalize an acceleration mechanism on a conceptual basis and it discusses its strategic relevance by using the resource-based view of the firm. It concludes that the existence of a self-propagating process of technological development would aggravate the potential of new technology adoption as a possible source of sustained competitive advantage. Chapters 5 and 6 make the nature of this acceleration mechanism mathematically explicit and empirically testable.

The relevance of considering interdependencies between various technologies in diffusion models has been demonstrated by Stoneman and Kwon (1994), Stoneman and Toivanen (1997) and Colombo and Mosconi (1995). Stoneman and Kwon (1994) analyze the simultaneous diffusion of multiple process technologies, using a probit model on survey data from the UK engineering and metalworking industries that includes the date of adoption of five different technologies. Their results indicate that the more complementary the technologies are, the greater the likelihood that firms will adopt both technologies simultaneously. Closely related is the study of Colombo and Mosconi (1995) who analyze the diffusion of multiple technologies, employing a hazard rate model on a sample of firms from the Italian metalworking industry. They pay particular attention to technological complementarities and learning effects associated with experience of previously available, related technologies. Their results confirm that technological synergies and cumulative learning by using effects are key determinants to a firm's adoption behavior. The legacy of a firm's technological history is found to greatly affect adoption choices. Stoneman and Toivanen (1996) study the simultaneous diffusion of five technologies, using panel data on UK manufacturing industries. Their results suggest that technological and strategic interdependencies between individual technologies do affect the diffusion path.

The following discussion and the empirical analysis in chapters 5 and 6 extends this line of research in a number of aspects. (1) A theoretical underpinning of the effects of related technologies is offered. Specifically, it is argued that complementarities, learning effects, rebates and imperfections in the financial markets can lead to a self-propagating mechanism that increases the probability of adoption the more related technologies a firm has previously installed. Thus, if technologies are based on the same principles but do not substitute another, the rate of progress upon a trajectory can be an increasing function of the position of a firm upon the trajectory. (2) A mathematical framework is offered to make these thoughts explicit and testable. (3) Various different econometric approaches and two different datasets are used that together allow for conclusive findings on the relationships analyzed. (4) The theory and econometrics are applied to two exceptional and very large data sets that include information on the usage of numerous e-business technologies.

Technological complementarity

The related technologies belonging to a paradigm can either be technological substitutes, partial substitutes, or complements. To illustrate, let's consider the most simple case of two technologies, A and B. Following Stoneman (2000) and Stoneman (2002), assume that the decision to invest in both technologies is a non-reversible, all-or-nothing decision which yields profit gains π_A and π_B greater than zero if only one of the two technologies is installed. If the firm decides to adopt both technologies, the profit gain will be $\pi_A + \pi_B + \nu$. Technologies A and B are defined as:

1. complements if: $\nu > 0$ and thus $\pi_A + \pi_B + \nu > \pi_A + \pi_B$
2. total substitutes if: $\nu < 0$ and thus $\pi_A + \pi_B + \nu < \pi_A + \pi_B$, but also $\pi_A + \pi_B + \nu \leq \pi_A$, $\pi_A + \pi_B + \nu \leq \pi_B$
3. partial substitutes if: $\nu < 0$, and thus $\pi_A + \pi_B + \nu < \pi_A + \pi_B$, but also $\pi_A + \pi_B + \nu > \pi_A$, $\pi_A + \pi_B + \nu > \pi_B$.

For the case that any of the above scenarios applies, 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 (or A). Also, the decision to install either A or B do not only depend on the price of A or B alone, but also on the price of the respective other technology. For example, as the degree of technological complementary between A and B increases, the "threshold prices" at which a firm will buy either A, B, or both will also increase (Stoneman 2000).

More generally, complementarity implies that "the sum of the changes in the payoff function when several arguments are increased separately is less than the change resulting from increasing all arguments together" (Milgrom and Roberts 1990). Mathematically, this corresponds to a payoff function that is supermodular in its arguments. The notion of complementarity implies increasing returns to adoption from any technology, given that other complementary technologies are also adopted. Note that in terms of progress upon a technological trajectory, this implies that the momentum of progress should be an *increasing* function of all complementary arguments of the underlying technological paradigm.

Complementarities between technologies seem to suggest that a firm would always upgrade or install all complementary components simultaneously, leading to radical changes instead of continuous development paths. However, this conventional wisdom must not be true. Jovanovic and Stolyarov (2000) show that if upgrading each input involves a fixed cost, firms may upgrade them at different times, asynchronously. Thus, complementarity does not necessarily imply comovement of all complementary variables, not even for a single decision maker. However, given that complementarity prevails, the chance that a given firm will invest into a technology will increase with the number of complementary investments it has already conducted.

A necessary condition for technological complementarity is that technologies are compatible (Economides 1996a). Compatibility means that technologies can be costlessly combined to produce a demanded good. Compatibility can for example be observed between hardware and software, CD players and CD's, computers and printers, fixed-line and mobile telephone networks etc. If technologies are compatible, one technology will be a prerequisite for the functioning of the other, or at least make the other technology more attractive.

Compatibility might also be expected among various e-business technologies. For example, online sales and online purchasing systems within an enterprise fulfill clearly different functional purposes – thus they are not substitutes. However, they make use of the same communication infrastructure of the firm (typically a LAN and the Internet protocol) and they might both be connected to an ERP and the in-house database system. In fact, many efficiency gains of e-business technologies arise because they run on a common infrastructure and have the ability to exchange information across applications. Many consulting projects have the explicit objective to establish these links and to integrate the various applications such that they can exchange data. A seamless integration of various applications is often viewed as an ideal because it promises to save in-house transaction costs and allows to speed up processes. Consider again the simple example of two technologies, A and B. Although the costs of making A and B compatible is not necessarily zero (in fact, consultants charge considerable amounts for such services), they could simply be integrated in the investment rule of the firm by assuming that $\nu > 0$ comes at some additional price $P_\nu \geq 0$. If P_ν is zero or the present value of $\nu > 0$ outweighs P_ν, it will be more attractive for a firm to purchase both A and B together, or increase the chances that a firm will purchase A (B) given that it previously installed B (A), respectively. Thus, the complementary story for technologies belonging to the same paradigm applies as long as P_ν is sufficiently small and technologies do not substitute each other in their functionalities, $\nu > 0$.

Complementary inputs

Complementarity between technologies can also arise if they require similar joint inputs to function properly. For example, this could be skilled labor or the presence of technical specialists. So even if technologies are completely independent and not connected in any way, they might be subject to a supermodular payoff function because they utilize joint complementary inputs. Thus, the sum of changes in the payoff function of a firm for increasing the arguments of the technologies and the joint inputs simultaneously might be higher than the sum of increasing each argument alone. The difference of complementary inputs to the technological complementary discussed above is as follows: While technological complementary requires compatibility of technologies to arrive at a supermodular payoff function, this is not the case for technologies that have complementary inputs. In this latter case, a supermodular payoff function arises via the presence of some third variable which is complementary to the technologies, although the technologies themselves might not be directly compatible or connected in any way. For the case of complementary inputs, it is immediately obvious that the payoff flow of each technology will at least partly depend on the quality and quantity of the joint input purchased or used. The net benefit of the technology will thus depend on the price and availability of the joint input; changes therein can therefore influence the adoption decision of a firm. An interesting example of this is Gandal et. al. (2000) who study the effect of CD prices and availability of CD's on the diffusion of CD players.

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, which leads to skill-biased technological change and eventually also impacts on wage structures, favoring well educated individuals with IT knowledge. In addition to skilled labor, 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.

Note again that this result is also strictly increasing in its arguments. Thus, the momentum of progress upon the trajectory should be an *increasing* function of all complementary inputs of the technologies belonging to the paradigm.

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 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.

Financial slack and imperfect capital markets

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 (see 2.3.7). 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). Again, this mechanism is strictly increasing in its arguments.

Development paths and the rate of progress

The above discussion identified four distinct theories that can be related to technological development paths (trajectories) and the rate of progress: technological complementarity, complementary joint inputs, learning-by-doing, and imperfections in capital markets. All four theories are strictly increasing in their arguments, implying that the development of a firm along a given technological trajectory could be a self-propagating mechanism with increasing momentum. In other words, the more “advanced” a firm already is, the more likely it will make further progress on the trajectory. This is in the essence the “success-breeds-success” story that was discussed earlier in section 2.3.7. While the literature cited in section 2.3.7 deals with the dynamic relationships of investments into innovative activities such as R&D and firm performance, this line of reasoning is applied here to investments into new technologies and the expected costs and benefits of future technological investments, which also relate to firm performance. The parallel between investments into R&D and new technologies is straight forward: Both activities involve sunk costs in the expectation of future rewards, and both activities can be considered as “innovative” in the Schumpeterian sense because they aim to “carry out new combinations” (see section 1.4.1).

The link of technological development paths to diffusion theory is also straight forward: A technological paradigm is associated with a number of concrete, related technologies. Suppose that these technologies are not substitutes in their functionality and that firms can vary in their characteristics. The normal course of development along the trajectory starts with the emergence of the new paradigm and the non-availability of any associated technology within a firm (or country), progresses with the adoption of various technologies, and possibly ends with the adoption of all available technologies belonging to the paradigm. The adoption of an additional technology associated with the paradigm is considered as progress upon the trajectory. Note that this is not a deterministic process. Not all firms need necessarily adopt all technologies because the expected payoff from a technology can vary among heterogeneous firms. Also, alternative paradigms might exist in parallel that offer viable substitute technologies, providing some firms with alternative investment opportunities.

Each technology from a given paradigm that the firm has not previously adopted is an investment opportunity at time *t*. Depending on the specific characteristics of each firm, the expected payoff from each investment opportunity can vary among firms (rank effects). In particular, the availability of complementary technologies, inputs, relevant experience, and financial resources will positively influence the expected payoff from adoption at time *t* and make adoption more probable. In analogy to the argument of Arrow (1962a), the continuous investment into knowledge, complementary inputs, and the resulting advantages are reflected in the technology a firm currently uses. Thus, the number of previously adopted technologies from the associated paradigm can serve as a proxy for the availability of complementary technologies, inputs, relevant experience, and financial resources. All of the above trigger a self-reinforcing mechanism that increases the momentum of progress. The more advanced a firm is upon the trajectory, the more likely it will make further progress. Or, in terms of technology adoption, the probability to adopt any technology should increase the more related but non-substitutable technologies the firm has previously adopted, ceteris paribus.

In other words, firm-specific resources are both a source and a consequence of the adoption of new technologies that are associated with some trajectory and development path. Thus, history matters for the *rate* and the *direction* of technological progress. The self-propagating development mechanism continues until firms have exhausted the potentials of a given trajectory. As pointed out above, this does not imply that all firms must necessarily adopt all technologies that are associated with a trajectory. Some may and some may not, it depends on their specific characteristics which combination of technologies and complementary inputs will be optimal *given their remaining characteristics*. Also, it depends on whether they have technological alternatives available that belong to a different paradigm.

The possibility of a self-propagating mechanism of technological development upon a given trajectory has important strategic implications. There is an explicit link between technology adoption and the resource-based view of the firm, which provides a conceptual framework to analyze the relationship between firm-specific resources and competitive advantage (Barney 1991). Firm resources are conceptualized to include all physical, organizational, and human capital resources controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness. A firm is said to have a *competitive advantage* when it is implementing a value creating strategy not simultaneously being implemented by any current or potential competitors. A *sustained competitive advantage* arises if other firms are unable to duplicate the benefits of the strategy that creates the competitive advantage.

The resource-based view assumes that firms are heterogeneous in the resources they control and that these resources may not be perfectly mobile across firms, which implies that heterogeneity might be a lasting phenomenon. Barney (1991) identifies four attributes of firm resources that are necessary if they are to be a source of sustained competitive advantage:

- The resource must be valuable in the sense that it improves the efficiency and effectiveness of a firm.
- It must be rare among a firm's current and potential competitors, i.e. not simultaneously implemented by a large number of other firms.
- It must be imperfectly imitable. This can occur if acquiring the resource is dependent upon unique historical circumstances, if there is causal ambiguity between the resources of the firm in its performance, or if it comprises of a socially complex phenomenon that is beyond managerial ability to systematically influence.
- There cannot be strategically equivalent substitutes for this resource that are valuable but neither rare or imperfectly imitable.

The technological endowment of a firm, including its integration into production processes, organizational structure, the social dynamics of the enterprise and its combination with other complementary assets of the firm (such as human capital) is clearly a firm-specific resource that is likely to be a source of sustained competitive advantage, as suggested by the resource-based view of the firm. The extent to which this holds for a particular technology depends on how well it fulfills the four above mentioned, necessary attributes.

The presence of a self-propagating process of technological development substantially increases the strategic importance of technology adoption decisions in general and their *timing* in particular, because it limits the extent to which the technological endowment is imitable once a firm got a head-start in its development vis-à-vis its competitors. Figure 2 illustrates these relationships.

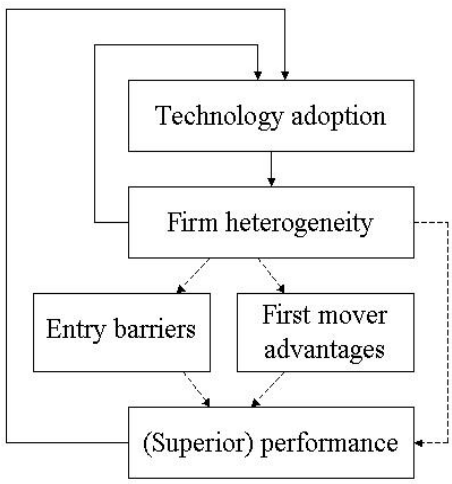


Figure 2 – Technology adoption as a source of competitive advantage

Asynchronous technology adoption decisions of enterprises obviously contribute to (temporary) firm heterogeneity. The different endowment with technologies can have a direct impact on firm performance, e.g. there might be productivity advantages for those firms that have adopted a new technology first. These differences in performance among companies might affect future technology adoption decisions, because companies that performed better in the past might have easier access to capital to finance additional investments (Abel and Blanchard 1986, Hubbard 1990 and Hubbard and Kashyap 1992). This is one mechanism how particular firm-specific resources can be both a source and a consequence of technology adoption decisions. In addition, if firms have the opportunity to invest into related technologies that belong to a particular paradigm and trajectory, their current technological endowment directly influences future adoption decisions via learning-by-doing, technological complementary and the availability of complementary resources, which makes the heterogeneous distribution of firm-specific resources a possibly lasting phenomenon which is contingent upon historical events. Also, there might be early mover advantages and the possibility to build up entry barriers. Both effects could be sustainable in the long run and have an impact on the performance of enterprises. For example, early movers might have advantages to hire scarce technical experts or to build up a positive reputation among customers that leads to long-term customer loyalty. In these cases, early progress on a new technological trajectory can yield sustainable competitive advantages. Hence, the decision to adopt a new technology and the timing of this decision can have important strategic consequences, especially if a self-propagation mechanism of technological development actually exists.

Are investments into e-business technology are a possible source of competitive advantage? According to the resource-based view, the answer is “yes”. Investments into e-business and ICT in general can be valuable because they promise to improve the efficiency and the effectiveness of a firm. Also, a particular endowment with ICT and e-business tools can be rare because the diffusion of these technologies takes times. If early movers make indeed continuously faster progress, this makes their unique set of implemented technologies rare compared to competing firms that adopt later. The presence of an endogenous acceleration mechanism suggests that the ability of firms to acquire and exploit technological resources depends upon their place in time and space. Once this particular unique time in history passes, firms that try to follow might not be able to perfectly imitate the resources and their benefits. In addition, investments into ICT and e-business technologies need to be organizationally imbedded to become beneficial and hence often require investments into complementary assets, such as organizational design and human capital. These complementary assets can also be rare, valuable, and hard to imitate, which adds to the strategic relevance of ICT and e-business adoption decisions. Finally, whether e-business and ICT related firm-specific resources can be substituted probably depends on the specific technology and the context in which it is embedded in the organization. In general, two valuable firm resources are strategically equivalent when they can be exploited separately to implement the same strategies (Barney 1991). For example, if the strategic advantage of a firm is build on its ability to manage large amounts of information quickly and to process it efficiently, this might be achieved either by a highly developed ICT infrastructure that is deeply imbedded in an organization. But the same benefits might accrue to a firm with a closely knit, highly experienced management team, without the use of ICT (Hambrick 1987). However, this substitute is also likely to be rare and not perfectly imitable. Therefore, according to Barney (1991), an embedded and highly developed ICT infrastructure might be a source of sustainable advantage.

In summary, the resource-based view of the firm suggests that the decision to invest into a new technology has clear strategic implications because it could be a source of a sustainable competitive advantage. This is especially likely to occur if technological investment decisions are dependent on each other over time, giving rise to a self-propagating mechanism. The presence of such an acceleration effects makes the unique set of technological competencies of a firm rare and imperfectly imitable, provided that competing firms start at different times with their progress upon a given trajectory. This self-propagating mechanism could arise due to technological complementarities, joint complementary inputs, learning-by-doing, or imperfections in capital markets. Chapters 5 and 6 will engage in a rigorous empirical analysis to test whether such a self-propagating mechanism actually exists. If so, this would indicate additional advantages of an early adoption strategy.

3.6. Implications for e-business diffusion

Chapter 3 has discussed numerous factors that influence the adoption and diffusion of new technologies. However, not all of them are testable in later chapters due to data limitations. I restrict the explicit wording of hypotheses to those aspects that can be addressed in the empirical parts.

First, as technologies become cheaper and their performance increases, more firms will adopt them. This mechanism was identified as driving the diffusion process in rank, stock, and order effect models. Rapid progress both in computer hardware and software (Moore’s law) suggests that the prices of ICT fall over time, while the performance simultaneously improves. Provided that this mechanism also holds for e-business technologies, we can expect that adoption becomes more probable as time proceeds. Second, the more firms already have adopted e-business technologies, the higher the probability that non-adopters will eventually switch to the new technologies as well. This may happen totally independent from possible network externalities of e-business technologies, purely as a result of better information conditions and less uncertainty about e-business, as pointed out by epidemic effect models. Both effects imply that the probability to adopt is strictly increasing with time:

Hypothesis 9: The probability to adopt e-business technologies strictly increases with time.

Furthermore, in the presence of technological complementarities, complementary joint inputs such as skilled human capital, learning-by-doing effects, and returns to new technology usage in conjunction with imperfect financial markets, a self-reinforcing mechanism can emerge that increases the momentum of progress for those firms that are already advanced in e-business usage, ceteris paribus. This results directly from the discussion about the diffusion of multiple related technologies in chapter 3.5:

Hypothesis 10 – The probability to adopt any e-business technology is an increasing function of the number of other e-business technologies that a firm has already adopted, provided that the technologies do not substitute each other in their functionalities.

Finally, better knowledge of the technologies will reduce the level of uncertainty and thus speed up diffusion. Also, better knowledge is indicative of the presence of complementary inputs (such as technical specialists or infrastructures) which will also make adoption more attractive. Thus, we might expect that industries that either have prior experience with intensive usage of ICT in general (e.g. banks, insurances, automotive, media) or industries that are somehow involved in the production of ICT goods and services (e.g. electronics industry, telecommunications) will show more rapid rates of e-business diffusion. This leads to Hypothesis 11:

Hypothesis 11 – Industries with ex ante better knowledge about ICT will adopt e-business technologies more rapidly.

Table 2 provides an overview of all hypotheses from chapters 2 and 3, which points out to which theories in both chapters the hypotheses are linked. It becomes obvious that there are numerous parallels between the literature analyzing the consequences of technological diffusion and the diffusion literature itself. In particular, those theories of technology diffusion that have a micro-economic foundation (stock and order effects) are closely linked to the game-theoretic literature on technological competition (e.g. patent races and models of technological competition with endogenous market structure). Also, the theory of rank effects provides an overarching framework to include factors that are related to firm heterogeneity and the unequal distribution of specific resources among firms and markets (e.g. economies of scale, network effects, market structure, managerial competence) into models of technological diffusion. Section 3.7 further elaborates on these interdependencies and how these different theories contribute towards a consistent view of technological change.

Table 2 – Overview of hypotheses

Number	Content	Theories	Chapters
1	Diffusion varies across sectors	Sutton (1991), Geroski (1994), rank effects, order effects, multiple techn.	2.3, 3.2.2, 3.2.4, 3.5
2	Sectors with high concentration ratios and high technological competition are more likely to adopt	Sutton (1991), Geroski (1994), absorptive capacity, rank effects, order effects, multiple techn.	2.3, 3.2.2, 3.2.4, 3.5
3	Large firms are more likely to adopt	Economies of scale, network effects, Schumpeter (1942); rank effects	2.3, 3.2.2
4	Firms with medium degree of market power are more likely to adopt	Comanor (1967), Scherer (1967), Mansfield (1977), rank effects	2.3, 3.2.2
5	Early movers enjoy excess returns	Patent races, stock effects, order effects	2.3.6, 2.3.7, 3.2.3, 3.2.4
6	Innovators are more likely to grow	Patent races, innovation and market structure, stock effects, order effects	2.3.5, 2.3.6, 2.5, 3.2.3, 3.2.4
7	Firms that are advanced in using e-business are more likely to reduce employment	Substitution effects	2.6
8	Firms that recently used technology to innovate are more likely to increase employment	Compensation effects	2.6
9	The probability to adopt e-business technologies strictly increases with time	Epidemic effects, network externalities, falling prices, technological improvements	2.3.3, 3.2.1, 3.2.2, 3.2.3, 3.2.4
10	The probability to adopt any e-business technology increases with the number of previously adopted e-business technologies	Complementarity, strategic behavior, learning-by-doing, absorptive capacity, imperfect capital markets, rank effects, multiple technologies	2.3.6, 2.3.7, 2.5, 3.2.2, 3.5
11	Industries with high ICT competence are more likely to adopt e-business technology	Learning-by-doing, absorptive capacity, rank effects, technical experts, reduced uncertainty, multiple technologies	2.3.7, 3.2.2, 3.2.5, 3.5

In addition to these hypotheses that can be empirically tested in later chapters, the above discussion of diffusion theories suggests a number of other relevant and interesting factors that will influence the diffusion of e-business technologies and are worth summarizing. First, one can substantiated in which industries diffusion will be particularly rapid (thus further specifying hypothesis 1): Industries that are characterized by low price-elasticity of demand will experience faster rates of diffusion, as pointed out by stock effect models. Second, according to order effect models, the presence of positive returns to scale, significant market reputation effects, or competition for scarce complementary inputs (such as skilled labor) in an industry can speed up the diffusion process because it makes pre-emptive adoption attractive. Third, industries and countries that are in a period of cyclical upswing will have a higher probability to adopt because they generally increase their investment spending in such periods (see 3.3).

Diffusion theory is also informative about who can be expected to benefit most from e-business adoption. According to stock, order, and multiple technology models early adoption should yield the highest overall returns. The presence of first mover advantages (resulting from complementarities, learning effects, increasing returns to scale, reputation etc.) may even lead to sustainable advantages of early adopters that cannot be perfectly copied by rivals that adopt at later times. Apparently, models involving rank effects, information acquisition, epidemic effects, or uncertainty are not very informative about who will be the likely winners of technology adoption. However, they provide reasonable explanations why firms may not adopt instantaneously, even though this might be the best strategy if purely competitive effects are considered.

3.7. The process of technological change

The preceding two chapters provided a literature review on the diffusion of new technologies and their implications. This section intends to highlight a number of parallels between these two research directions and to show how they jointly contribute to a consistent, market-based view of technological progress.

Figure 3 shows a flowchart that gives a simplified illustration of the process of technological change. Technological change, meaning changes in the goods or services produced and the means by which they are produced, can be broken down into four main stages:

1. Invention of a new product or process: This can be the result of coincidence or purposeful R&D activities. A new product or service might also arise as a by-product of an investment into a new technology which is introduced to a company.
2. Market entry: Once the new product or service has been invented, it is introduced to the market. Potential customers of the invention can be either private consumers and households or other firms.[7] Once the invention gains practical use in a market or process, it turns into an innovation.
3. Diffusion: A new product is adopted by consumers and / or firms over time until it reaches its market potential. Alternatively, it can also fail if neither consumers nor firms are willing to purchase the invention. If firms invest into the new product, their gain from it is usually not direct but requires an implementation process which can either trigger a new product or service offer by the adopting company, or / and a process innovation within the adopting company. Alternatively, the implementation can also fail, usually ending in a write-off of the investment.
4. Market adjustments: Finally, numerous market adjustments can occur as a consequence of the diffusion process. In the case of the successful diffusion of a new consumer product or service, the purchasing habits of consumers changes, possibly affecting the demand on markets for products that are substitutes or complements to the innovation. This can trigger further complex adjustment processes

[7] A process invention is usually not offered to a market for sale, but directly implemented in the company it was invented in. In case the company decides to sell the knowledge about the new process to other companies, it becomes a product or service invention.

on the supply side of these related markets, possibly also affecting the labor market. In the case of a successfully introduced process innovation, the adopting company expands its production[8], which leads to total output growth[9], a decrease in prices[10] and changes in market shares[11].

This very simplified illustration leaves out important elements that also contribute in important ways to technological change. For example, the role of entrepreneurship and new firm foundation is not explicitly considered, although it does have a crucial role in the process of technological advance. However, this price was paid for the purpose of clarity and for investigating the role of technology diffusion in the process of technological change, which is the main objective of this study.

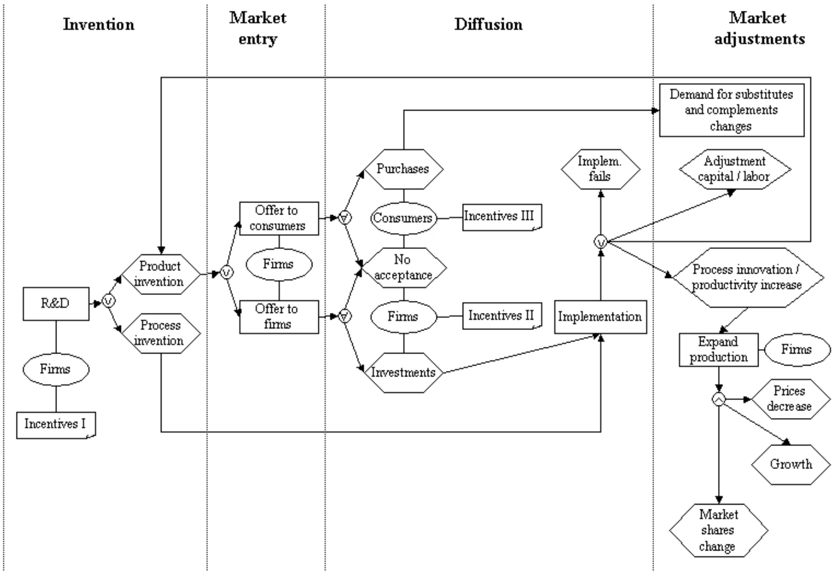
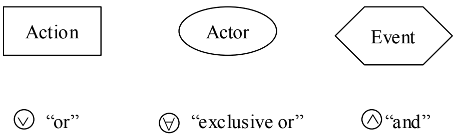


Figure 3 – Simplified process of technological change



Legend to Figure 3

Interestingly, the literature cited in chapters 2 and 3 points out that the four stages of the process of technological change mentioned above are closely related. In particular, firm's expectations of the market adjustments *succeeding* the successful introduction of a new product or process provide an incentive for *investing* into new products or processes, either via R&D efforts or through the investment into a new technology sold by someone else. Also, the realization of profits from such investments is inseparably connected with the market adjustments outlined above. Table 3 summarizes the incentives that drive the decision of firms and customers to invest into innovative activities, products or services.

[8] Lower production costs lead to higher optimal production quantities, ceteris paribus.
[9] Provided that demand is somewhat price-elastic.
[10] Because the demand curve slopes downward.
[11] Provided that not all companies serving the same product market adopt the new process at the same time.

Table 3 – Incentive scheme to Figure 3

Incentives I	- Opportunities for profitable investment - Opportunity to gain strategic advantage - Capturing market shares from rivals via production cost advantages or market entry - Achieving (temporary) monopoly position via entry to a new market
Incentives II	- Opportunities for profitable investment - Opportunity to gain strategic advantage - Capturing market shares from rivals via production cost advantages or market entry - Achieving (temporary) monopoly position via entry to a new market
Incentives III	- Utility gains from consumption

Remarkably, it appears that the selfish motives of consumers and companies seem to be the engine that drives technological progress and hence spurs the creation of wealth and economic growth. These selfish motives seem to unfold their creative and productive impacts particularly well in free-market societies where firms are engaged in fierce competition, as recently pointed out by William Baumol (2002):

"What differentiates the prototype capitalist economy most sharply from all other economic systems is free-market pressures that force firms into a continuing process of innovation, because it becomes a matter of life and death for many of them… Firms cannot afford to leave innovation to chance. Rather, managements are forced by market pressures to support innovative activity systematically and substantially, and success of the efforts of any one business firm forces its rivals to step up their own efforts. The result is a ferocious arms race among the firms in the most rapidly evolving sectors of the economy, with innovation as the prime weapon." (p. viii-ix)

In the context of this study, it becomes obvious that investments into new technologies are an essential part of this "ferocious arms race" that spurs economic growth, creates prosperity and enables firms to gain competitive advantages. Table 4 summarizes the connections between the four main steps of technological progress and the various theories that were discussed in the preceding two chapters.

Table 4 – Theories relating to technological change

Process step	**Theories**	**Chapter**
Invention and R&D	Patent races, market structure and innovation incentives, appropriability problems	2.2, 2.3.4, 2.3.6
Market entry	Patent races, market structure and innovation incentives	2.3.4, 2.3.6
Diffusion	Epidemic-, rank-, stock- and order effects, risk and uncertainty, multiple related technologies, Roger's criteria	3.2, 3.4, 3.5
Market adjustment	Innovation and market structure, patent races, economies of scale and scope, network effects, employment effects, productivity and growth, stock- and order effects	2.3.1, 2.3.2, 2.3.3, 2.3.5, 2.3.6, 2.4, 2.6, 3.2.3, 3.2.4

This concludes Part I of this study, which aimed to provide an overview of what we currently know about how new technologies gain increasing usage among firms and how innovation diffusion is embedded in the more general process of technological progress. Chapter 2 emphasized that the diffusion of new technologies can have far reaching consequences for the competitiveness of individual firms, the organization of production processes and market structures, the demand for labor and certain types of qualifications, and for productivity growth and the creation of prosperity and wealth. In particular, the strategic relevance of technology adoption decisions was stressed. Chapter 3 provided an overview of the current literature on technology diffusion. The primary objective of this research is to rationalize and to explain the puzzling observation that new technologies – even if they promise clear benefits and are objectively superior to old technologies – are not immediately adopted by all firms that could possibly profit from them. Rather, diffusion appears to be a dynamic process that often takes surprisingly long until the new technologies have gained saturation levels in usage. Different theories have been suggested to explain this phenomena. Some of these theories complement each other (e.g. the rank effects theory and the majority of the management literature on technology diffusion), while others are based on conflicting assumptions to explain the same phenomena (e.g. epidemic effects versus stock effect models). In particular, we found that some of the most interesting and challenging effects occur when firms' investment decisions are observed as a dynamic sequence, i.e. when past investment decisions influence the probability and the payoff of future investment decisions, which can lead to non-linear dynamics, lock-in effects and path-dependent developments. Also, the existing literature suggests that such non-linear dynamics are especially likely to occur if firms are faced with a new technological paradigm that offers various, related investment opportunities instead of just one stand-alone technological solution that is independent from any other technology the firm uses or could purchase in the future. However, there is still a gap in the literature analyzing explicitly how such dynamic interdependencies influence the adoption behavior of firms and also a clear lack of empirical evidence for such dynamics. In addition, there is still only very few empirical work on the diffusion of e-business technologies and on the relationship of e-business usage with firm performance[12].

Part II continues with original research that is carried out to address these gaps in the literature and to empirically test the hypotheses that were developed in Part I. The estimation results will be indicative about which of the above identified theories abides the test of the data and which particular factor has the strongest and most dominant influence on the diffusion dynamics of e-business technologies. In addition, the analysis of the interrelationship of e-business usage, innovative activities and firm performance yields interesting and new insights into the strategic relevance of ICT. Last but not least, a number of implications can be derived based on the empirical evidence.

[12] Primarily because this technological paradigm is still relatively new and firm level data that is adequate and useful for academic purposes is still rare.

PART II

4. Data description

The data used for the empirical analysis in the following chapters originates from enterprise surveys of the *e-Business Market W@tch*, an observatory initiative sponsored by the European Commission. The *e-Business W@tch* monitors the adoption, development and impact of electronic business practices in different sectors of the European economy. The initiative was launched in late 2001 with the purpose to provide reliable and methodically consistent empirical information about the extent, scope, and factors affecting the speed of e-business development at the sector level in an internationally comparative framework, information which have previously not been available from other sources such as official register-based statistics or market research studies.

The European Commission launched the project to get more in-depth information about e-business development in Europe in order to identify possible needs for policy action to concur with the eEurope 2005 Action Plan, which was endorsed by the Seville European Council in June 2002. In that Action Plan, the European Council agreed on the goal "to promote take-up of e-business with the aim of increasing the competitiveness of European enterprises and raising productivity and growth through investment in information and communication technologies, human resources (notably e-skills) and new business models".

Until 2004, the *e-Business W@tch* initiative had conducted three large scale enterprise survey rounds and published Sector Impact Studies on 17 different sectors in the European economy, three comprehensive synthesis reports, statistical pocketbooks and other resources[13]. These various publications and resources contain a very comprehensive collection of descriptive statistics from the three enterprise survey waves, thus making an additional descriptive analysis of the data for the purpose of this study dispensable. Results from the *e-Business W@tch* received high attention among policy makers, industry representatives and have been quoted and utilized by other research institutions, for example EITO (2003) and OECD (2004).

The three enterprise surveys were carried out in July 2002, March 2003 and November/December 2003. Each survey used a slightly modified questionnaire and had a different coverage of industrial sectors and countries. Thus, no real panel data were collected. Instead, the surveys are based on independently drawn random samples from pre-specified country-sector combinations, stratified by three enterprise size classes (<49 employees, 50-250 employees, >250 employees) to enable a representative representation of the respective country-sector findings. A consistent survey method was used, interviewing decision makers in companies (e.g. IT managers, managing directors or the owner) by computer-aided telephone interviews (CATI). Translation of the questionnaire into the respective languages and fieldwork was carried out by specialized polling companies.

Each interview collected basic information about the company, including confirmation of sector membership, number of employees, number of establishments, and basic financial information such as turnover development. The majority of questions related to the availability and usage of various ICT and e-business technologies. In addition, companies were asked about their IT training efforts. Also, various questions related to the perceived importance and impact of e-business at the firm level. The average interview time was close to 15 minutes for all three survey waves, thus a comprehensive set of firm-specific information could be gathered.

Due to budgetary constraints, not all sectors and all European countries could be included in each survey. Instead, the choice of sectors and countries varied in each survey round in order to get an increasingly broad cov-

[13] all available free of charge at the project's website at www.ebusiness-watch.org.

erage, which was desired by the European Commission. The definition of all sectors was in accordance with NACE Rev. 1 statistical classification of economic activities.

Table 5 shows the number of successfully completed interviews in each country-sector cell for the first *e-Business W@tch* survey which was carried out in July 2002. In sum, the dataset contains 9,264 valid observations from 15 sectors in 15 European countries. However, not all 15 sectors were covered in each country with the exception of the four largest European countries – France, Germany, Italy, and the UK – which exhibit a complete and homogeneous sector coverage that enables cross-country and cross-sector comparisons.

Table 5 – Country-sector coverage *e-Business W@tch* survey July 2002

	Country														
Sector	**A**	**B**	**DK**	**FIN**	**F**	**D**	**GR**	**IRL**	**I**	**L**	**NL**	**P**	**E**	**S**	**UK**
01			99		100	100			102		96	100	101		100
02					101	100	51		102		102		100		101
03		101			50	100		36	100					51	100
04				60	103	100	53		133	31					100
05	105				100	100			129					54	105
06				61	100	100			102					50	104
07					50	100			104				100	53	102
08	102				101	100	52		105		84	100			100
09	101				100	100	100		96				100		102
10		97			103	100			99	41			101		100
11					50	100	52		41	30				52	101
12			104	61	101	100			101			100			101
13			101		103	100		63	103		117				105
14				63	100	100			100		101				103
15		102		63	100	100		56	100						114

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

The July 2002 survey covered seven manufacturing industries and eight service sectors. Table 6 provides the exact definition of the sectors according to NACE Rev. 1 codes. Within each sector, sampling was adjusted according to the relative size of sub-sectors measured by value-added. Thus, sub-sectors with a relatively larger share of contribution to national GDP were included with a proportionately larger number of interviews, allowing to get an approximately representative picture at the country-sector level.

Table 6 – Sector definition of *e-Business W@tch* survey July 2002

	Sector short name	**NACE Rev. 1 Codes**
01	Food	15 – Manufacture of food products and beverages 16 – Manufacture of tobacco products
02	Publishing	22 – Publishing, printing and reproduction of recorded media 92.1 – Motion picture and video activities 92.2 – Radio and television activities
03	Chemicals	24 – Manufacture of chemicals, chemical products and man-made fibers 25 – Manufacture of rubber and plastic products
04	Metal products	28 – Manufacture of metal products
05	Machinery	29 – Manufacture of machinery and equipment
06	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
07	Transport Equipment	34 – Manufacture of motor vehicles, trailers and semi-trailers

		35 – Manufacture of other transport equipment
08	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
09	Tourism	55.1 – Hotels 55.2 – Campsites and other forms of short-stay accommodation 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
10	Monetary Services	65.12 – Total credit institutions 65.2 – Other monetary intermediation
11	Insurances	66 – Insurances and pension funding, except compulsory and social security
12	Real Estate	70 – Real estate activities
13	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
14	ICT Services	64.2 - Telecommunications 72 – Computer-related activities
15	Health Services	85.1 – Health activities 85.3 – Social work activities

The same surveying and sampling methods were maintained for the March 2003 and November/December 2003 survey waves. The March 2003 survey covered only the five largest European countries (France, Germany, Italy, Spain and the UK) and seven sectors (four manufacturing, three service sectors), but all sectors were covered in all countries, thus yielding a homogenous coverage that allowed to make representative cross-country and cross-industry comparisons. In total, 3,515 interviews were successfully conducted in March 2003. Table 7 provides a detailed breakdown of the number of interviews per country-sector cell.

Table 7 - Country-sector coverage *e-Business W@tch* survey March 2003

Country	Sector						
	01	**02**	**03**	**04**	**05**	**06**	**07**
F	100	100	100	101	101	99	100
D	100	100	100	100	100	101	100
I	102	101	101	100	102	102	101
E	100	100	100	100	100	100	100
UK	100	101	101	100	101	100	101

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

Some of the sectors that were covered in June 2002 were surveyed again in March 2003. The definition of sectors was maintained to achieve some level of comparability of results, with the only exception of the tourism sector that now also included restaurants, cafes and bars.

Table 8 shows the respective definitions.

Table 8 - Sector definition of *e-Business W@tch* survey March 2003

	Sector short name	**NACE Rev. 1 Codes**
01	Food	as above
02	Chemicals	as above
03	Electronics	as above
04	Transport Equipment	as above
05	Retail	as above
06	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
07	ICT Services	as above

The November/December 2003 survey extended the scope of the project to the 10 Acceding Countries and to two new sectors that were previously not covered (textile industries and crafts & trade), now covering a total of 25 countries and 10 sectors. This, however, resulted in a loss of homogeneity in country-sector coverage and a loss of cross-country and cross-sector comparability on the aggregate level due to budgetary constraints. In total, the November/December 2003 survey included 7,302 successfully completed interviews; 4,670 in the old EU and Norway, 2,632 in the Acceding Countries. Table 9 shows the detailed coverage break-down.

Table 9 - Country-sector coverage *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 number of successfully completed interviews, country names abbreviated by their international license plate codes

Table 10 again shows the definition of the 10 sectors covered in the November/December 2003 survey. Eight of the sectors had already been part of the June 2002 survey, and their definition was retained, with the only exception of the tourism sector that included restaurants, cafes and bars as in May 2003. The textile and the crafts & trade sectors were, however, covered for the first time in November/December 2003. Crafts & trade is not an official industry according to NACE Rev. 1 codes. The *e-Business W@tch* considered crafts & trade to be a group of professions in which “workers apply their specific knowledge and skills to produce or process goods” and in which “the tasks call for an understanding of all stages of the production process, the materials and tools used and the nature and purpose of the final product”. The operational definition was “firms with less than 50 employees in craft-related NACE Rev. 1 business activities” (*European e-Business Market W@tch* 2004a, p. 122).

Table 10 - 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	as above
03	Electronics	as above
04	Transport Equipment	as above
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	as above
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	as above
09	Health Services	as above
10	Business Services	as above

During the course of the project, changes have also been made to the questionnaire that was used for the surveys. These changes partially reflected prior experience with survey results (including response rates, wording of questions), identification of additional aspects that deserved more attention (including an extension of available background information about companies and a retrospective time dimension on some technology variables), but also changes in the technological environment due to newly emerging trends and specific interests of the client or of consortium members that needed to be reflected in the questionnaire. The implemented changes necessarily led to inconsistencies between the surveys, thus making a comparison of time trends from one survey wave to another a dodgy exercise from a methodical point of view. Thus, for purposes of academic analysis it is more useful to consider each survey wave as an independent, stand-alone cross-sectional dataset that cannot be easily compared or connected to other survey waves. While this might be viewed as a disadvantage (we have three cross-sections that are neither poolable nor a true panel), it also has merits because each survey focused on slightly different aspects and generated a slightly different set of variables that can be used to analyze different questions. Also, each survey wave by itself is large enough to draw some fairly representative conclusions about the underlying sampling population. The complete questionnaires for all three survey waves are publicly available on the website of the *e-Business W@tch* project at:

http://www.ebusiness-watch.org/menu/The_European_e-Business_Survey/[14]

For the purpose of this study, the most important features of each survey wave are 1) which and how sectors and countries were covered, 2) which background information about companies are available, and 3) which information on technology usage are available.

Table 11 – Features of the three cross-sectional datasets

Survey	**Coverage**	**Background information variables**	**Technology usage variables**
June 2002	- Homogeneous coverage of 15 sectors in 4 countries - Heterogeneous sector coverage in 11 additional countries - Largest cross-section with 9,264 valid observations	- Limited to *size class*, *country*, *sector*, *number of establishments, turnover development last year*, *primary customers of the enterprise* and information about *IT training* efforts	- A large number of ICT and e-business technology variables are available. - Disadvantage: No information about *when* technologies have been used for the first time.
March 2003	- Homogeneous coverage of 7 sectors in five countries	- Same as in June 2002	- Comparable to June 2002, however for 8 technologies companies were also asked *when* they first started to use it
Nov/Dec 2003	- Heterogeneous coverage of 10 sectors in 25 countries, no comparability across countries or sectors on the aggregate level	- Important additional variables have been added, including *profitability last year, % of employees with college degree, market share, product innovations last year, process innovations last year, Internet-related innovations last year (product or process)*	- Comparable to March 2003, including the retrospective time dimension for 8 technologies

According to Table 11, the major advantage of the June 2002 survey is its comprehensive and homogeneous coverage of 15 sectors in 4 countries. Also, this is the survey with the highest number of successfully completed interviews. Since the main objective of this study is to analyze technology adoption and its impact at the level of

[14] Link active as of April 1st, 2005.

the individual firm, the major disadvantage of this dataset is the lack of a time dimension and a lack of important background information about each company (e.g. market share, employee qualification, innovative activities), including a lack of objective performance variables such as profitability that could be related to technology usage in a meaningful way. However, for a static analysis of adoption patterns this dataset is very attractive due to its sheer size and the comprehensiveness of technology usage variables that were collected.

The major advantage of the March 2003 survey for the purposes of this study is the introduction of a retrospective time dimension on eight technology variables: Firms that confirmed in the interview that they currently use a particular e-business application (e.g. online purchasing or e-learning) were asked when they first started to use that technology. This enables a dynamic view of the diffusion process. Of course, there is some additional variance in the data due to the fact that respondents may not precisely remember since when their enterprise has been using a particular technology. Nevertheless, the ratio of missing values on these questions were always below 20% of the respective subjects indicating that most respondents were at least able to make an “educated guess”. Also, one might reasonably assume that the error distribution will not be significantly skewed towards one or the other side of the true values. Thus, without additional information or conflicting evidence, it is most reasonable to treat the reported adoption date as the true adoption date.

An additional advantage of the March 2003 survey is the achieved level of homogeneity in country-sector coverage. However, compared to the June 2002 survey, less country and sectors were included, yielding less degrees of freedom in the explanatory variables for diffusion analyses. The major disadvantage of the March 2003 survey is that important background information about companies and objective financial performance variables are still missing.

This shortage was overcome by the Nov/Dec 2003 survey, which also included information on market shares, profitability, and innovative activities within firms. Especially the questions on innovative activities turned out to yield very interesting insights. Two introductory questions that were asked to every respondent elicited whether a company had introduced substantially improved products or services to its customers during the past 12 months prior to the date of the interview. It was also asked if the company had introduced new internal processes during the past 12 months. These introductory questions were adopted from the Community Innovation Survey (CIS 2004) to determine the share of companies that recently introduced product or process innovations. The advantage of adopting the questions from CIS was that it enabled to use a well accepted and tested survey instrument. In addition to the introductory questions on innovation, the interest was also on the share of innovative activity that is directly related to or enabled by Internet-based technology. Therefore, companies that indicated in the introductory questions that they have conducted innovations in the past 12 months were asked follow up questions. In addition to these new and important background information, the Nov/Dec 2003 survey maintained the retrospective dynamics introduced in March 2003, thus yielding a particularly rich dataset with a pseudo-dynamic perspective. The only disadvantage of the survey is the high level of heterogeneity in country-sector coverage that does not allow to compare results across countries or sectors. However, econometric techniques can be used to overcome this problem (see chapters 6 and 7).

For the studies in the following chapters, the choice was made to use the June 2002 survey for the static analysis of e-business adoption due to the comprehensive and homogeneous coverage of 15 sectors in 4 countries, which yielded an exceptionally large dataset with detailed information about e-business technology usage. To study the dynamics of e-business adoption and the relationship of e-business technology usage, innovation and firm performance, the Nov/Dec 2003 survey is used because it contains the required retrospective time dimension of the data and the necessary background information which are lacking in the previous surveys. The disadvantage of heterogeneity in this sample is accommodated with panel-econometric techniques. Thus, no use is made of the March 2003 data, primarily because they are lacking important variables for the purposes of this study. The dataset may, however, turn out to be a useful source for other studies[15].

[15] The European Commission grants access to the dataset for non-profit research purposes.

5. Static analysis of e-business adoption

This chapter presents a static analysis of the adoption of various e-business technologies. A theoretical underpinning of the effects of related technologies on diffusion processes is offered. Provided that the technologies do not substitute another, it is hypothesized that the probability to adopt any technology is an increasing function of the number of other related technologies that a firm is also using. A simple mathematical framework is introduced to make these thoughts explicit and testable. Two structural parametric approaches are used to test the proposed relationships using enterprise survey data on various e-business technologies. Furthermore, non-parametric classification and regression trees (CART) are used to identify clusters of firms that exhibit significantly different adoption probabilities. The parametric and non-parametric approaches together suggest that technological interdependencies are a crucial determinant of adoption decisions. The technological legacy of a firm has a systematic influence on its investment decisions and its future technological development. In particular, firms might experience an endogenous acceleration mechanism that leads to higher adoption rates and faster "progress" among those firms that are already technologically advanced.

5.1. Theory

Most studies on technology diffusion focus on isolated, stand-alone technologies (see chapter 3, Stoneman 2002). However, in reality many technologies are not completely independent from other technologies or firm-specific resources. Neglecting these interdependencies may lead to biased estimates and erroneous conclusions. The complication arises because the usage of some technologies within a firm might influence the costs and gains of adopting another technology, influencing adoption decisions and technological development in a systematic way. The only previous studies dealing with the diffusion of multiple technologies (Stoneman and Kwon 1994, Stoneman and Toivanen 1997, Colombo and Mosconi 1995) have demonstrated that the presence of related technologies greatly affects adoption decisions. This line of research is extended here by making the nature of the interdependencies theoretically explicit and empirically testable, relating it to Dosi's (1982) concept of technological trajectories.

To formalize the argument, a decision theoretic adoption model based on investment principles is introduced: To analyze differences in adoption probabilities, the model simultaneously analyzes a large number (N) of companies. Let N be a number of heterogeneous, profit-maximizing firms without strategic interaction. In addition, assume certainty with respect to expected payoffs and costs of a technology. Each firm $i = 1...N$ is characterized by a vector of $\overline{x}_i$ individual covariates. This vector captures variables indicating relevant differences between firms, e.g. firm size and market specifications.

The focus of this study is on the initial purchase of a new technology and it abstracts from intra-firm diffusion and from the level of use of the technology by the acquirer. 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. It is specified below how technologies could be related in an economic sense and which effects can be associated with the concept of a joint technological paradigm. But non-substitutability is the crucial assumption for the following argument.

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

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

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

$$(5.1)\quad \begin{aligned}&[f(Y) - f(\min(Y', Y))] + [f(Y') - f(\min(Y', Y))]\\ &\leq f(\max(Y', Y)) - f(\min(Y', Y))\end{aligned}$$

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 supermodular (Milgrom and Roberts 1990).

Consider the decision of a firm to invest into 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[16]:

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

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

$$(5.2)\quad C_i(Y_i' \mid \bar{x}_i, Y_i) = p_i(Y_i' \mid \bar{x}_i, Y_i) + c_i(Y_i' \mid \bar{x}_i, Y_i)$$

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

Acquisition costs C_i can depend on other technological variables in three distinct ways. First, provided that the K technologies belong to the same technological paradigm, it is possible that they will require joint complementary inputs to function properly, such as specialized labor (Acemoglu 2002, Brynjolfsson and Hitt 2002, Greenwood 1997, Krueger 1993). Second, learning-by-doing effects (Arrow 1962a, Sheshinski 1967) may occur: Some experience gained with the usage of one particular technology might be transferable to another related

[16] One could also include a third cost component that reflects the option value of delaying the investment (Huisman 2001), which is lost once the firm decides to invest. However, this would not change the results and is therefore not explicitly considered.

technology. In such cases, some part of c_i will not have to be paid again when a firm considers to invest into an additional technology from the same paradigm, and c_i will fall if the firm is already more advanced. Third, firms that purchase more than one technology may achieve discounts on p_i. If any or all of the above applies, this will lead to lower acquisition costs for firms that are already more advanced. Thus, the presence of complementary joint inputs, learning-by-doing effects, or discounts for multiple purchases would all result in investment cost advantages for adopting an increasing number of technologies. Note that all three effects are strictly increasing in their arguments, without a natural point of inflection. Consequently, if any or all of the above effects apply, C_i will be submodular in Y_i:

Assumption 1 - A(1): The investment cost function $C_i(Y_i' \mid \overline{x}_i, Y_i)$ is submodular in Y_i.

In addition to the adoption costs, the present value of benefits from adopting additional technologies, g_i, could also depend on the current technological endowment of the firm in two distinct ways: First, technologies could be complementary, i.e. they could be compatible and not substitute each other in their functionalities. In this case, the payoff from installing these technologies together will be greater than installing each of these technologies alone. Provided our understanding 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 lead to positive returns on investment, i.e. a rise in profits. This additional financial slack could enable easier access to external funding due to information asymmetries between financial intermediaries and borrowers (Abel and Blanchard 1986, Hubbard 1990, Hubbard and Kashyap 1992). Thus, previous investments into 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.

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

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

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

A profit maximizing firm will invest into $Y' > Y$ if $G_i > 0$.

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

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

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

Two caveats are worth to reiterate at this point: First, theorem 1 does *not* imply that all firms will eventually adopt all K technologies since G_i also depends on $\overline{x}_i$ with an undetermined effect. Second, theorem 1 does also *not* imply that firms will install all technologies simultaneously. A simple reason could be that prices and qualities of the technologies change at different rates over time, such that it makes sense to delay the adoption of some technologies while adopting others immediately. Also, firms may not have complete information about all technologies when they are first introduced to the market. Thus, asynchronous adoption may occur due to epidemic effects: firms might be "infected" by information about each technology at different times, instead of receiving all information about all technologies at once.

5.2. A logistic model of technology adoption

In the real world, the net present value G_i of installing one or more additional technologies will not be directly observable. What is observable, however, is the result of the investment decision - Y_i, the vector of binary indicator variables describing whether a firm has adopted a particular technology or not. The index for each technology is j with $j = 1...K$ and $y_{ij} = 1$ if firm i has adopted technology j and $y_{ij} = 0$ otherwise. Since Y_i is a vector of K binary arguments, Theorem 1 implies that G_{ij} for each additional technology is increasing in the number $k_{i,-j} \in [0,1,2,...,K-1]$ of other adopted related technologies. Firms adopt if the non-observable latent variable y^*_{ij} exceeds a critical value $\overline{y}^*$, which depends on the net present value of technology j, G_{ij}:

$$(5.4) \quad G_{ij} > 0 \rightarrow y^*_{ij} > \overline{y}^* \rightarrow y_{ij} = 1\,.$$

Theorem 2: Assume (A1) and (A2) - The probability to adopt $P(y_{ij} = 1)$ is an increasing function of the number of other related technologies a firm also uses.

Proof: Apply Theorem 1 to (5.4).

Theorem 2 can be explicitly tested. We introduce a term α to describe the baseline probability to adopt a technology at time *t* of the observation and an error term ε_i to capture unobserved heterogeneity of firms which is independent from $\overline{x}_i$ and $k_{i,-j}$. For simplicity, we assume an index function with a linear structure. This yields

$$(5.5) \quad y^*_{ij} = \alpha + \overline{\beta' x_i} + \gamma k_{i,-j} + \varepsilon_i$$

where $k_{i,-j}$ is the count number of other related technologies that the firm also uses. Given that diffusion processes can often be well described by a logistic function (Griliches 1957, Mansfield 1961), we assume that the error terms ε_i are independently distributed following a logistic probability density function. Then we can write the probability of firm i to adopt technology j as

$$(5.6) \quad y^*_{ij} = P(y_{ij} = 1 \mid \overline{x}_i, k_{i,-j}) = \frac{1}{1 + \exp(-\alpha - \overline{\beta' x_i} - \gamma k_{i,-j})}$$

The log-likelihood for observation i is consequently a function of ($\overline{x}_i, k_{i,-j}, y_i$) given the data:

$$(5.7) \quad \begin{aligned} &\ell_i(\beta,\gamma) = y_i \log[G(\alpha + \overline{\beta' x_i} + \gamma k_{i,-j})] + \\ &(1 - y_i)\log[1 - G(\alpha + \overline{\beta' x_i} + \gamma k_{i,-j})] \end{aligned}$$

where G is the logistic cdf. The unknown parameters α, $\overline{\beta}'$ and γ can be estimated by maximizing (5.7) given the data. Positive and significant estimates of γ and strictly increasing values of γ for higher values of $k_{i,-j}$ would support theorem 2.

Equation (5.7) was estimated using a large sample of enterprise data from the June 2002 e-Business Market W@tch survey. The dataset has no time dimension but contains a homogenous coverage of 15 sectors in the four largest European countries and a wide range of technology variables. The considered $K = 11$ related technologies and their relative frequency of occurrence is listed in Table 12. Each of these solutions serves a different purpose for supporting processes and information flows within a company, or between a company and its environment. Only specific e-business applications are included in the analysis, not the platform technologies that these applications run on (e.g. Intranet or LAN). This choice was made in order to compare only technologies that are on the same level of conceptualization[17]. Because some basic ICT are prerequisites for the usage of any e-business technology, those enterprises that did not fulfill these basic requirements (computers, Internet access, email usage and WWW usage) are excluded from the sample[18].

Table 12 shows pronounced differences in observed occurrence among the 11 e-business technologies. While some applications, like purchasing online (Purch) and sharing documents online to perform collaborative work within a company (Share doc), had already gained wide acceptance among companies in June 2002, other applications, such as Supply Chain Management (SCM) and Knowledge Management (KMS), were not widely diffused yet. According to rank effects theory, this could be explained by different expectations of firms regarding the benefits and the costs of various technologies. Both sharing documents online and purchasing online are applications with immediately obvious benefits and comparably low setup costs[19]. SCM and KMS, on the other side, are relatively complex specialized solutions that often involve considerable implementation, maintenance, and integration efforts.

Table 12 – Relative frequency of 11 related e-business technologies

Technology	**Occurrence in sample**
Content Management System (CMS)	14.4%
E-learning	17.2%
Sharing documents online to perform collaborative work within company (Share doc)	46.5%
Customer Relationship Management System (CRM)	12.0%
Designing new products online (Design)	18.8%
Purchasing online (Purch)	46.9%
Selling online (Sell)	15.6%
Human Resource Management System (HRM)	18.4%
Enterprise Resource Planning System (ERP)	16.6%
Knowledge Management System (KMS)	8.0%
Supply Chain Management System (SCM)	3.6%
N=4,852, all firms included have computers, Internet access, use the WWW, and email. Unweighted results. Abbreviations in ( ) indicate variable names for the regression analyses.	

The sample distribution of the parameter k_i, which includes all eleven technologies from K, is shown in the next figure. The average enterprise in the sample has 2.18 installed technologies from group K in June 2002, the median value is 2. Only 3 (0.1%) out of 4,852 enterprises in the sample had installed all 11 technologies, while 966 (19.9%) had installed none of the above, although all enterprises had the necessary technological prerequisites available (computers, Internet access, usage of WWW and email). The distribution of k_i clearly indicates that most enterprises in the sample were still in an early stage of e-business development at the time of the survey (78.1% of all enterprises have less than 4 technologies from K installed), while a few firms were already very advanced (1.9% have more than 7 technologies installed). Thus, there is considerable variance in the sample in terms of e-business usage of firms.

In the terms of Dosi (1982), one can interpret parameter k_i as a proxy of the technological development level of firm i on the given trajectory. The higher k_i, the more "advanced" firm i is on the e-business trajectory. Similarly, the distribution of all k_i's could be interpreted as the distribution of firms on the trajectory.

[17] Including infrastructural technologies like LAN, WAN, Extranet, and Intranet in the regression does not change the main results: Compare Köllinger and Schade (2004).

[18] Again, it is also possible to include these observations and add the technological prerequisites to the analysis as a part of K. This also does not change the main regression results. However, it would confound the effects we are interested in with plain technological dependence.

[19] Purchasing online does not necessarily require the installation of an e-procurement technology, it could also be realized by simple participation in online marketplaces via WWW.

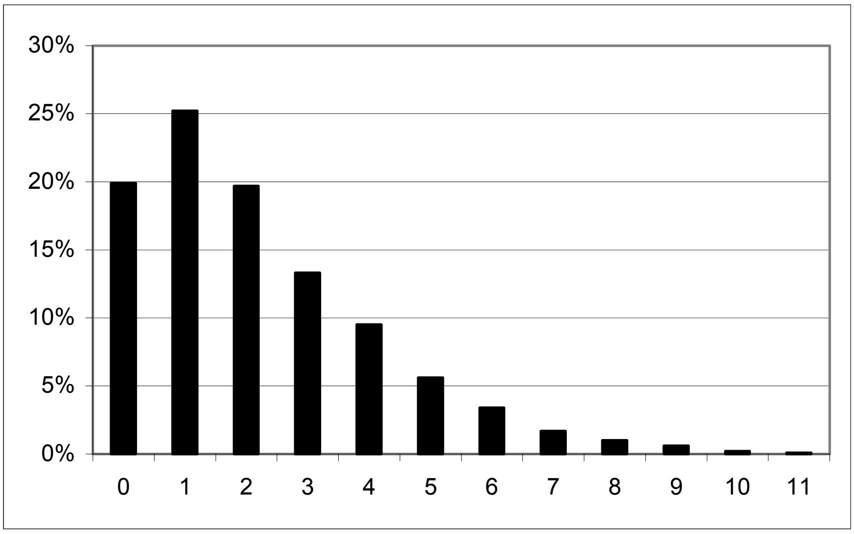


Figure 4 - Relative frequency of overall k's

Two different versions of regression model (5.7) were estimated. The first version treats the technology parameter $k_{i,-j}$ [20] as an integer variable. We are interested in whether the adoption probabilities for any of the $K = 11$ technologies increases in $k_{i,-j}$. However, there might also be non-linear effects. Thus, in order to identify whether adoption probabilities are strictly increasing in $k_{i,-j}$, a second version of all models was estimated with $k_{i,-j}$ coded in 5 categories. The highest category ($k_{i,-j} \geq 4$) typically contains around 10% of all observations. Categories with less observations do not change the main results, however they tend to yield insignificant parameter estimates. In addition to $k_{i,-j}$, $\overline{x}_i$ control variables are included in the regression, namely country of residence, size class, sector membership and whether a firm has more than one establishments. According to descriptive evidence on e-business usage, it can be expected that these control variables have a strong influence on the results (European E-Business Market W@tch 2004, OECD 2004, Preissl 2003).

All elements in $\overline{x}_i$ are specified as dummy variables. Thus, the regression coefficients of $\overline{x}_i$ can be interpreted as group-specific differences in adoption probability with respect to the pre-specified reference groups which are indicated at the bottom of the respective tables. To identify the significance of each coefficient in the regression, robust covariance estimates are employed using the sandwich estimation procedure (Huber 1967, White 1982, Lian, Zeger and Qaqish 1992). The sandwich estimation procedure has the desirable properties of yielding asymptotically consistent covariance standard error estimates without making distributional assumptions. Thus, the significance levels of the estimated parameters are independent of our assumption that G is the logistic cdf. The large sample size in our study makes robust covariance estimates particularly attractive (Kauermann and Carroll 2001).

We analyzed the adoption probability for each of the $K = 11$ technologies separately. Tables 10-12 present the results with $k_{i,-j}$ as an integer variable, tables 13-15 the results for the same technologies with $k_{i,-j}$ coded in five categories.

[20] $k_{i,-j}$ is the count of installed e-business technologies from group *K* for each enterprise, excluding the technology under scrutiny. Thus, $k_{i,-j}$ varies for each firm according to which technology is used as a dependent variable.

Table 13 – Logit regression results for 4 e-business technologies (k as integer)

	CMS	E-learning	Share doc	CRM
Co-variables				
Sector				
Publishing	0,663**	-0,037	0,257	-0,095
Chemicals	0,115	-0,340	0,248	0,215
Metal products	-0,475	0,019	-0,076	-0,310
Machinery	-0,168	-0,341	0,095	-0,147
Electronics	0,293	-0,170	0,400*	0,073
Transport equip.	-0,363	-0,190	-0,124	-0,144
Retail	0,047	0,040	-0,363	0,190
Tourism	0,527*	0,093	-0,334	0,255
Monetary services	0,384	0,587*	0,791**	0,409
Insurances	0,682*	0,381	0,340	0,706*
Real estate	0,500	0,006	0,508**	-0,011
Business services	0,369	0,203	0,302	0,122
ICT services	0,814**	0,238	0,501**	0,885**
Health services	-0,069	0,252	0,276	-0,796*
Country				
Germany	0,080	0,266*	-0,625**	0,524**
Italy	0,605**	0,460**	-0,519**	0,462**
France	-0,067	0,738**	-0,230*	0,665**
Size class				
50-249 empl.	0,334**	-0,306**	0,537**	0,214*
> 250 empl.	0,546**	-0,128	0,656**	0,824**
> 1 establishments	0,227*	0,210*	0,106	0,136
$k_{i,-j}$	0,360**	0,497**	0,541**	0,543**
Constant	-3,441**	-3,245**	-1,180**	-4,411**
Model Diagnostics				
N	4,843	4,843	4,843	4,843
Pseudo-R2	0.1311	0.1550	0.1553	0.2267
LL	-1,740	-1,878	-2,826	-1,371
Prob > chi2	0.000	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment.

Table 14 - Logit regression results for 4 e-business technologies (k as integer)

	Design	Purch	Sell	HRM
Co-variables				
Sector				
Publishing	1,112**	0,352*	1,006**	0,250
Chemicals	0,639*	-0,212	0,035	0,476
Metal products	0,570*	-0,147	-0,258	0,634*
Machinery	0,659**	0,186	-0,345	0,751**
Electronics	0,895**	0,489**	-0,004	0,691**
Transport equip.	0,801**	0,110	0,192	0,488
Retail	0,060	0,179	1,029**	0,257
Tourism	0,391	0,078	1,911**	0,248
Monetary services	-0,103	0,118	0,749**	0,739**
Insurances	0,137	-0,250	0,780**	0,707*
Real estate	-0,030	-0,041	0,252	0,697*
Business services	0,577*	0,486**	0,014	0,821**
ICT services	1,067**	1,436**	0,552*	0,572*
Health services	0,086	0,039	-0,401	1,096**
Country				
Germany	-0,298*	1,365**	0,647**	-0,481**
Italy	-0,011	-0,106	-0,010	-0,023
France	-0,019	0,953**	0,375**	0,328**
Size class				
50-249 empl.	0,050	-0,108	-0,199	0,743**
> 250 empl.	0,123	-0,403**	-0,101	1,141**
> 1 establishments	0,193*	0,000	0,135	0,210*
$k_{i,-j}$	0,329**	0,284**	0,300**	0,502**
Constant	-2,796**	-1,324**	-3,153**	-3,846**
Model Diagnostics				
N	4,843	4,843	4,843	4,843
Pseudo-R2	0.1017	0.1221	0.1207	0.1979
LL	-2,102	-2,939	-1,846	-1,852
Prob > chi2	0.000	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment.

Table 15 - Logit regression results for 3 e-business technologies (k as integer)

	ERP	**KMS**	**SCM**
Co-variables			
Sector			
Publishing	-0,856**	0,354	-1,071*
Chemicals	0,331	0,461	-0,351
Metal products	0,258	0,099	-0,207
Machinery	0,429*	0,065	-0,168
Electronics	0,459*	-0,095	-0,408
Transport equip.	0,359	-0,559	0,262
Retail	-0,855**	0,609	-0,492
Tourism	-1,294**	-0,034	-0,956*
Monetary services	-1,588**	0,407	-2,421**
Insurances	-1,638**	0,384	-1,132*
Real estate	-1,473**	0,708	-0,623
Business services	-0,929**	0,708*	-1,770**
ICT services	-0,456*	0,839*	-1,482**
Health services	-1,352**	0,972**	-1,192**
Country			
Germany	-0,370**	0,615**	0,118
Italy	0,284*	1,228**	0,277
France	-1,144**	0,373	0,247
Size class			
50-249 empl.	1,130**	0,028	0,360
> 250 empl.	1,533**	-0,093	0,758**
> 1 establishments	0,126	0,338*	0,029
$k_{i,-j}$	0,376**	0,548**	0,533**
Constant	-2,614**	-5,234**	-4,780**
Model Diagnostics			
N	4,843	4,843	4,843
Pseudo-R2	0.2191	0.2112	0.2070
LL	-1,704	-1,068	-594
Prob > chi2	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment.

Table 1 - Logit regression results for 4 e-business technologies (k in 5 categories)

	CMS	**E-learning**	**Share doc**	**CRM**
Co-variables				
Sector				
Publishing	0,710**	-0,059	0,264	0,008
Chemicals	0,131	-0,383	0,239	0,188
Metal products	-0,457	-0,025	-0,091	-0,319
Machinery	-0,119	-0,368	0,085	-0,143
Electronics	0,377	-0,142	0,399*	0,164
Transport equip.	-0,314	-0,186	-0,137	-0,123
Retail	0,076	0,041	-0,374	0,201
Tourism	0,565*	0,081	-0,336	0,313
Monetary services	0,401	0,531*	0,786**	0,400
Insurances	0,676*	0,345	0,339	0,661*
Real estate	0,503	-0,050	0,513**	-0,046
Business services	0,400	0,186	0,307	0,181
ICT services	0,897**	0,246	0,507**	0,948**
Health services	-0,012	0,257	0,293	-0,666
Country				
Germany	0,127	0,291*	-0,635**	0,564**
Italy	0,630**	0,482**	-0,518**	0,522**
France	-0,006	0,740**	-0,238*	0,701**
Size class				
50-249 empl.	0,343**	-0,351**	0,526**	0,204
> 250 empl.	0,608**	-0,081	0,678**	0,890**
> 1 establishments	0,271**	0,259**	0,124	0,205
$k_{i,-j} = 1$	0,208	1,009**	0,572**	0,684*
$k_{i,-j} = 2$	0,511**	1,733**	1,244**	1,456**
$k_{i,-j} = 3$	1,005**	2,425**	1,984**	2,123**
$k_{i,-j} \geq 4$	1,664**	3,016**	2,353**	2,909**
Constant	-3,413**	-3,868**	-1,244**	-4,781**
Model Diagnostics				
N	4,843	4,843	4,843	4,843
Pseudo-R2	0.1198	0.1574	0.1540	0.2048
LL	-1,763	-1,873	-2,830	-1,410
Prob > chi2	0.000	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment, $k_{i,-j} = 0$.

Table 16 - Logit regression results for 4 e-business technologies (k in 5 categories)

	Design	**Purch**	**Sell**	**HRM**
Co-variables				
Sector				
Publishing	1,121**	0,347*	1,015**	0,293
Chemicals	0,631*	-0,222	0,014	0,469
Metal products	0,570*	-0,159	-0,266	0,614*
Machinery	0,676**	0,188	-0,345	0,742**
Electronics	0,914**	0,486**	0,032	0,718**
Transport equip.	0,805**	0,112	0,215	0,495
Retail	0,077	0,182	1,039**	0,274
Tourism	0,400	0,076	1,924**	0,264
Monetary services	-0,100	0,111	0,729**	0,713**
Insurances	0,139	-0,262	0,762**	0,686*
Real estate	-0,044	-0,050	0,238	0,698**
Business services	0,598*	0,492**	0,037	0,838**
ICT services	1,095**	1,434**	0,606*	0,650**
Health services	0,115	0,055	-0,366	1,139**
Country				
Germany	-0,275*	1,379**	0,666**	-0,445**
Italy	0,005	-0,095	0,014	0,008
France	-0,002	0,959**	0,400**	0,327**
Size class				
50-249 empl.	0,027	-0,131	-0,218*	0,698**
> 250 empl.	0,174	-0,394**	-0,044	1,163**
> 1 establishments	0,225*	0,009	0,161	0,259**
$k_{i,-j} = 1$	0,395**	0,323**	0,287	1,274**
$k_{i,-j} = 2$	0,835**	0,647**	0,695**	1,768**
$k_{i,-j} = 3$	1,216**	1,080**	1,209**	2,429**
$k_{i,-j} \geq 4$	1,732**	1,382**	1,548**	3,086**
Constant	-2,944**	-1,374**	-3,263**	-4,578**
Model Diagnostics				
N	4,843	4,843	4,843	4,843
Pseudo-R2	0.0982	0.1224	0.1185	0.1945
LL	-2,110	-2,938	-1,851	-1,860
Prob > chi2	0.000	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment, $k_{i,-j} = 0$.

Table 17 - Logit regression results for 3 e-business technologies (k in 5 categories)

	ERP	KMS	SCM
Co-variables			
Sector			
Publishing	-0,811**	0,420	-0,879
Chemicals	0,339	0,414	-0,339
Metal products	0,265	0,085	-0,207
Machinery	0,433*	0,073	-0,093
Electronics	0,476*	0,054	-0,226
Transport equip.	0,375	-0,454	0,307
Retail	-0,813**	0,599	-0,435
Tourism	-1,269**	0,035	-0,841
Monetary services	-1,547**	0,355	-2,218**
Insurances	-1,607**	0,324	-1,132*
Real estate	-1,492**	0,670	-0,622
Business services	-0,891**	0,715*	-1,535**
ICT services	-0,360	0,934**	-1,141**
Health services	-1,289**	0,977**	-1,009*
Country			
Germany	-0,352**	0,653**	0,249
Italy	0,319**	1,227**	0,363
France	-1,084**	0,461*	0,386
Size class			
50-249 empl.	1,108**	0,012	0,335
> 250 empl.	1,570**	0,085	0,884**
> 1 establishments	0,169**	0,424**	0,129
$k_{i,-j} = 1$	0,843**	1,017**	0,600
$k_{i,-j} = 2$	1,146**	1,309**	0,709
$k_{i,-j} = 3$	1,521**	2,270**	1,681**
$k_{i,-j} \geq 4$	2,156**	3,185**	2,906**
Constant	-2,998**	-5,729**	-5,047**
Model Diagnostics			
N	4,843	4,843	4,843
Pseudo-R2	0.2130	0.1898	0.1845
LL	-1,717	-1,097	-611
Prob > chi2	0.000	0.000	0.000

Note: All firms included have computers, Internet access, use the WWW, and email.
*: sign. at 95%, **: sign. at 99%.
Reference categories: Food sector, France, 1-49 empl., one establishment, $k_{i,-j} = 0$.

All 22 models show highly significant, positive coefficients for $k_{i,-j}$. Also, in the 11 models with $k_{i,-j}$ coded in categories, the group with $k_{i,-j} \geq 4$ always has the highest, and the group with $k_{i,-j} = 0$ always the lowest probability to adopt. The regression coefficients for the intervals in between these two extremes are almost linearly increasing in $k_{i,-j}$. This supports Theorem 2 and **Hypothesis 10**, which stated that the probability to adopt is an increasing function of the number of other related technologies a firm already uses. In other words, the more advanced a firm already is in the adoption of e-business, the more likely it is to "go another step" and vice versa. On the grounds of this observation, we can hypothesis a growing "digital divide" among firm: There are pioneers with very timely adoption of many e-business technologies and other firms that never adopt any such technology. Given the observed adoption pattern, the gap between the two extremes will grow as long as the observed acceleration mechanism is at work. This idea is further explored in chapter 6.3.

Furthermore, **Hypothesis 1** claimed that diffusion patterns will vary among industries. This is certainly also supported by our results. For example, firms in the retail sector are more likely to adopt online sales than the food, beverages and tobacco sector; but the opposite is true for ERP systems. Naturally, these sector differences in adoption reflect differences in market structure but also differences in the type of activities pursued in the various sectors. Consequently, firms from different sectors may have varying net present values of technologies which leads to different adoption decisions.

The results also provide strong support for **Hypothesis 3**, stating that large firms will be faster in adopting technologies that are primarily used in-house, exhibiting positive returns to scale. Such technologies are CMS, sharing documents online internally, CRM, HRM, ERP and KMS. For all of the above, large firms have a significantly higher adoption probability. Vice versa, positive size effects are not as pronounced and in some cases even reversed for those e-business technologies that primarily deal with processes and information flows that are connected to the environment of the firm, and not primarily internal. E.g., E-learning, online collaboration with business partners to design new products (Design) and selling online do not exhibit significantly higher adoption probabilities of larger enterprises.

The regression results provide mixed evidence on **Hypothesis 11** which argued that industries with ex ante better knowledge of ICT will have higher probabilities to adopt e-business technologies due to learning effects and experience-based advantages. Generally "IT savvy" industries are those that are either involved in the production of ICT goods or services (electronics, ICT services, business services) and those that traditionally exhibit high levels of IT use (monetary services, insurances, transport equipment manufacturers). The evidence is mixed, and results vary greatly among different e-business technologies. For example, firms from the ICT services sector exhibit very high adoption probabilities for purchasing online, CRM, CMS, Design, Share doc, selling online, KMS and HRM. However, they also show significantly lower adoption probabilities than the "IT-distant" food sector for ERP and SCM solutions, primarily because ERP and SCM solutions help to optimize material and information flows in manufacturing businesses, they are generally less relevant in the services industries.

Hypothesis 2stated that industries with high levels of competition and high concentration ratios will be among the group of early adopters of a technology. This is not directly supported by our results. For example, the transport equipment sector which has the highest industry concentration ratio of all sectors included in the sample (e-Business W@tch 2002), shows only average or below average adoption probabilities for most technologies. No clear statement can be made about the relationship of competition levels and adoption probability provided our data and results because our data do not allow unambiguous inference about the level of competition each firm in the sample is facing.

5.3. A simultaneous equation model of technology adoption

The econometric results of the previous section hinge on a number of fairly strict assumptions. In this section, three of these assumptions are relaxed to gain more conclusive evidence on the technological interdependencies outlined above. In particular, we are interested to check whether the acceleration mechanism identified in the previous section is endogenous (as suggested by the theory) or merely a statistical artifact of some unobserved factor which is driving the results, such as an "inherent need" of firms to invest in e-business technologies.

For this purpose, an iterative, simultaneous equation framework can be used. In particular this allows to relax the following assumptions from the previous section. First, we do not assume anymore that all technologies have an equal influence on one another. The parameter $k_{i,-j}$ does not distinguish between technologies, it only counts them one by one. It might be that the regression results on $k_{i,-j}$ depend on only a few of the analyzed technologies, while others have a negligible or even negative influence. This is addressed by analyzing technological interdependencies in a pair-wise manner. Second, we allow for unobservable factors that might have a joint, systematic influence on the adoption of technologies. This enables to distinguish between the direct influence of technologies on another and exogenous factors that drive adoption decisions. Third, the possibility of simultaneous adoption decisions is explicitly accounted for by setting up an iterative simultaneous equation framework instead of assuming that all technologies other than the one under scrutiny are exogenous.

Obtaining estimation results is possible because we are not interested in the precise marginal effect of each explanatory factor, a consistent estimate of its direction is sufficient for our purposes. Mainly, we want to know the pair-wise relationship of technologies and whether they provide evidence for the acceleration mechanism identified in the aggregate analysis. Consistent estimates of partial effects will suffice for this purpose because we are only interested in the sign and the significance level of the coefficients, not in their absolute magnitude.

The following recursive simultaneous bivariate probit model is considered:

$$(5.8)\quad P(y_1 = 1, y_2 = 1 \mid \overline{x}) = \Phi_2(\overline{x}'\beta_1 + \delta y_2, \overline{x}'\beta_2, \rho)$$

with Φ_2 being the bivariate normal cdf. The corresponding latent variable equations are:

$$(5.9)\quad \begin{aligned} y_1^* &= \overline{x}'\beta_1 + \delta y_2 + \varepsilon_1 \\ y_2^* &= \overline{x}'\beta_2 + \varepsilon_2 \end{aligned}$$

In this study, the variables have the following meaning:

y_1 - technology 1

y_2 - technology 2

x_1 - a constant term

x_2 - a dummy vector indicating the home country of a firm

x_3 - a dummy vector indicating the sector of a firm

x_4 - a dummy vector indicating the size class of a firm

x_5 - a dummy that indicates if the firm has more than one establishment

All other technologies are excluded from the respective models. The following assumption are necessary for identification:

$$(5.10)\quad \begin{aligned} & E(\varepsilon_1 \mid \overline{x}) = E(\varepsilon_2 \mid \overline{x}) = 0 \\ & Var(\varepsilon_1 \mid \overline{x}) = Var(\varepsilon_2 \mid \overline{x}) = 1 \\ & Cov(\varepsilon_1\varepsilon_2 \mid \overline{x}) = \rho \end{aligned}$$

Also, the error terms must be independent from $\overline{x}$. Both equations contain an intercept term in $\overline{x}$. Note that this is a recursive, simultaneous-equations model. It has some desirable properties that are worth mentioning. As Maddala (1983, p. 123), Burnett (1997) and Greene (2003, pp. 715-719) show, the endogenous nature of one of the variables on the right-hand side of the equation can be ignored in formulating the log-likelihood. Thus, the log-likelihood for (5.9) is the same as for a standard bivariate probit model of the form

$$(5.11)\quad \begin{aligned} y_1^* &= \overline{x}'\beta_1 + \varepsilon_1 \\ y_2^* &= \overline{x}'\beta_2 + \varepsilon_2 \end{aligned}$$

in connection with (5.10). This enables to use a standard bivariate probit estimation procedure for (5.9) that is implemented in econometric packages like STATA. The second nice property of the model is that it allows a rigorous test for the presence of some unobserved factor which influences both y_1 and y_2 simultaneously. If the error terms of both equations are not correlated, $\rho = 0$, this suggests that there is *no* joint unobserved factor that influences both variables. In this case, one can ignore ρ and simply run single equation models for y_1 and y_2 separately. One can evaluate $H0: \rho = 0$ with a Wald test. The correlation of the error term has its own interpretation: It measures (roughly) the correlation of y_1 and y_2 *after* controlling for the direct effect of y_2 on y_1. Any such correlation is an indicator of some third unobserved factor that systematically influences both variables. Note, however, that there might be an unobserved factor which systematically influences y_1 but not y_2 or vice versa. This would not show up in ρ, however it would still lead to scaling biases in running the single equation models. However, neglected heterogeneity still leads to consistent estimates of the direction and the magnitude of β in probit models. To illustrate, consider the following model

(5.12) $P(y = 1 \mid \bar{x}, c) = \Phi(\bar{x}'\beta + \gamma c)$

and the equivalent latent variable equation

(5.13) $y^* = \bar{x}'\beta + \gamma c + \varepsilon$.

If $\bar{x}$ includes an intercept, one can set $E(c) = 0$ without loss of generality. If c is independent of $\bar{x}$, $c \sim N(0, \tau^2)$ and $\varepsilon \mid x, c \sim N(0,1)$, running probit of y on $\bar{x}$ consistently estimates $\hat{\beta} = \beta / (\gamma^2 \tau^2 + 1)^{1/2}$. For the purpose of estimating the direction and magnitude of β, this degree of accuracy is sufficient (Wooldridge 2002, pp. 470-472). Thus, we can consistently estimate β up to scale in both parts of (5.9) even though ε_1 and ε_2 might have unobserved systematic effects on y_1 and y_2 respectively that are independent of the other equation. Any unobserved effect that has a systematic effect on both y_1 and y_2 will be captured by ρ, as outlined above.

The further steps as follows: First, $11^2 - 11 = 110$ bivariate regression models are estimated according to (5.8) to test for $H0: \rho = 0$ between all technology pairs in our data. This is a specification test that indicates whether bivariate regression or singular equation regressions should be estimated. The results are reported in Table 18. Next, another 110 single equation regressions of all y_2 on y_1 have to be estimated. Then, according to the results of the Wald test of Table 18, the results of the appropriate regression model for y_2 on y_1 are reported in Table 19. If $H0: \rho = 0$ is not rejected, the results from the single equation regression are reported, otherwise the results of the bivariate regression model.

Table 18 – Wald tests for pair-wise independence of regression equations

	CMS	Elear	Share	CRM	Desig	Purc	Sell	HRM	ERP	KM	SCM
CMS		.432	.086 *.37*	.026 *.89*	.614	.823	.219	.981	.011 *.38*	.000 *.63*	.000 *.51*
Elear	.806		.991	.779	.000 *.99*	.611	.357	.904	.491	.720	.640
Share	.077 *.44*	.001 *.69*		.161	.309	.422	.018 *.506*	.226	.075 *.20*	.609	.251
CRM	.419	.447	.020 *.48*		.608	.520	.834	.855	.019 *.40*	.014 *.80*	.003 *.61*
Desig	.000 *.69*	.192	.148	.008 *.65*		.294	.063 *1*	.072 *.42*	.279	.009 *.61*	.004 *.36*
Purc	.167	.627	.057 *.68*	.887	.179		.04 *-.46*	.431	.137	.198	.059 *.39*
Sell	.083 *.94*	.621	.851	.000 *.82*	.000 *1*	.056 *.45*		.000 *-.12*	.813	.633	.165
HRM	.223	.496	.005 *.58*	.905	.062 *.67*	.942	.420		.050 *.80*	.001 *.71*	.000 *.41*
ERP	.006 *.73*	.020 *.49*	.700	.000 *.79*	.028 *.59*	.071 *.32*	.004 *.89*	.600		.000 *.75*	.002 *.49*
KM	.497	.033 *-.43*	.157	.084 *.79*	.319	.841	.040 *1*	.423	.090 *.25*		.047 *.70*
SCM	.305	.301	.354	.096 *.70*	.718	.91	.000 *.95*	.038 *.59*	.266	.297	

Table reports Wald test of rho=0, Prob > chi2 for bivariate probit SUR models with row regressed on column, robust covariance estimation. Significant values for Rho are reported in *italics*.

The results in Table 18 suggest that in 61 out of 110 cases, there is no unobserved effect that has a significant influence on both technologies, i.e. $H0:\rho=0$ cannot be rejected according to a Wald test. In these cases, the single equation model

$$(5.14)\quad \begin{aligned} &P(y=1\,|\,\overline{x},y_2)=\Phi(\overline{x}'\beta+\delta y_2) \\ &y_1^*=\overline{x}'\beta_1+\delta y_2+\varepsilon_1 \end{aligned}$$

is appropriate to test for the direct effect of y_2 on y_1. Note that in these 61 cases, y_1 and y_2 are only related through the magnitude and size of δ. In the remaining 49 cases, model (5.9) is appropriate to measure the direct effects of y_2 on y_1 and the remaining correlation of both variables after controlling for direct effects.

Table 19 – Direct relationships between technology pairs

	CMS	Elear	Share	CRM	Desig	Purc	Sell	HRM	ERP	KM	SCM
CMS		++	o	--	++	++	++	++	o	--	--
Elear	++		++	++	--	++	++	++	++	++	++
Share	o	-		++	++	++	-	++	o	++	++
CRM	++	++	o		++	++	++	++	o	o	o
Desig	--	++	++	--		++	--	o	++	--	o
Purc	++	++	--	++	++		++	++	++	++	o
Sell	--	++	++	--	--	o		o	++	++	++
HRM	++	++	o	++	--	++	++		++	--	o
ERP	--	o	++	--	--	o	--	++		--	o
KM	++	++	++	o	++	++	--	++	o		o
SCM	++	++	++	o	++	++	--	o	++	++	

Table reports sign of the regression coefficients, technology row regressed on technology column. The underlying regression model is single equation if Rho in Table is not significant, and bivariate probit otherwise. All regression with robust standard error estimation.
++ denotes a positive coefficient at >95% confidence
+ denotes a positive coefficient at >90% confidence
o denotes no significant direct influence
- denotes a negative coefficient at >90% confidence
-- denotes a negative coefficient at >95% confidence

Table 19 displays the estimated direction of the direct effects of technology y_2 (row) on technology y_1 (column). Together with the results on ρ in Table 18, they allow a detailed interpretation of the relationships of the 55 analyzed technology pairs. It is crucial to consider the direct effects and possible unobserved factors that influence both technologies (ρ) together. There are 36 possible parameter combinations for each pair of technologies. Some of these combinations suggest that an endogenous acceleration mechanism between the two technologies exists, some would suggest the opposite (a “slowing down” or substitution effect), and some yield ambiguous evidence. The findings are consolidated in Table 20 accordingly.

Table 20 – Interpretation of bivariate regression results

Coeffi-cient	2way +	2way -	1way + 1way 0	1way – 1way 0	2way 0	1way + 1way -	Sum
Rho							
2way 0	++ 16	-- 0	+ 0	- 0	- 0	? 0	16
1way 0 1way +	++ 1	? 0	+ 9	? 0	+	? 17	27
2way +	++ 0	? 1	++ 0	? 4	+ 4	? 0	9
1way 0 1way -	+ 1	- 0	? 1	- 0	- 0	? 0	2
1way - 1way +	? 0	? 0	? 1	? 0	? 0	? 0	1
2way -	? 0	-- 0	? 0	- 0	- 0	? 0	0
Sum	18	1	11	4	4	17	55

Table indicates which parameter constellation are evidence for or against the presence of an acceleration mechanism:
++ strong positive evidence
+ positive evidence
? unclear effect
- negative evidence
-- strong negative evidence
Numbers below indicate the count of technology pairs for which a parameter constellation occurred.

When ρ is zero or positive, technologies that have a positive direct impact on each other that goes both ways will exhibit an acceleration effect: The presence of one technology makes the adoption of the other more likely. Thus, they support Theorem 2. Vice versa, a negative direct effect of two technologies that goes both ways suggests the opposite when ρ is either zero or negative: The presence of one technology makes the adoption of the other less likely. The effect of ρ is particularly relevant for those technology pairs that have either no direct influence on another or a varying impact, depending on the direction of the relationship. For example, if two technologies have no direct influence on another (the parameter coefficients are not significantly different from zero in both directions – column 5), the presence of a significant and positive ρ will still lead to an acceleration mechanism: The probability to adopt technology 2 will increase when a firm has adopted technology 1 and vice versa. However, this will only be due to some unobserved third factor which is driving the results, not due to a direct relationship of both technologies. In those cases where ρ and the coefficients have opposite signs, the direction of the total effect is ambiguous and will depend on the absolute magnitude of ρ and the coefficients.

Table 20 shows that 31 of the 55 technology pairs exhibit evidence for the presence of an acceleration mechanism. 24 pairs have an undetermined effect, and no technology pair provides clear evidence against a possible acceleration mechanism.

The 24 pairs with an undetermined effect require closer examination. In column one, we have one technology pair (KMS and E-Learning) with a two-way positive direct effect, but a one-way negative ρ. The positive coefficients indicate that each of the two makes the adoption of the other directly more likely. However, once we control for this significant direct effect, some firms that need E-Learning do not need KMS (negative ρ).

In column 2 we find one technology pair (Sell and Design) with negative direct effects but positive ρ for both equations. This suggests that firms that use either one of these technologies are directly less likely to adopt the other. However, once we control for this direct effect, both technologies are perfectly correlated ($\rho = 1$), which suggests that they have a strong tendency to occur together due to some unobserved factors (e.g. the presence of other e-business technologies).

Column 3 exhibits two additional technology pairs with undetermined effect which is due to different inherent needs. The pair in row 4 (Sell and HRM) exhibits a positive direct effect of selling online on the probability to adopt HRM. However, once this direct effect is accounted for, some firms that use HRM have no need for selling online (negative ρ). A similar case appears in row 5 (Purc and Sell): Purchasing online has a direct positive influence on the probability to adopt online sales as well. However, after taking account of this effect, firms have different inherent needs which is reflected in a negative ρ: Some firms that do online purchasing have no need to sell online as well.

Column 4 has four technologies which have a negative one-way direct relationship, but still a strong tendency to occur together due to unobserved exogenous effects. The technology pairs are ERP and CMS, ERP and CRM, ERP and KMS, and HRM and Design. In each case, the former has a negative direct effect on the occurrence of the latter. ERP systems can partially substitute the functionalities of specialized CMS, CRM or KMS systems. However, this depends on the configuration of the particular ERP system. Smaller ERP systems might rather be complements than substitutes to specialized solutions. This rationalizes the highly positive remaining correlation after controlling for the negative direct effect.

In column 6 we find 17 technologies with a positive direct influence one way, and a negative or no direct influence (but a positive ρ) the other way. For these technology pairs, the order of adoption is important for whether an acceleration mechanism occurs or not. For example, firms that share documents online are more likely to adopt HRM as well, but HRM has no direct effect on sharing documents online. However, both technologies are likely to occur together because of the positive direct effect of sharing documents online on HRM.

All together, out of the 55 technology pairs analyzed, all of them showed significant correlation – either due to a direct effect between the technologies, or due to joint exogenous factors. This shows that technological interdependencies are crucial determinants of adoption decisions. The technological legacy of a firm has a systematic influence on its future technological development path. Hence, history matters and ignoring technological interdependencies in technology diffusion studies will likely lead to biased estimates.

Furthermore, 31 of the analyzed pairs provide direct and unambiguous evidence for an endogenous acceleration mechanism (the adoption of technology A makes adoption of technology B more likely and vice versa). This suggests that an endogenous acceleration mechanism of technological development can occur which is not purely the result of unobserved heterogeneity, as suggested by **Theorem 2**. 19 technology pairs provide mixed evidence: An acceleration mechanism can occur depending on which technology is installed first, and only 4 technology pairs suggest that technology A makes adoption of technology B less likely. For three of these 4 technologies we can suspect a partial substitution effect, in which case **Theorem 2** does not apply and we would not expect an acceleration effect anyway. However, these 4 technology pairs are still strongly positively correlated due to exogenous factors (such as other technologies). Thus, the predominant share of analyzed technology pairs suggests that an endogenous acceleration mechanism can occur, which is in accordance to our theory.

5.4. CART – identification of clusters with different adoption probabilities

Up to this point, two parametric approaches were used to test technological interdependencies and their influence on adoption decisions. In this section, a novel non-parametric technique is introduced to identify clusters of firms that exhibit significant differences in their adoption probability. The analysis complements the parametric results in three ways: First, CART simultaneously identifies clusters and significant predictor variables that characterize the clusters. An identification of clusters is not possible with parametric regression models. The cluster results from the CART analysis are of high practical value for marketing purposes because they allow qualified predictions about the adoption probability of a firm for various technologies, based on very few (only the most relevant) parameters. Marketers of e-business technologies and consultants can use the results to evaluate for a given customer which investment into e-business technologies the customer is most likely to undertake next. Also, the identification of clusters allows to focus marketing activities on those market segments that are most likely to purchase. Second, CART identifies complex, non-linear relationships between technological and structural variables (such as firm size and market of operation) that were not captured by the parametric models presented above. As such, they provide unique and additional insights into the relationships that are present in the data. Third, CART relaxes important restrictions of parametric models: It does not make any assumptions about the distribution of error terms and the functional form of the explanatory variables. Also, CART is robust to outliers and invariant to monotone transformations of predictors (Gatnar 2002). Thus, the identification of relevant predictor variables and clusters is independent from any prior assumption that might not actually be justified by the data. Finally, in contrast to the parametric regression models, CART uses an out-of-sample validation procedure to eliminate an over-fitting of the model. For all of the above reasons, CART can be used to "double check" the results of the earlier sections: If CART detects relationships in the data that are inconsistent with the parametric regression results, this suggests that the parametric results might be erroneously influenced by their restrictive assumptions.

CART was first introduced by Breiman et. al. (1984). It can loosely be codified as a combination of non-parametric regression and cluster analysis. The result, a "tree" presented in graphic form, is both parsimonious and easy to interpret. CART has recently been used in numerous studies in the medical sciences (Zhang and Bracken, 1995; Zhang and Singer, 1999) with a focus on classifying patients into risk groups. For example, this is important for physicians in emergency rooms who need to decide on appropriate levels of medical care for arriving patients when only few clinical factors are available. To my knowledge, however, the application of CART in a managerial or economic context is still novel. Therefore, a short description of the method is included at this point and a short technical introduction to CART is given in Appendix 1.

The basic idea of CART is to systematically split the dataset into homogeneous groups with respect to the dependent variable based on the best set of predictors. The final tree is computed in four steps.

In the first step, called *recursive partitioning*, the sample of subjects is systematically sorted into completely homogeneous subsets until a saturated tree is found. In this study, complete homogeneity means that a node contains either only adopters or non-adopters. The root node of a tree contains the sample of subjects from which the tree is grown. Then, based on the parameter value that is most predictive for the outcome, the root node is split into two daughter nodes that now form a second layer of the tree. All nodes in the same layer constitute a partition of the root node. The process of splitting nodes is continued and the partition becomes finer and finer as the layer gets deeper and deeper. For each split, CART considers the entire set of available predictor variables to determine which one maximizes the homogeneity of the following two daughter nodes. This is a hierarchical process that reveals interdependencies between covariates. Also, a predictor might show up numerous times in different parts of the tree. Each case of the sample is sorted into one of the daughter nodes at each layer of the tree, according to the splitting rule that was used. Those subsets that are not split are called terminal nodes. When a case finally moves into a terminal subset, its predicted class is given by the class label attached to that terminal subset (e.g. "adopter {Y=1}" or "non-adopter {Y=0}" for node t). The process is continued until the nodes are completely homogeneous and cannot be split any further. This is the saturated tree. The saturated tree is usually too large to be useful. In the worst case, it is trivial because each terminal node could consist of just one case. The resulting model is subject to over-fitting problems. Therefore, one must find a nested sub-tree of the saturated tree that exhibits the best "true" classification performance and satisfies statistical inference measures.

To proceed, a series of nested optimal sub-trees of the saturated tree is generated. This second step in the process is called *pruning*. The cost-complexity pruning algorithm suggested by Breiman et. al. (1984) is used here, which ensures that a uniquely best sub-tree can be found for any given tree complexity.

In a third step, one of the trees must be selected from the pruning sequence. The solutions lies in finding an honest estimate for the true classification performance and selecting the sub-tree that minimizes the estimated true misclassification costs. This is usually done with an independent test sample, boot-strapping, or cross-validation. In this study, a 20-fold cross validation procedure is employed because it makes better use of the information contained in the original dataset than the independent test sample method and outperforms bootstrapping in terms of reduced bias (Breiman et. al., 1984, pp. 72-78, 311-313).[21]

Following these steps, the best classifying tree can be identified. However, because we are mainly interested in interpreting the revealed structures, it must also be ensured that the model satisfies the usual significance tests. The final tree is computed by calculating significance tests for all splits in the tree and dropping those splits (and their successors) that are not significant at the 95% confidence level or above.

The same dataset as before is used for the CART analysis, originating from the June 2002 enterprise survey of the e-Business Market W@tch. CARTs are computed for all 11 technologies listed in Table 12. For each of the technologies, the remaining 10 technologies are included as predictors and all additional predictor variables are listed in Table 21. No abbreviation is specified for variables that did not show up as a relevant predictor in any of the 11 trees.7

[21] Estimation was carried out with CART 5.0 by Salford Systems.

Table 21 – Predictor variables in CART models

Predictor variable	Abbreviation
Country	COUNTRY
Sector	SECTOR
Sizeclass	SIZE
Company has a website (yes/no)	WEBSITE
More than one establishment (yes/no)	N/A
Company offers in-house computer or IT training (yes/no)	N/A
Company offers employees to participate in computer or IT training offered by third parties (yes/no)	N/A
Company provides tools for self-learning, for instance books or software (yes/no)	N/A
Company offers employees to use some of their working time for learning activities (yes/no)	N/A
Company judgement on importance of informal "learning on the job" (very, fairly, less, not important)	N/A
Company judgement on importance of formal training schemes (very, fairly, less, not important)	N/A
Company judgement on importance of self-learning activities (very, fairly, less, not important)	N/A
Company has recruited or tried to recruit staff with special IT skills during the last 12 months (yes/no)	IT_STAFF
Company has experienced difficulties in finding staff with special IT skills (yes/no)	N/A
To what extent has e-business changed the way in which company conducts business (significantly, somewhat, not changed)	EBIZ_CHANGE

All firms included in the sample fulfill the necessary technological requirements to engage in e-business (use of computers, Internet, Email, and WWW). The terminal nodes can be ordered according to the ratio of adopters they contain. The numbers below the terminal nodes indicate this order, with 1 being the cluster with the highest adoption probability. The CART results for E-learning, CRM, and online sales are presented in the text. All remaining CART models are included in Appendix 2. They can easily be interpreted in a likewise manner.

Figure 5 shows the final tree model for the usage of e-learning technologies. In the dataset, e-learning is defined as the usage of online, Internet-based technologies to support employee training. The final tree consists of four terminal nodes. CART uses three different predictor variables to construct the tree. Each of the terminal nodes exhibits different fractions of e-learning users. The root node contains 4,852 firms, 17.2% of them use e-learning. The most e-learning affine segment (number 1) contains 63.4% of adopters, whereas in the least e-learning affine segment (number 4) a fraction of only 7.6% uses e-learning. The terminal nodes each contain a different number of firms. Some of the nodes are rather small and describe rare, but statistically relevant subgroups (like number 1, which contains only 153 firms or 3.2% of the sample), whereas others are very large (like number 4, which contains 2,594 firms or 53.5% of the sample). Note that the impact of each predictor variable on the ratio of adopters can be followed along the tree branches. For example, the fraction of e-learning users increases from 17.2% in the root node to 28.2% for firms that share documents online. It again increases sharply if these firms also use an Internet-based Human Resource Management system. It is interesting to observe that all co-variables in the tree are good predictors only for a specific sub-set of the sample, in interaction with other predictors, and do not turn out to be relevant in other parts of the tree. This is one of the unique insights into the data structures revealed by CART.

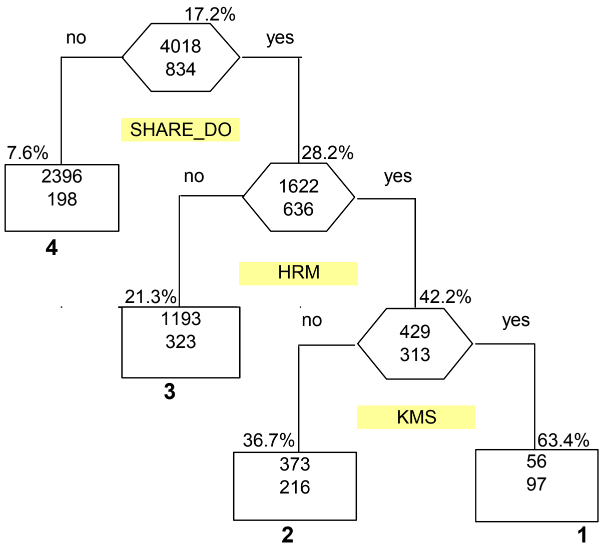


Figure 5 – CART for E-learning

The results of the tree illustrate the importance of technological interdependencies. In fact, all three relevant predictor variables in the tree directly relate to the usage of other e-business technologies.

Segment 1, which exhibits almost 63.4% per cent of e-learning users, consists of firms that are already very advanced in the usage of Internet-based technologies. The average number of other Internet technologies installed ($k_{i,-j}$) in this segment is 6.14, the highest among all terminal nodes in the tree. Segment 1 is sufficiently characterized by just three predictor variables: It includes firms that share documents online, use Internet technologies to support human resource management functions (HRM), and use Knowledge Management Systems (KMS) that run on the Internet. At least HRM and KMS can be seen as rather advanced e-business applications that are not yet used by many companies.

The probability to adopt e-learning decreases sharply if any of technologies (Share_do, HRM, KMS) is not used by a company. The lowest adoption probability is observable in cluster 4 that only contains 7.6% of e-learning users. This clusters is sufficiently characterized by just one predictor variable: it contains firms that do not use the Internet to share documents online. No additional predictor variable can improve the classification performance of this node. Cluster 4 contains a large share of the dataset (53.5%). Also, cluster 4 has the lowest average number of other Internet technologies installed ($k_{i,-j} = 1.02$). Thus, the cluster that contains the firms that are “least advanced” in the usage of e-business technologies also has the lowest probability to adopt e-learning.

Other indicators in the dataset that reflected firm heterogeneity, such as size class or sector membership, do not turn up as relevant predictors in the tree. This should not be mistaken to indicate an irrelevance of other factors leading to rank effects, such as firm size, sector, or country of origin. Indeed, several of these variables exhibited a significant impact on e-learning adoption in the logit regression (see table Table 13). The reason why they do not show up in the tree lies in the CART method, which only uses the predictor that minimizes node impurity. The second best predictor that might even be closely related does not show up in the tree. Firm size, sectors, or country of origin are candidates for such factors, based on previous analysis.

It has to be kept in mind that the usage of other e-business technologies as explanatory variables in the tree does not imply a causal relationship. It only implies that these variables are the best predictors for whether a firm uses e-learning or not, it does not say anything about the direction of the relationship or the presence of some other factor which could cause the correlation. However, the results are consistent with our findings from above, suggesting that more advanced firms exhibit higher adoption probabilities.

Figure 6 shows the results for online sales. The final tree consists of 5 terminal nodes. CART uses only 3 predictor variables to construct the tree, one of the variables (sector membership) appears twice in the tree. The root node contains all 4,852 subjects again, the overall ratio of companies using the Internet to sell goods or services is 15.6%. The first layer splitting variable (which is the variable with the highest classification performance with respect to the dependent variable) is whether a firm has a website or not. The probability that a company is selling online drops sharply from 15.6% to 3.3%, if the company does not have a website (cluster 5). Cluster 5 has the lowest overall probability for online sales. The result is intuitive – having a website is not only a basic indicator for the "e-readiness" of company, but also an important channel for online sales. Consequently, firms that do not exhibit this basic characteristic do not have a high probability to adopt online sales. Cluster 5 is also the cluster with the lowest average number of other adopted technologies ($k_{i,-j} = 1.28$).

The second lowest probability for online sales occurs in cluster 4. Firms in this group do have a website, but they belong to an industry sector were anonymous remote orders and delivery are generally rare (food, chemicals, metal products, machinery, electronics and electrical machinery, transport equipment, real estate, business services, health services). The ratio of firms selling online in cluster 4 is 12%, compared to 30.1% in the other daughter node which contains all firms with a website from the remaining sectors (publishing, retail, tourism, monetary services, insurances, ICT services). The best splitting variable for this cluster is whether firms use the Internet to purchase online. Provided that purchasing online is already quite frequently used by all firms in the sample (46.9%), this can again be interpreted as a proxy for the "e-readiness" of a company. Cluster 3, which contains those firms that do not purchase online also exhibits a low number of other adopted technologies ($k_{i,-j} = 1.5$) and the chance of selling online in this cluster drops from 30.1% to 22.9%, whereas otherwise it increases to 35.7%. The cluster with the highest probability to sell online are those enterprises that have a website, purchase online, and belong to either the retail or the tourism sector. This tree structure is interesting because it points out two insights: First, the general technological development level again turns out to be a good predictor for adoption decisions (website, purchasing online). Second, some technologies – such as online sales – are clearly more valuable and relevant in some industries than in others. Thus, depending on the type of activity a firm is pursuing, some firms will probably never adopt online sales even though they might be very advanced in using e-business applications otherwise. However, the probability to adopt still increases the more advanced a firm already is, ceteris paribus.

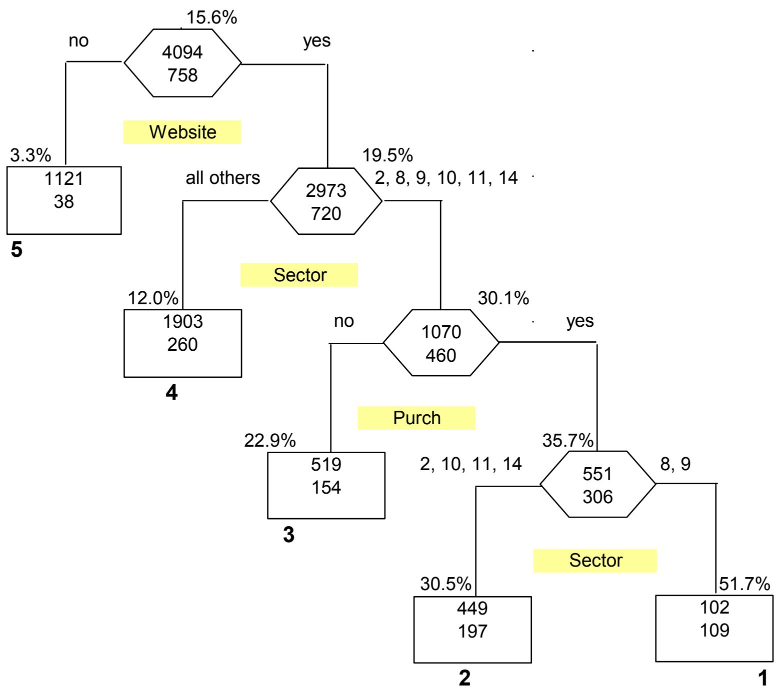


Figure 6 - CART for Selling online

Figure 7 shows the CART for Customer Relationship Management (CRM). This is the most parsimonious model. The root node contains 12% of CRM users, and the only relevant splitting variable is whether a firm uses a Knowledge Management System (KMS). If a firm does use KMS, the probability to adopt CRM increases to 47.8%, otherwise it drops to 8.8%. Again, this relationship does not imply any direct causality. Instead, KMS is again a proxy for the general development level of a firm: Whereas cluster 1 exhibits $k_{i,-j} = 4.76$, cluster 2 exhibits only $k_{i,-j} = 1.83$.

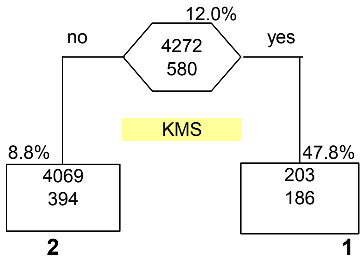


Figure 7 – CART for CRM

All CART models together emphasize technological interdependencies. Whenever a company uses any of the technologies identified in the tree models, the probability to adopt the technology under scrutiny increases and vice versa. This is in accordance to the findings in 5.2 and 5.3. Also, the CART models show interesting and diverse adoption patterns for various technologies: The adoption probability for some technologies can be best predicted solely by the technological profile of a firm, while for other technologies information about the size of the firm or its sector of operation are also important.

Besides from the analytical value of this explorative analysis of data structures, the CART results have a very appealing practical value for technology providers, consultants, and marketers of e-business technologies. Provided that the collected data are fairly recent, the identified clusters can help to optimize marketing and sales strategies. For example, a technology provider might decide to focus his marketing activities on those clusters that have been identified as showing high probability to adopt. Also, a technology provider who is already conducting business with a client might use the CART results to make an "educated guess" about what will be a likely future investment of the client. This knowledge could be used to increase the chances of getting a follow-up job. In a similar way, CART can generally be used as a market research instrument for any kind of product, service or technology where useful and preferably large datasets are available.

5.5. Discussion

This chapter introduced a theory and an empirical analysis of the adoption of related technologies. If firms have the possibility to invest into a number of related technologies that are based on joint technological principles, technological interdependencies can have a crucial impact on investment and adoption decisions. In particular, firms might experience an acceleration mechanism in adopting related technologies, if the technologies do not substitute each other in their functionalities. An acceleration effect can occur for various reasons:

- availability of joint complementary inputs, such as specialized labor, suitable organizational structures, or technological infrastructures
- learning-by-doing effects
- discounts for the purchase of more than one technology
- technological complementarity, if technologies are directly compatible and do not substitute each other in their functionalities
- better possibilities to finance investments due to successful earlier investments into related technologies

If any of the above applies, the probability to adopt a technology will increase with the number of related technologies that a firm also uses because all of the above effects are strictly increasing in their argument, without a natural point of inflection. In other words, the net present value of a technology can be higher for a firm that is already more advanced in using related technologies than for an otherwise identical firm. This suggests that early movers will make continuously faster progress on a given technological trajectory, building up a technological leadership position until they have adopted all related technologies with a positive net present value. However, this does not imply that all firms will adopt all technologies because the net present value of a technology also depends on other firm-specific characteristics that are independent from its current level of technological development (e.g. market of operation or the size of a firm).

Empirical evidence for this acceleration mechanism was provided by analyzing the adoption of 11 e-business technologies in a large cross-sectional dataset covering 15 industrial sectors from the four largest European economies. Three different methods were used to analyze the data: A logistic adoption model with fairly strict assumptions, a bivariate simultaneous equation model with less restrictive assumptions, and a non-parametric classification and regression procedure without any prior assumptions. The main result in all cases is that technological interdependencies have a crucial impact on adoption decisions. This suggests that the technological legacy of a firm – and thus its history – has a systematic influence on its investment decisions and hence on its future development. Strong evidence is found that an acceleration mechanism of technological development can occur. Firms that are already more advanced in using e-business technologies are found to be more likely to invest into additional e-business technologies than otherwise comparable firms. The results suggest a "growing digital divide" among firms that could continue until the most advanced firms of a particular type have fully exhausted the potential of e-business technologies and stop making progress on that trajectory. This could ceteris paribus lead to initially growing advantages of technological pioneers vis-à-vis late adopters, if they directly compete against each other.

In addition to this main result, the influence of structural variables, such as sector membership, size class, and country of origin were also analyzed. The results support previous evidence that e-business usage patterns vary significantly among industries and countries (European E-Business Market W@tch 2004, OECD 2004, Preissl 2003). However, which sectors and countries exhibit high usage rates varies substantially with the technology being analyzed. For example, firms in the retail sector are more likely to adopt online sales than the food, beverages and tobacco sector; but the opposite is true for ERP systems. No clear evidence was found for the hypothesis that industries with ex ante better knowledge of ICT will have higher probabilities to adopt e-business technologies. Industries with good ex ante knowledge of ICT are those that are either involved in the production of ICT goods or services (electronics, ICT services, business services) and those that traditionally exhibit high levels of ICT usage (monetary services, insurances, transport equipment manufacturers). The results vary greatly among different e-business technologies. For example, firms from the ICT services sector exhibit very high adoption probabilities for purchasing online, CRM, CMS, Design, Share doc, selling online, KMS and HRM. However, they also show significantly lower adoption probabilities than the "IT-distant" food sector for ERP and SCM solutions, primarily because ERP and SCM solutions help to optimize material and information flows in manufacturing businesses, they are generally less relevant in the services industries.

The empirical results also provide evidence for size class effects. In particular, it was found that large firms exhibit higher probability to adopt technologies that are primarily used in-house, exhibiting positive returns to scale. Such technologies are CMS, sharing documents online internally, CRM, HRM, ERP and KMS. For all of the above, large firms have a significantly higher adoption probability. Otherwise, positive size effects are not as pronounced and in some cases even reversed for those e-business technologies that primarily deal with processes and information flows that are connected to the environment of the firm, and not primarily internal. E.g., E-learning, online collaboration with business partners to design new products (Design) and selling online do not exhibit significantly higher adoption probabilities of larger enterprises.

In addition to the analytical findings, the usefulness of CART was demonstrated to analyze innovation adoption data. CART enables to identify clusters of firms that exhibit significant differences in their probability to adopt a particular technology. The results are parsimonious, easy to interpret and can be presented in an intuitive, graphical form. They have an appealing practical value for marketing purposes. For example, a technology provider might decide to focus his marketing budget on those firms that have been identified as high probability clusters in the CART analysis. Or, a technology provider who is already conducting business with a client might use CART results to make an "educated guess" about what will be a likely future investment of the client. This knowledge could help to increase the chances of getting follow-up contracts.

The research presented in this chapter is subject to some limitations. First, a cross-sectional dataset was used that does not contain information about when technologies have been adopted. Since innovation diffusion is a dynamic process, lacking information about the timing of events means that we are missing an important part of the story. Hence, one can only speculate about the consequences of the observed technological interdependencies, the "growing digital divide", it cannot be actually observed in the data. Second, having only cross-sectional data puts clear limits on the possibility to rule out alternative explanations for the observed relationships, i.e. there is no general test to rule out a significant effect of unobserved heterogeneity. Thus, it cannot be finally concluded whether the observed acceleration effect is truly endogenous and independent from unobservable firm characteristics. Third, while the data are quite rich in terms of the technologies they cover, they have no indication about the actual level of use of the technologies within firms or how “sophisticated” their solutions are. For example, purchasing online can be conducted in many way: A firm might infrequently buy a small number of items on an internet marketplace, or it might install a complex e-procurement software system that systematically aggregates and automates a substantial amount of ordering processes. In the data used for this chapter, both cases are simply treated as a positive adoption of online purchasing. Having more detailed information would possibly enable additional insights. However, there are clear budgetary and time restrictions for collecting additional levels of details in this type of enterprise survey.

The most severe limitation of this chapter – the lack of a time dimension – is resolved in the next chapter which uses a different dataset to analyze the same fundamental questions that were examined in this chapter: How do technological interdependencies influence diffusion processes? And what role do structural variables and firm heterogeneity play?

6. Dynamic analysis of e-business diffusion

The previous chapter presented a static analysis of the adoption of various related e-business technologies. The results indicated strong and persistent relationships between the observed technologies. In particular, their was support for the hypothesis that the probability to adopt is increasing in the number of other related technologies a firm has also installed. The results indicated that technological progress can be subject to an endogenous acceleration mechanism if firms have the choice to invest in numerous related technologies that are not substitutes.

In this chapter, the analysis of this phenomenon is extended to a dynamic diffusion model. Are the results of chapter 5 replicable in a dynamic setting using a different dataset? To answer this question, a flexible discrete time hazard rate model is introduced. It has various advantageous compared to the static analysis. First of all, the complications arising from simultaneous adoption decisions can be avoided because in the dynamic framework one can test for the effect of technological investments that have been undertaken in the past: Such investments are sunk and do not depend on today's investment decisions anymore. Therefore, they can be treated as an exogenous variable. Thus, instead of running simultaneous equations with multiple endogenous technology terms, one can simply analyze each technology separately and only control for technologies that have been installed in the past. Second, the time dimension in the data provides multiple observations for each firm. This enables to control for unobserved heterogeneity explicitly. Thus, it is possible to measure whether an acceleration effect in technological development occurs endogenously, after controlling for unobserved alternative explanations such as an "inherent need" of firms to invest. Third, the time dimension of the data also allows to observe the possible consequences of an acceleration effect. If such an effect is present and not all firms start adopting the same technologies at the same time (i.e. if there are rank effects due to differences among firms), we would expect that the technological equipment of early adopters is continuously upgraded faster than that of late adopters, leading to growing differences among firms.

The chapter is organized as follows: First, a short introduction to hazard rate models is given to set up the required notations. Then, I relate to the theory of chapter 5.1 and introduce the diffusion model. Next, the regression results are presented and discussed. After that, I examine whether there is evidence for a growing "digital divide" among firms. Finally, the results are summarized and some implications are discussed.

6.1. Discrete time hazard rate model with unobserved heterogeneity

To study the diffusion of technologies over time, a hazard rate estimation framework can be used.[22] In general, hazard rate models are concerned with explaining the time interval until the occurrence of a state transition of an observed subject. In this study, the time interval from the introduction of a new technology until a firm decides to adopt the technology is the variable of interest. Each adoption decision is a single, non-repeatable and non-reversible event. Obviously, not all firms will adopt within the observation period or thereafter. Let t indicate at which point in time a firm is observed. The time from the beginning of the observation until the adoption decision is noted as T. At each point in time t, we are interested in the adoption probability of each firm, given that the firm has not adopted before t. This is the *hazard rate*, which is formally defined as

[22] Alternative terms for hazard rate models frequently found in the literature are „survival analysis", „failure time models", „life-time models", or „response-time models".

(6.1) $\lambda(t) = \lim_{dt \to 0} \frac{\Pr ob(t \le T < t + dt \mid T \ge t)}{dt}$

By standard arguments, there are two functions associated with the hazard function: The *failure function* $F(t)$, which indicates the fraction of the population that has left the initial state at time t, and the *survivor function* $S(t)$, which states the share of the population that has not yet adopted at time t. Consequently, $S(t) \equiv 1 - F(t)$ and $F(t)$ is the cumulative distribution function (cdf) of all adoption events over time. The associated probability density function (pdf) is noted as $f(t)$, with $f(t) = F'(t)$. A natural interpretation of $f(t)$ is the unconditional probability of adopting exactly in the infinitesimally small interval of time $[t, t + \Delta t]$. By definition:

(6.2) $\lambda(t) = \frac{f(t)}{1 - F(t)} \equiv \frac{f(t)}{S(t)}$

In this application, the actual exact time of adoption T is unobservable in the available dataset. We only know from the data that T falls into a specific year. Hence, a discrete time formulation is needed. For this purpose, it can be defined that a duration of interest t is in the vth interval so that it satisfies, $t_{v-1} \le t < t_v$, 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. Right censoring implies that at the time of the survey, the adoption of the technology had not yet occurred (T is unknown). Given entry at $v = 1$ and observation at time t, we only know that $T > t$ for right censored observations.

The analysis is carried out with a dataset that contains a large number N of heterogeneous enterprises that are assumed to have no strategic interaction. As before, each firm $i = 1...N$ is characterized by a vector of firm specific characteristics $\overline{x}_i$ and a K-component vector Y of binary variables $Y = (y_1, y_2, ..., y_K)$ with $y_j \in \{0,1\}$ and $j = 1...K$, which indicates the current endowment of a firm with related technologies. **Theorem 1** implies that under the assumption that none of the elements of Y is substituting any other element of Y, the net present value G_{ijv} associated with each technology is increasing in the number $k_{i,-j,v-1} \in [0,1,2,...,K-1]$ of related technologies which have been adopted in the past. The integer variable $k_{i,-j,v-1}$ is a simple proxy for "how advanced" a firm is in using any of the K available technologies. Firms adopt technology j in period v if $G_{ijv} > 0$.

The net present value G_{ijv} is not directly observable. However, in each period v, the endowment of firms with technologies Y_{iv} can be observed where each element takes a value of $y_{ijv} = 1$ when the enterprise has adopted and $y_{ijv} = 0$ otherwise, $j = 1...K$. Firms adopt if the non-observable latent variable y^*_{ijv} exceeds a critical value $\overline{y}^*$, which depends on G_{ijv}:

(6.3) $G_{ijv} > 0 \to y^*_{ijv} > \overline{y}^* \to y_{ijv} = 1$

Theorem 3 – Assume (A1) and (A2) – The hazard rate to adopt a technology belonging to Y is an increasing function of the number of elements of Y which have been adopted in the past.

Proof: Apply theorem 1 to (6.3).

To test Theorem 3, the following discrete time hazard rate model of technology adoption is introduced:

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

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

The unobserved additional error term is assumed to be strictly independent from the observable covariates $\overline{x}_i$, $k_{i,-j,v}$ and observation period v. The introduction of this unobservable error term allows to relax some of the assumption that were necessary in the static adoption model. Explicitly, we do not need to assume anymore that only observable firm characteristics influence the adoption decision in a systematic way. It is only necessary to assume that unobservable characteristics that might have a systematic influence on adoption probability, like quality of management, organizational structure, specific characteristics of the market of operation, or an "inherent need" of firms to upgrade their technology etc., are normally distributed, independent of the observable characteristics, and that the sample is randomly drawn from the population. Compared to the static adoption model in the previous chapter, this yields a more flexible modeling approach that is only possible because time-series observations of individuals have a three-dimensional structure (varying in time periods v, firm i, and all observable variables) and hence contain more information than cross-sectional data. The additional information can be used to account for unobserved heterogeneity by grouping observations on i. The close relationship between survival models including unobserved individual effects and panel econometric methods has recently been emphasized in the literature (Jenkins, 2004; Kiefer, 1990; Wooldrigde, 2002, 20.4).

Theorem 1 and **Theorem 3** implied that the decision to adopt depends on the observable characteristics $\overline{x}_i$, and explicitly also on the number of previously adopted, related technologies $k_{i,-j,v-1}$. In addition, diffusion processes are time-dependent. Epidemic effects, reduced uncertainty, stock effects, qualitative improvements in technology or falling prices all lead to higher adoption probabilities in later periods. Hence, the probability to adopt is generally time-dependent following some function $h_v(t)$. Furthermore, the random unobserved firm-specific effect specified in (6.4) can influence the timing of adoption. Hence, a time-varying index function with the following form can be specified:

$$(6.5)\quad Z_{ijv}(t) = \overline{\beta_j' x_i} + \gamma k_{i,-j,v-1} + h_{jv}(t) + u_{ij}$$

For simplicity, the index function is assumed to have a linear additive structure.[23] Given these preliminary definitions and following the general framework of Sueyoshi (1995), the hazard function can be specified as

$$(6.6)\quad \lambda_{ijv}(t, \overline{x}_i, \beta_j, k_{i,-j,v-1}, \gamma_j, u_{ij}) = h'_{jv}(t) \left\{ \frac{f_v(Z_{ijv}(t))}{1 - F_v(Z_{ijv}(t))} \right\}$$

where v indexes the interval of interest, i the firm, and where f_v and F_v are the density and cumulative distribution function for the continuous random variable T. Note that $Z_{ijv}(t)$ is allowed to vary with time, since $k_{i,-j,v-1}$ (the number of previously adopted related technologies) is dynamic. The full specification of the hazard depends upon the pair $\{F, h\}$. The survival probabilities for the *v*th interval may be viewed as the probability that a random variable exceeds the aggregator, $\Pr(\varepsilon_{ijv} > Z_{ijv}(t))$, where the cumulative distribution of ε_{ijv} is described by F (Sueyoshi, 1995). This is a straightforward extension of the static adoption model presented in chapter 5.2 to a dynamic scenario. Note, however, that in addition to the classic disturbance term ε_{ijv} another error term u_{ij} is introduced in (6.4) and (6.5). While the influence of ε_{ijv} on λ_{ijv} is a function of time and randomly "redrawn" for each firm in each observation period, u_{ij} captures additional firm-specific effects that do not vary with time but could have a systematic influence on the individual hazard. The interpretation is straight forward: u_{ij} contains the influence of all relevant firm-specific characteristics that cannot be observed in the data but that stay with firm *i* over time, while ε_{ijv} are all remaining, time-specific random shocks that influence the probability of adoption. The value of both error terms for each firm can obviously vary with the technology *j* under scrutiny.

To complete the specification of (6.6), one needs to chose $\{F, h\}$. Given that diffusion processes can be well-described by a logistic function (Griliches, 1957; Mansfield, 1961), an obvious candidate to specify λ is *F* to be the logistic cdf,

[23] Alternatively, one could also specify a semi- or non-parametric functional form. However, this makes the evaluation of hypotheses more difficult. Also, to my best knowledge, unobserved heterogeneity cannot be tested yet in non-parametric models.

$$(6.7)\quad F(z) = \frac{\exp(z)}{1+\exp(z)}$$

which corresponds to a pdf

$$(6.8)\quad f(z) = \frac{\exp(z)}{(1+\exp(z))^2}$$

for $-\infty < z < \infty$. The baseline hazard rate of each period can be specified as a flexible semi-parametric piecewise constant function:

$$(6.9)\quad h_{jv}(t) = \alpha_{jv}\theta_{jv}$$

for all $v = 2,...,V$, choosing $v = 1$ as the reference category for estimation[24], θ_{jv} being a vector of dummy variables such that $\theta_{jv} = 1$ if $t_{v-1} \le t < t_v$ 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 $h_{jv}(t)$. It only implies the assumption that observations within a given time-interval v have the same baseline hazard rate. Hence, the model does not assume that adoption probability strictly increases in t, and thus allow for period-specific demand shocks, e.g. due to cyclical variation. Furthermore, the model also does not assume that all firms will adopt each technology because $h_{jv}(t)$ must not necessarily go to infinity as t becomes very large. This is an important advantage vis-à-vis most fully parametric specifications of the hazard function that assume $\lambda(t) \to \infty$ as $t \to \infty$. The semi-parametric specification in (6.9) is more appropriate to study 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 because an implausible assumption is avoided.

Equation (6.6) can be explicitly written as

$$(6.10)\quad \lambda_{ijv} = \frac{1}{1+\exp(-\alpha_{jv}\theta_{jv} - \beta_j'\bar{x}_i - \gamma_j k_{i,-j,v-1} - u_{ij})}.$$

Note that (6.10) is equivalent to a random effects logit model applied to survival data organized in firm-period form. Survival data in firm-period form contain observations for firm *i* for each period v until either censoring or exit occur. This yields an unbalanced panel dataset, where each firm can have at most one observation period for which $y_{ijv} = 1$. Hence, the number of observed periods varies between firms. This specific form of data organization is necessary if one wants to apply standard panel estimation commands in statistical packages for survival analysis. To clarify the point: The binary response logit model estimates the unconditional likelihood function $f(z)$ for observing $y_{ijv} = 1$ in exactly period v, where f is the logistic pdf. The hazard function λ, however, is the conditional probability of making a transition in period v, provided that firm i has "survived" up to $v-1$. Data organized in firm-period form fulfill the requirement that during the periods prior to the transition, all observations on the dependent variable have values of zero. Hence, the conditioning of $f(z)$ is provided by the specific form of data organization, and estimating (6.10) becomes equivalent to estimating $f(z)$.

Furthermore, it is interesting to observe that (6.10) is a proportional hazard model, i.e. one can separate the effects of a "baseline hazard" function which only depends on time period v and is equal for all firms, and firm-specific effects captured by the co-variables that scale the baseline hazard for each observation. The model is

[24] hence maintaining an intercept term in Z

also referred to as "proportional odds" because it assumes that the relative odds of making a transition in period v, given survival up to the previous period, can be summarized by

$$(6.11)\quad \frac{\lambda_{ijv}}{1-\lambda_{ijv}} = \left[\frac{F(\alpha_{jv}\theta_{jv})}{1-F(\alpha_{jv}\theta_{jv})}\right]\exp(\beta_j'\bar{x}_{iv} + \gamma_j k_{i,-j,v-1} + u_{ij}),$$

where F is the logistic cdf (Jenkins, 2004). The term in the left parentheses on the right-hand side of the equation is the baseline hazard which arises if all other co-variables are zero. This expression is scaled by the expression outside of the parenthesis, which do not depend on time period v. Hence, the estimated parameter coefficients of this model have an intuitive interpretation. The θ_{jv} coefficients give the period-specific baseline hazard of technology *j* for a firm with all other covariables equal to zero. The β_j' and γ_j coefficients can be interpreted as the extent to which $\bar{x}_{it}$ and $k_{i,-j,v-1}$ scale the baseline hazard.

Because (6.10) depends on the unobserved heterogeneity u_{ij}, it cannot be used directly to construct the likelihood function to consistently estimate α_j, β_j', and γ_j. However, recalling the assumptions of (6.4) that u_{ij} is independent of all other variables and has a normal distribution, a conditional maximum likelihood approach is available for estimating α_j, β_j', γ_j and σ_u^2 (Wooldrige, 2002, 15.8.2). To find a likelihood function that does not depend on u_{ij} anymore, one needs to integrate out u_{ij}, conditional on all observable covariables. Given (6.4) the likelihood contribution of each uncensored observation can be expressed as

$$(6.12)\quad L = \int_{-\infty}^{\infty}\left[\prod_{v=1}^{V} g(y_{ijv})\right](1/\sigma_u)\,\phi(u_j/\sigma_u)\,du$$

where $g(y_{ijv}) = F(z)^{y_{ijv}}[1-F(z)]^{1-y_{ijv}}$, F is the logistic cdf and ϕ is the pdf of the normal distribution. Censored observations in the sample are included with values of $y_{ijv} = 0$ for all v, whereas uncensored observations are included up to the period when exit occurs and observations with $y_{ijv} = 1$ for $t > t_v$ can be dropped because they do not contain any additional information that would contribute towards $\lambda(t)$. Plugging in y_{ijv} for all v and taking the log of (6.12) gives the conditional likelihood function for each *i*.[25] Summing up over all *i* gives the complete sample likelihood. To estimate this function, one simply has to maximize the complete sample likelihood with respect to α_j, β_j', and γ_j.[26] The integral can be approximated with an *M*-point Gauss-Hermite quadrature (StataCorp, 2001, p. 384). As mentioned above, this is equivalent to applying a random effects logit model to survival data organized in person-period form. 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 panel-level variance component since the idiosyncratic error in latent variable models is unity (Wooldrige, 2002, p. 486). When $\rho = 0$, the panel-level variance component is unimportant and the panel estimator is not different from the pooled estimator. The pooled estimator would results from applying the standard logit model to the survival data organized in person-period form, without grouping observations on i. This approach yields consistent and efficient estimates if and only if no unobserved individual-specific effects exist. A likelihood ratio test that formally compares the pooled and the panel estimator can be used to evaluate the presence of significant unobserved individual effects.[27]

The estimation approach outlined above has four explicit advantages.

(1) By accounting for unobserved heterogeneity, it is possible to get consistent and efficient estimates of the observable covariates[28] even if some of the unobservable characteristics have a significant influence on adoption behavior. If unobservable heterogeneity is important but ignored, one will get biased estimates of the included

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[25] The integration of (6.12) does not yield a simple estimator because of the mixed distributions.

[26] In most econometric software packages, this is implemented either as Fisher-scoring or the Newton-Raphson-procedure.

[27] This implies that the results of the pooled and the panel estimator are equivalent if no unobserved individual effects exist. Hence, controlling for unobserved heterogeneity in the model does not lead to biased estimates if individual effects are not significant.

[28] Provided that the assumption of u are satisfied by the data. The independence of u from the observable variables can be tested by comparing the random effects model with a fixed effects model via the Hausman test. However, this test is only required if significant observed effects are reported in the random effects model. An unresolved issue is how possible interaction effects between observable and unobservable variables on the dependent variable could be identified.

covariates. Also, one typically over-estimates the degree of negative duration dependence in the hazard and an under-estimates of the true proportionate response of the hazard to a change in a regressor. In addition, the proportionate response of the hazard rate to changes in a regressor will no longer be constant, but declines with time. Lancaster (1979, 1990) gives an extensive treatment of these issues. Also, controlling for unobserved heterogeneity does not lead to biased estimates even if unobserved effects are not important because the estimator of the pooled logit and the panel logit are asymptotically identical if $\sigma_u \to 0$. Hence, controlling for unobserved heterogeneity yields a much more robust test of the hypothesis regarding the observable characteristics, in particular the effect of $k_{i,-j,t}$.

(2) A dynamic model is estimated that utilizes all individual- and time-specific information that is available in the data. No information is lost due to any kind of data aggregation. In particular, by specifying $k_{i,-j,v-1}$ as a time-dynamic covariable that counts the number of other adopted technologies at time *t* for each firm, the maximum amount of information contained in the data is used.

(3) The flexible, semi-parametric specification of duration dependence in (6.9) does not assume that all firms will eventually adopt the innovation as $t \to \infty$, in contrast to many fully parametric specifications. Hence, an important source of biased estimates is excluded. See Kamakura, Kossar and Wedel (2004), Litfin (2001), or Sinha and Chandrashekaran (1992) for a discussion of the assumption that the entire population will eventually adopt. The simple piece-wise constant specification employed here is an attractive alternative to the computationally demanding split-hazard models that are otherwise proposed in the literature.

(4) The estimation framework applied here is easily extendable to other empirical studies of innovation diffusion, where time and individual specific information are available and the primary focus is not on forecasting. One simply needs to adapt the index function Z_{ijt} in an appropriate way.

6.2. Empirical results

Equation (6.12) was estimated using a large sample of enterprise data from the Nov/Dec 2003 e-Business Market W@tch survey. The dataset consists of 7,302 successfully completed computer-aided telephone interviews with enterprises from 25 European countries and 10 sectors[29]. Available are basic background information about each company, including size class, number of establishments, % of employees with a college degree, market share and primary customers of the enterprise. Also, the dataset contains information on the adoption of 7 e-business technologies, 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 on these questions was always below 20% of the respective subjects indicating that most respondents were at least able to make a fairly educated guess[30]. Also, one might reasonably assume that the error distribution will not be significantly skewed towards one side or the other side of the true values. Thus, without additional information or conflicting evidence, it is most reasonable to treat the reported adoption date as the true adoption date.

Table 22 shows some descriptive results for the occurrence of the technologies for November 2003. Similar to the evidence in chapter 5.2, there are pronounced differences in the observed frequencies among the 7 e-business technologies. Online purchasing is most widely diffused (46%), whereas other solutions such Knowledge Management (KMS) or Supply Chain Management (SCM) exhibit rare occurrence. Each of the considered 7 technologies serves a different purpose for supporting processes and information flows within a company, or

[29] The composition of the sample does not allow comparability across sectors or countries on the aggregate level. Thus, the model does not control for sector- or country-specific effects explicitly, but treats them as part of the unobserved heterogeneity term u_{ij}.

[30] The estimation results could be non-representative for the entire population if the missing values were not independent from the time of adoption, e.g. if those who could not recall the date of adoption had adopted particularly early. However, such an effect cannot be tested in the data and is hence not explicitly considered here.

between a company and its environment. Thus, it can be assumed that these technologies do not substitute each other in their functionalities, which is the basic assumption underlying our theory. In parallel to the static analysis of e-business adoption, only those enterprises are included in the sample that fulfill the basic requirements to conduct e-business (usage of computers, Internet access, email and WWW).

Table 22 - Relative frequencies of 7 related e-business technologies, Nov 2003

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

Information about when a technology was adopted by a company is coded in yearly intervals. 1994 was chosen as the first period of observations[31]. This is approximately the time when the Internet became available for commercial use in Europe. All adoption decisions occurring after 2002 are censored observations. Thus, there are 9 valid observations periods for each technology.

Figure 8 and Figure 9 show two examples of survivor functions. The year of observation is recorded on the x-axis (2 corresponds to 1994, 10 corresponds to 2002). The proportion of remaining non-adopters in the sample is depicted on the y-axis. Both survivor functions show that diffusion of online purchasing and online sales started slowly in the first few years, and then rapidly gained momentum. The highest annual rate of new adoptions occurred from 2001 to 2002, shortly after the peak of the "Internet-hype". Both figures show that the diffusion of e-business had not yet surpassed its peak in 2002. Thus the adoption of these new technologies is analyzed in a relatively early stage of the diffusion process. The survivor functions for the other e-business technologies in the sample exhibit comparable shapes.

[31] A few companies stated implausible adoption dates, saying that they adopted a particular e-business solution before 1994. These responses were coded as missing values. For all technologies, less than 5% of the adopters had to be excluded due to stating implausible adoption dates. The respective companies could be referring to ICT solutions that fulfill similar objectives as the e-business technologies, but are based on proprietary networks, such as EDI. However, because of the definition and the reasoning provided in chapter 1.4.4, proprietary ICT solutions are not part of this analysis.

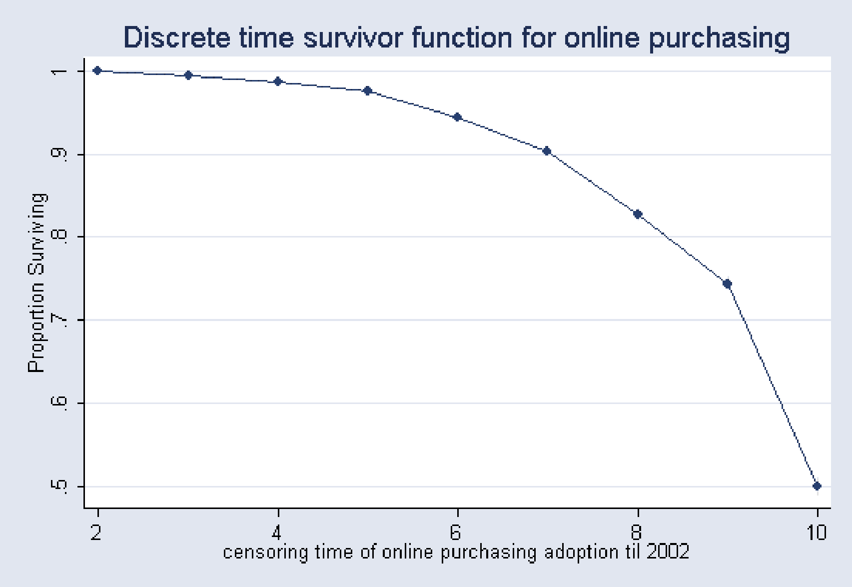


Figure 8 – Discrete time survivor function for online purchasing

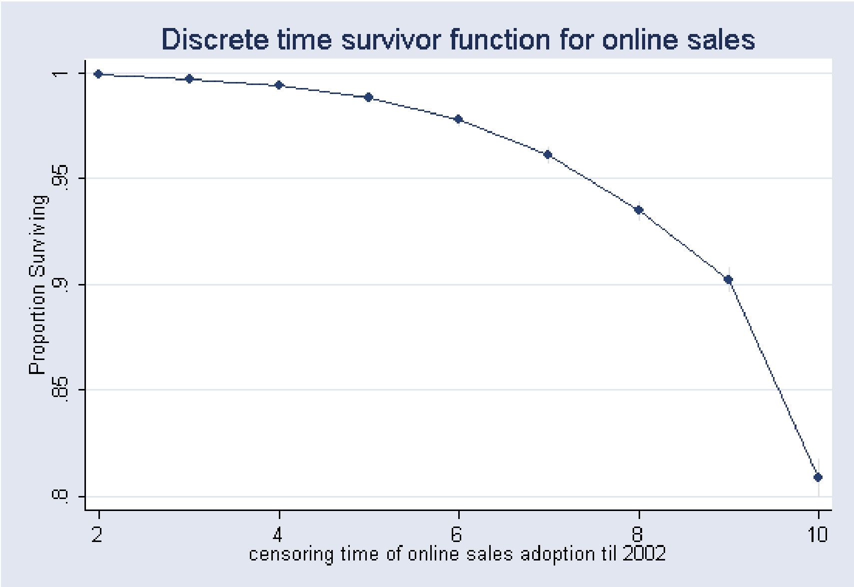


Figure 9 - Discrete time survivor function for online sales

Two different versions of the model in (6.12) were estimated. The first version included the proxy variable for current technological development, $k_{i,-j,v-1}$, as an ordinal variable. The results are reported in Table 23 and Table 24. In the second version, $k_{i,-j,v-1}$ was decomposed into dummy variables ($k_{i,-j,v-1} = 0$ to $k_{i,-j,v-1} = 5$).[32] The decomposition into dummy variables was conducted to test for possible non-linear effects of $k_{i,-j,v-1}$.

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

Table 23 – Hazard rate regression results for 3 e-business technologies (k as integer)

Co-variables	**Online sales**	**Online purchasing**	**CRM**
v = 2	1.253**	1.954**	0.603
v = 3	1.447**	2.396**	0.496
v = 4	2.228**	3.358**	1.172**
v = 5	2.843**	4.781**	1.819**
v = 6	3.313**	5.498**	1.603**
v = 7	3.650**	6.721**	2.430**
v = 8	3.890**	7.514**	2.465**
v = 9	4.315**	9.093**	3.552**
$k_{i,-j,v-1}$	0.257**	0.731**	0.525**
10-49 empl.	0.042	0.033	0.734**
50-249 empl.	0.067	0.167	0.967**
>250 empl.	0.155	0.188	1.137**
> 1 establishment	0.297**	0.568**	0.377**
Primary customers:			
other businesses	-0.465**	0.443**	0.426**
public sector	-0.596**	0.068	-0.190
no primary customers	0.065	0.121	0.171
% empl. w. university degree	0.001	0.010**	0.013**
Market share:			
<1%	0.164	0.647**	-0.472**
1%-5%	0.415**	0.778**	-0.179
6%-10%	0.456**	0.645**	0.170
11%-25%	0.546**	0.586**	0.203
> 25%	0.340**	0.564**	0.081
Constant	-7.356**	-11.283**	-8.284**
Model diagnostics			
N obs	44,545	42,310	45,257
N groups	5,116	5,116	5,116
Log-likelihood	-3,773	-7,439	-2,411
Rho	<0.01	0.668	<0.01
LL-ratio test for rho=0	1.00	0.00	1.00

** denotes significance at the 95% confidence level, * denotes significance at 90% confidence.
Reference categories: v = 1, 1-9 empl., primary customers: consumers, market share: unknown.
All firms included have computers, Internet access, use the WWW, and email.

Table 24 - Hazard rate regression results for 4 e-business technologies (k as integer)

Co-variables	**E-Learning**	**ERP**	**KM**	**SCM**
v = 2	0.401	0.153	0.131	-0.697
v = 3	0.900	0.204	0.752	0.680
v = 4	1.843**	0.765**	0.521	1.365*
v = 5	2.149**	0.719**	1.056**	1.754**
v = 6	2.309**	1.048**	0.909**	1.800**
v = 7	3.351**	1.356**	1.742**	2.459**
v = 8	3.513**	1.079**	1.621**	2.023**
v = 9	4.719**	2.513**	2.854**	3.648**
$k_{i,-j,v-1}$	0.435**	0.265**	0.465**	0.328**
10-49 empl.	0.051	1.116**	0.384**	1.001**
50-249 empl.	0.234*	1.776**	0.689**	1.693**
>250 empl.	0.770**	2.353**	1.099**	2.514**
> 1 establishment	0.519**	0.187**	0.322**	0.385**
Primary customers:				
other businesses	-0.092	0.601**	0.144	0.045
public sector	0.151	-0.004	-0.020	-0.817**
no primary customers	-0.008	0.126	-0.010	-0.287
% empl. w. university degree	0.012**	0.004**	0.012**	0.006**
Market share:				
<1%	-0.106	-0.480**	-0.173	0.211
1%-5%	0.104	-0.052	0.201	-0.355
6%-10%	-0.042	0.253	-0.182	0.519**
11%-25%	0.193	0.304**	0.290	0.130
> 25%	0.066	0.187*	0.289*	0.152
Constant	-8.688**	-7.550**	-7.799**	-9.571**
Model diagnostics				
N obs	45,562	44,889	45,504	45,800
N groups	5,116	5,116	5,116	5,116
Log-likelihood	-2,121	-2,550	-1,689	-957
Rho	<0.01	<0.01	<0.01	<0.01
LL-ratio test for rho=0	1.00	1.00	1.00	1.00

** denotes significance at the 95% confidence level, * denotes significance at 90% confidence.
Reference categories: v = 1, 1-9 empl., primary customers: consumers, market share: unknown.
All firms included have computers, Internet access, use the WWW, and email.

Table 25 - Hazard rate regression results for 3 e-business technologies (k in 5 categories)

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

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

Table 26 - Hazard rate regression results for 4 e-business technologies (k in 5 categories)

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

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

The most important result from the regression analysis is that $k_{i,-j,v-1}$ has a positive and significant influence on adoption rates in all models. Furthermore, the hazard rate for adoption increases the higher the value of $k_{i,-j,v-1}$: All significant coefficients on $k_{i,-j,v-1}$ decomposed into dummies exhibit an almost linear increase of adoption probability. The results are very similar to the static adoption analysis from chapter 5.2. They provide strong support to Theorem 3 and **Hypothesis 10**, which stated that more advanced firms are more likely to further improve their technologies, suggesting an endogenous acceleration mechanism of technological development. Thus, the technological history and legacy of a firm have a crucial, systematic impact on future investments and technological developments. This suggests that the diffusion of technological innovations among firms should be studied as a path dependent, evolutionary phenomenon, where firm-specific resources are both a cause and a consequence of technology adoption.

Furthermore, significant size-class effects are found in the regressions. Companies with more than one establishment are more likely to adopt any of the 7 analyzed technologies. Also, large firms with many employees are systematically more likely to adopt e-business solutions that are primarily used in-house, such as CRM, E-learning, ERP and KMS. This supports **Hypothesis 3**. 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.

Hypothesis 9 is also supported by the regression results: The probability to adopt is low in the early periods of the diffusion process and always the highest for the last observed period ($v = 9$). In between, the probability to adopt increases in an almost linear fashion, with some random fluctuations in between.

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

In addition, the regression results show that the percent of employees with a university degree within a company always has a positive and significant influence on the hazard rate to adopt, with the only exception 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 into 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. Also, it supports the view that technological progress is biased towards more skilled labor (Acemoglu 2002, Pianta 2004).

The results also show that market share (a proxy for market power) is a significant indicator for the adoption of all analyzed technologies, except for e-learning. On the one hand, firms with less than one percent market share show lower adoption rates than firms with higher market shares. On the other hand, firms with more than 25 percent of market share do usually not show the highest hazard rates for adoption, except for KMS. The peak usually occurs somewhere in between the two extremes. This lends some support to **Hypothesis 4**, which states that firms with a medium degree of market power are more likely to adopt.

Finally, the estimated Rho and their significance levels indicate that unobserved heterogeneity is never significant in the models, except for online purchasing. Thus, neither sector nor country of origin nor any other factor that is not explicitly included in our analysis does have a systematic influence on adoption rates. This provides additional evidence for an endogenous acceleration mechanism because it rules out any unobserved firm-specific factor as an alternative cause for the observed effects of $k_{i,-j,v-1}$. According to the regression results, controlling for relevant technological history, time, size class, primary customers, human capital and market share is sufficient to explain the differences in adoption rates for most e-business technologies. This seems to be in contrast to descriptive evidence on e-business usage patterns, which usually shows pronounced differences among sectors and countries (European E-Business Market W@tch 2004, OECD 2004). Also, it provides a new perspective on the results from the static analysis in chapter 5.2 that found varying but significant sector and country influences. Interestingly, different dynamic test regressions revealed that controlling for the technological *history* ($k_{i,-j,v-1}$) of a firm makes the panel level variance component Rho insignificant[33], and therefore indirectly accounts for part of the variance that is otherwise captured in the country and sector dummy variables. Rather than suggesting that country and sector effects are not important, this result could imply that real economic differences among countries and sectors (institutions, regulation, competition, cyclical effects etc.) are captured to a great extent in the investment history of firms into new technologies.

Like most research, these results are also subject to some potential limitations. The dataset that was used does have certain advantages for the purposes of this study (e.g. the large number of observations, the detailed information about technology usage), but it also has some potential disadvantages. Certainly, the sample has been collected long after the diffusion process started. Thus, it is likely that the sample has a selection bias towards the "survivors" of technological competition. This could possibly have an influence on our estimation results, although related diffusion studies using survey data with information about the time of adoption suggested that such biases were not severe (Stoneman 2002). Also, the nature of the data forces us to assume that structural variables (such as market share, size of the firm) are exogenous and constant over the entire observed period from 1994-2002. This is arguably a tough assumption to make, but the only feasible one in lack of a true panel. However, treating structural variables as exogenous rather than endogenous actually seems warranted: Treating structural variables as endogenous would only be required if they would have an unambiguous influence on adoption rates and if the analyzed technologies would have a direct significant and unambiguous positive influence on firm-level productivity. Productivity effects, however, may not occur immediately. In fact, Brynjolfsson and Hitt (2003) suggest that the contribution of computerization to productivity only occurs with a large time lag (5 to 7 years). In the meantime, no major direct effects of technology deployment on market shares and firm size should be expected. Also, the results suggest that large firms with high market shares are not necessarily the most likely to adopt all e-business technologies. Therefore, treating structural variables as exogenous in the model does not appear to be a critical assumption, i.e. making them endogenous would probably not change the main message of this study.

Finally, there is one restriction in the estimation model which puts some limits on the conclusion that the identified acceleration mechanism is truly and beyond any doubt endogenous to the process. Although the estimation model already controls for unobserved firm-specific factors explicitly, there is the theoretical possibility that some unobserved factor does not have a direct impact on the adoption decision, but an indirect one via an interactions effect with any of the observable variables. The presence of such an interactions effect cannot be ruled out by the finding that there is no direct effect of the unobserved error term. In particular, if such an interactions effect would occur with one of the explanatory variables that varies with time (such as $k_{i,-j,v-1}$), it would be impossible to differentiate between the true effect of the explanatory variable itself and the time-varying error term (ε_{ijv}). However, to my best knowledge, there is currently no econometric solution available yet to solve this potential identification problem. In addition, the finding that controlling for the technological *history* ($k_{i,-j,v-1}$) of a firm makes the unobserved firm-specific error component insignificant makes it hard to argue that the observed acceleration effect is driven entirely by some exogenous unobserved interactions effect: Whatever firm-specific effects have contributed to the observed level of $k_{i,-j,v-1}$ in the past, they are now included in the information that $k_{i,-j,v-1}$ contains because they are part of the technological history of the firm. And, consistent with the theoretical prediction, the technological history of the firm shows the expected systematic effect on future investment decisions *and* it makes the remaining unobserved firm-specific characteristics irrelevant for the adoption decision of most e-business technologies in period v. This is quite strong evidence for the argument that the observed acceleration mechanism is indeed endogenous.

6.3. Growing digital divide

The finding that the technological development along a given trajectory of related technologies can be subject to an endogenous acceleration mechanism has some important implications. If not all firms start at the same time to adopt the new technologies, i.e. if there are some pioneer users and some followers, the endogenous acceleration mechanism will lead to growing differences in technological endowment between them. The differences will continue to grow until the most advanced firms do not find any additional technologies belonging to the as-

[33] Without $k_{i,-j,v-1}$ Rho is significant, whereas Rho remains significant for $k_{i,-j,v}$.

sociated 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 upon the trajectory between early and late movers. Provided that technological investments do on average yield positive returns, this growing gap could have important consequences if early and later adopters are directly competing against each other. According to standard arguments, this acceleration mechanism could benefit early adopters, allowing them to capture additional market share, achieving higher profits, and increasing their probability of survival in the market, ceteris paribus.

A growing digital divide among firms can be demonstrated in the data: Let k_{iv} 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_{iv} over time, while a growing gap will show up as a growing variance of k_{iv} over time. The results are reported in Table 27.

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

Table 27 - Mean value and standard deviation of k over time

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

Figure 10 provides an illustrative representation of the phenomena. In the first period, 99% of all firms have adopted none of the 7 technologies, and 1% has adopted 1 technology. As time proceeds, the fraction of firms that have adopted none technology continuously decreases and the distribution of k_{iv} spreads out, leading to higher mean values and a greater disparity in technological endowment in the early periods of the diffusion processes. In 2002, the fraction of firms having adopted none of the technologies is 51%, 30% have adopted one technology, 13% have adopted two technologies, and 6% have adopted more than two technologies. Clearly, the differences in technological endowment between pioneer adopters and followers have continuously increased from 1994 to 2002.

Following the logic of the endogenous acceleration story, the "growing divide" will continue to increase, until the more advanced firms stop making progress on the trajectory and adoption decisions of followers will eventually lead to a convergence in technological equipment again. This is another interesting insight from this analysis: In the presence of an endogenous acceleration mechanism, a growing divergence in technological equipment is a logical consequence in the early phases of the diffusion process, a convergence will only occur in the later phases. Maybe a surprising result from this study is that the early phase of e-business diffusion has continued for such a long period of time (1994-2002), with an ever increasing divergence over the entire observed time frame.

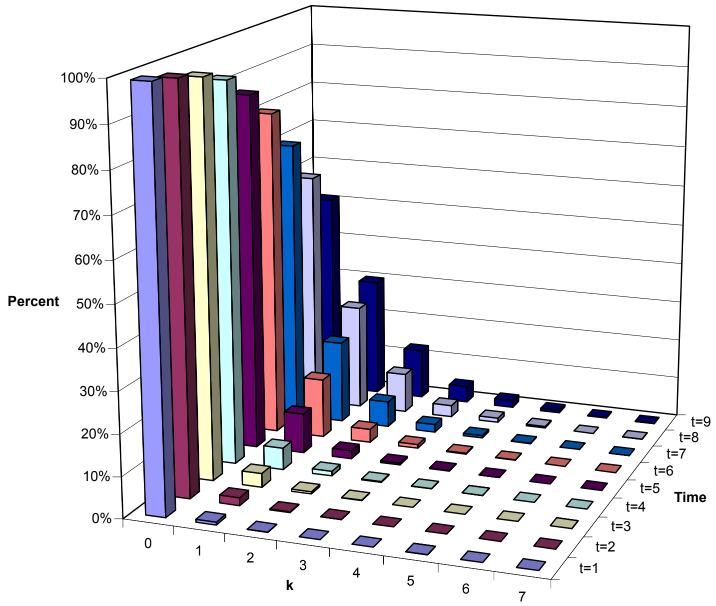


Figure 10 - Distribution of k over time

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

6.4. Discussion

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

The observation of an endogenous acceleration mechanism of technological development along a given trajectory suggests that early mover advantages can exist that are sustainable until the early mover has exhausted the possibilities of the trajectory, and followers begin to catch up. 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, Quirmbach 1986). In addition, early mover advantages can be sustainable even in the long run if there is free entry and exit in the market, and if firms are not ex ante identical, for example if there are positive returns to scale, learning-by-doing effects, scarce complementary resources to the new technology, market reputation effects, or discount rates that are lower for previously more profitable companies. If first mover rents may not be completely extinguished by other 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 decision can lead to competitive advantages (see section 3.5): 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[34]. The presence of the acceleration mechanism implies that imitating rivals will not be able to perfectly copy these resources until the early mover has exhausted the development potential of the new technological trajectory. Furthermore, it is very likely that some of these competitive advantages will be sustainable, because in reality such development processes occur over a long time span where entry and exit to a market take place. In addition, there are numerous reasons why positive returns to scale, learning-by-doing effects and imperfectly mobile complementary assets can exist in the real world.

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

1. Is there an alternative technological trajectory available to solve the same problems or to build up the same strategic resources? If alternatives do exist, then the adoption decision becomes not only a problem of optimal timing, but also a choice between alternative technological development paths. In this case, firms also need to evaluate early on whether the entire industry will eventually choose one of these alternative development paths. This could be the case if there are some kind of network externalities involved that imply that only one dominant industry standard will finally emerge and firms that are on the "wrong trajectory" might lose out in the competition (see section 2.3.3). 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[35] 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 (see section 3.2). 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 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 (see section 3.5). A quantitative analysis of their data on cus-

[34] Provided that firms can on average appropriate some private returns from their technology investments, see Chapter 2.2.

[35] Technological uncertainty in the sense of the risk of an investment project to fail due to technological or implementation reasons, such as unexpected incompatibility, unexpected implementation costs, or plain technological malfunction.

tomer behavior (for example based on the methods of section 5.3 and 5.4) could help them to optimize their product portfolio and their cross-product marketing and sales activities.

7. E-business, innovation, and firm performance

7.1. Does IT matter?

In a much debated article, Nicholas Carr (2003) argued that IT doesn't matter anymore as a strategic device for companies to gain competitive advantage. His reasoning was both simple and convincing: As IT becomes ubiquitous, it turns into an infrastructure technology (just like electricity or telephones) possessed by everyone, instead of a resource that is only available to few. Therefore, IT loses its potential for creating sustainable competitive advantage because it is scarcity, not ubiquity, that enables a company to gain an edge over rivals. Carr concludes that IT should be viewed and managed as a commodity and not as a strategic asset.

In this chapter, it is argued that Carr's argument is not entirely correct because it overlooks an essential property of information technology: IT creates numerous, company-specific opportunities to improve processes and to generate new products and services for customers that did not previously exist. Hence, IT is inherently strategic because it enables innovation and is therefore a medium to competitive advantage. However, it is not IT per se that matters, but what firms do with it. Hard- and software tools offer sets of technologically feasible opportunities. But they can often be customized and they leave plenty degrees of freedom to the user to decide how, when, or for what purpose the technology will be used. One and the same IT tool can have varying impacts in two different firm (Chan 2000)– the impact depends on how the two firms decide to utilize the technology, and to what extent they take advantage of a new technology to introduce innovations to their business.

Innovation is a strategic tool because it fulfills two purposes: Firms conduct innovation because they seek profitable investment opportunities (profit incentive) and they seek to give themselves a strategic advantage over their rivals (competitive threat). A strategic advantage may occur because a better process or a better product can enhance a firm's market share. If a firm knows that its rivals are engaging in innovative activities, it will see its own competitive position as being under threat. This creates an incentive to also invest in innovation in order not to lose out to rivals (Beath et. al. 1995, Götz 1999).

From this reasoning, four main questions arise that can be addressed in this empirical study. First, how much innovation is actually enabled by IT, in particular by Internet-based technologies? Second, do innovative firms generally perform better? Third, is there a difference between IT-related innovation and other kinds of innovation in terms of correlation with firm performance? And fourth, does a high endowment with Internet-based technologies translate into better performance?

In this study, organizational performance is measured in terms of profitability, turnover development and employment development. The objective is to analyze the relationship between these performance variables and different kinds of innovation, including IT-related and non-IT-related innovations.

Scholars of firm performance have made numerous contributions to identify the determinants of organizational performance. However, a fundamental problem is the identification of causality in such studies. As March and Sutton (1997) noted: "Most studies of organizational performance are incapable of identifying the true causal relations among performance variables and other variables correlated with them through the data and methods they normally use. Although there are studies that mitigate these shortcomings, the emperor of organizational performance studies is for the most part rather naked." It has to be admitted upfront that in this regard this study can only offer additional invisible clothing to the poor emperor. With respect to the relationship of innovation and organizational performance, the principal question that is so hard to answer is whether firms' perform well *because* they are innovative, or if they are able to innovate *because* they perform well. It is not the purpose of this study to resolve this question, and the results of the study can be interpreted in both ways.

Yet, the empirical evidence presented in this chapter is sufficient to demonstrate that IT can matter for gaining competitive advantage because it enables innovation. It is found that more important than the absolute endowment with information technologies is whether and how firms use them to conduct innovation. Also, the study is unique because it provides new insights into the relationship between IT- and non-IT-based innovative activities and performance measures. The results suggest that IT-based innovation are not inferior to other kinds of innovation and that appropriability problems can occur with both IT- and non-IT-based innovations. The econometric model introduced in this article is particularly suitable to study organizational performance because it allows to control both for unobserved firm- and market-specific effects that can influence corporate performance. The data set used here is also unique because it is timely, containing a very large sample of enterprises from various sectors and countries in the European Union, and because it allows to differentiate between IT-based and non-IT-based innovation. Together, the data and the methods used here enable a more differentiated discussion about the strategic relevance of IT.

7.2. Theoretical background

Various scholars have stressed the importance of innovation for corporate performance. Audretsch (1995) finds that new firms that are able to innovate experience higher growth rates and greater chances of survival. Cefis and Marsili (2003) also find a positive effect of innovation on firms' survival. In addition, their findings suggest that small and young firms can benefit most from innovation in order to survive in the market. Geroski et al. (1993) show that successfully innovating firms are more profitable due to the direct effect of the new product or process, and because of the indirect effect associated with the transformation of a firm's internal capabilities that enable the firm to better profit from knowledge spillovers and relative insensitivity to macroeconomic shocks. Mansfield (1968) reports that innovators are more likely to grow than other firms during the years after an innovation. Czarnitzki and Kraft (2004) report better credit ratings among innovative firms up to a certain threshold, whilst too many innovative activities reduce the rating. Griliches (1981) and Blundell et al. (1999) report greater stock market values for innovating firms.

Despite these generally positive impacts of innovation on performance, many innovating firms fail to obtain significant economic returns from an innovation, while customers, imitators and other industry participants benefit. Thus, there are often appropriability problems for the innovator because of the difficulties to protect the innovation from imitation by rivals (Levin et al. 1987, Teece 1987). To accommodate, firms typically try to appropriate private returns from innovation with a range of mechanism, including patents, secrecy, lead time advantages and the use of complementary capabilities (Cohen et al. 2000). Methods of appropriability vary markedly across and within industries and not all methods work well in all cases.

Patents rarely yield perfect appropriability because they can be "invented around" at modest costs and are only effective in a few industries (Harabi 1994, Teece 1987). Arundel (2001) presents survey results showing that a higher percentage of firms in all size classes rate secrecy as more valuable than patents. Levin et al. (1987) and Harabi (1995) find evidence that for process innovations lead time is the most effective means of appropriability. For product innovations, superior sales and service efforts are most effective, followed by lead time. Baumol (2002) stresses that the advantages of being first to innovate have successfully sped up the pace of technological progress in free market societies, because "time is money".

A different stream of literature analyzes the firm-level impacts of IT investments on performance variables, without linking them explicitly to innovation. The effect of IT investments is still subject to debate, because not all studies have demonstrated clear payoffs from IT investment (Chan 2000, Kohli and Devaraj 2003). Also, the results vary depending on how performance and IT payoffs are measured and analyzed. For example, Hitt and Brynjolfsson (1996) find positive impacts of IT investments on productivity, but not on profits. Prasad and Harker (1997) did not find positive effects of IT capital on productivity, while IT labor positively contributed to output and profitability.

Positive effects of IT spending on firm-level productivity are reported, for example, by Brynjolfsson and Hitt (1996, 2000, 2003), Greenwood and Jovanovic (1998), and Bertschek and Kaiser (2004). Many of these studies stress that the effect of IT on productivity is rather indirect, arising if IT investments are combined with complementary investments into work practices, human capital, and organizational restructuring.

Analyzing the profitability of IT, Stoneman and Kwon (1996) show that the profits of non-adopters of IT are reduced as other firms adopt new IT and that the gross profit gains of IT adoption are related to firm and industry characteristics and the number of other users of the technology. Similarly, Weill (1992) suggests that early adopters of IT are likely to benefit, but once the technology becomes common the competitive advantage is lost.

Analyzing the effects of IT investments on firm level growth, Devaraj and Kohli (2000, 2003) find positive effects of IT investments and IT usage on revenue development in the health care sector. Using data from the insurance industry, Harris and Katz (1991) found that top performing firms with high premium income growth had higher IT expense ratios and lower non-IT costs. Weill (1992) found positive effects of IT investment on sales growth among valve manufacturing firms.

In a meta analysis of studies on IT payoff, Kohli and Devaraj (2003) find that positive impacts of IT on performance are more likely to be found in studies using large data sets from primary sources. Also, studies using longitudinal firm-level data that allow to control for time-lag effects are more likely to find positive impacts of IT. Results tend to vary greatly among different industry sectors. In addition, different results tend to be reported for different kinds of dependent variables being analyzed. Generally, more studies suggest positive impacts of IT investments on productivity and growth than on profitability.

Variations in performance outcomes of firms investing into IT can be related to firm-specific resources that are unequally distributed among firms (Melville et al. 2004, Bharadwaj 2000). This reasoning is related to the resource-based view of the firm (Barney 1991) that proposes that firms could obtain competitive advantage based on firm-specific resources that are specific, valuable, rare, imperfectly imitable, and not strategically substitutable by other resources. Following the resource-based view, Santhanam and Hartono (2003) find that IT capability is related to superior firm performance. Richardson et al. (2003) show that performance differences can be attributed to the IT conversion capability of firms, which is conceptualized as reflecting the ability of firms to leverage the potential of information technologies.

The resource-based view, which focuses on firm-internal factors influencing performance differences, can be complemented by the conceptual link between IT adoption and innovation that is proposed in section 1.4.4. In particular, a possible reason why various studies did not find positive relationships between IT investments and performance is because it is not the investment into new technology per se that determines performance, but how these investments are transformed into process and service innovations. Firm-specific resources such as managerial skills, know-how, experience, the presence of technical experts and prior technological investments may be responsible for the ability of firms to transfer IT investments into innovation. After the IT investment has successfully triggered an innovation within the firm, the performance outcome of the investment will depend on the type of the innovation that was carried out and the market response of competitors and customers. In this context, the timing of the innovation is important and the appropriability strategy of the firm, i.e. the ability of the firm to protect its innovation from imitation by competitors.

7.3. An error component model of firm performance

It is obvious that, besides innovative activities, numerous other factors also influence the performance of an enterprise. For example, this includes the market in which a firm operates, the presence of economies of scale and the size of the firm, the prevailing market structure and the market share of the enterprise, as well as firm-internal structures and resources, including the technology the firm uses, its organizational structure, human resources, and managerial competence. Lenz (1981) provides an interdisciplinary summary of numerous “determinants” of organizational performance.

Hence, in order to identify the relationship between innovation and firm performance, one needs to control for alternative factors that influence performance. The challenge in this study (as well as in most other studies with a similar objective) is that not all factors that could play a role are actually observable in the data.

Because not all relevant factors can be observed, it is necessary to make some preferably non-critical assumptions about them. For this purpose, an error component model of firm performance is introduced here that enables to control separately for firm-specific and market-specific unobserved effects when estimating the influence of the observable characteristics on performance variables. This enables to disentangle the effects of unobservable market characteristics and the effects of the observable firm level characteristics, for which we obtain coefficient estimates.

We observe a cross-section of a large number N of heterogeneous firms with index $i = 1,...,N$. Each firm operates primarily on one market, and there are J different markets with index $j = 1,...,J$. We are interested in the performance of firm i in market j, which is recorded in the dependent variable y_{ij}. Performance depends on a vector of observable firm-specific characteristics $\overline{x}_{ij}$. In addition, performance also depends on unobservable market-specific effects u_j and unobservable firm-specific effects ε_{ij}. Thus, performance is a function of various firm-specific characteristics and two unobservable error terms:

$$(7.1)\quad y_{ij} = f(\overline{x}_{ij}, u_j, \varepsilon_{ij})$$

In this study, $\overline{x}_{ij}$ consists of the following variables:

x_1 = dummies indicating four different kinds of innovative activity

x_2 = firm size (measured by number of employees in four categories)

x_3 = market share (measured in % in six categories)

x_4 = % of employees with a university degree

x_5 = number of e-business technologies installed by the firm

The technologies which are included in x_5 and their relative frequency of occurrence are listed in Table 22. A more detailed description of the data follows in 7.4.

The economic conditions within one market are comparable for all firms operating in that market, but they can vary greatly among markets. Hence, u_j is equal for all firms operating in market j, but u_j can vary. All relevant firm-specific effects are captured in ε_{ij}. Identification requires to assume that ε_{ij} is independent of all observable factors $\overline{x}_{ij}$.

Yet, the advantage of the model is that we do not need to assume that the market-specific effect u_j is independent from the firm specific effect ε_{ij}, $E[u_j \mid \varepsilon_{ij}] \neq 0$. Also, we do not assume independence of u_j from the observable firm-specific characteristics $E[u_j \mid \overline{x}_{ij}] \neq 0$. Clearly, such an assumption would violate basic economic reasoning. Consider the relationship of market structure and the observed market share of an individual enterprise: If a market is characterized by perfect competition, we will not expect to find a firm with a high share in that market. Vice versa, a highly concentrated market may only exhibit a low number of firms with high market shares. Hence, market structure and market share of each firm are correlated. In our case, it is possible to observe the market share of each firm in the data, but we do not know the exact market structure in which each firm operates. However, this unobservable market structure, which is captured in u_j, is very likely to effect firm performance. Similar arguments can be made with respect to the other observable characteristics.

We consider a qualitative indicator variable y of firm performance that takes a value of $y = 1$ if a specific criteria is observed, and $y = 0$ otherwise. For example, y could be profitability taking a value of $y = 1$ if the firm has been profitable last year and $y = 0$ otherwise. Hence, y is a Bernoulli distributed random variable and the occurrence of y is conditional on various observable and unobservable characteristics, as defined in (7.1). Assuming that the influence of the conditional characteristics is linear, the probability that a firm observes $y = 1$ can be written as

$$(7.2)\quad p_{ij} = \Pr[y_{ij} = 1 \mid \overline{x}_{ij}, u_j] = E(y_{ij} \mid \overline{x}_{ij}, u_j) = F(\overline{\beta' x_i} + u_j)$$

where F is the cdf of the individual specific error term ε_{ij} that maps $(\overline{\beta' x_i} + u_j)$ into the (0;1) range. In order to get consistent estimates for β in (7.2), it is necessary to eliminate the unobserved market-specific effects u_j from the equation. Following Chamberlain (1980), the solution to this problem lies in specifying F as the logistic cdf and writing the likelihood function based on the conditional distribution of the data, conditioned on a set of sufficient statistics for u_j. By definition of a sufficient statistic, the distribution of the data given this sufficient statistic will not depend on u_j anymore.

Chamberlain (1980) showed that a sufficient statistic for u_j is $\sum_i y_{ij}$ and that the conditional log-likelihood function will only depend on β, $\bar{x}_i$, and y_{ij}:

$$(7.3)\quad L = \sum_j \ln[\exp(\bar{\beta}'\sum_i \bar{x}_{ij}y_{ij}) / \sum_{d \in B_j} \exp(\bar{\beta}'\sum_i \bar{x}_{ij}d_i)]$$

where

$$B_j = \left\{ d = (d_1, ..., d_{n_j}) \mid d_i = 0 \text{ or } 1 \text{ and } \sum_i d_i = \sum_i y_{ij} \right\}$$

and n_j is the number of firms in market j. L is in conditional logit form (McFadden 1974) with the alternative set (B_j) varying across the markets. The estimator only considers markets where $0 < \sum_i y_{ij} < n_j$, because the individual likelihood contribution of a market with no single positive observation or all positive observations is zero according to (7.3). Since L is in the form of a conditional logit log-likelihood function, it can be maximized by standard programs and all inference follows directly from conditional MLE theory (Wooldridge, 2002, p. 492). Thus, by conditioning the log-likelihood function on $\sum_i y_{ij}$, the u_j are swept away and a consistent estimator is obtained that does not place any restrictions on the distribution or co-variance of the unobservable group-specific effect. Solution (7.3) critically depends on choosing F to be the logistic cdf, a similar simplification for probit models has not yet been found (Baltagi, 2001, p. 209).

7.4. Empirical results

The dataset used for this study originates from the Nov/Dec 2003 enterprise survey of the e-Business Market W@tch. Survey participants were randomly selected from 10 sectors and 25 European countries, but not all sectors were covered in each country. However, the number of enterprises sampled in each country-sector cell was large enough to be representative of the underlying population. The economic conditions within each sector can be very different depending on the country. In addition, market structures and the 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 belongs unambiguously to a specific country-sector group of enterprises, which we define as the relevant market in our study. Overall, the sample contains 101 markets (the market index in the regression model is defined as $j = 1,...,101$). On average, we observe approximately 60 firms per market and a total of 7,302 firms.

The dataset contains qualitative information about firm performance. In particular, firms were asked the following questions relating to their performance:

- Has your company been profitable over the past 12 months? (yes / no / don’t know, not applicable)
- Has the turnover of your company increased, decreased or roughly stayed the same when comparing the last financial year with the year before? (increased / decreased / roughly stayed the same / don’t know, not applicable)
- Has the number of employees in your company increased, decreased, or roughly stayed the same during the past 12 months? (increased / decreased / roughly stayed the same / don’t know)

Based on these questions, seven binary performance variables were computed that serve as dependent variables in the analysis[36]. In this study, all seven binary variables are analyzed in separate regression models. This

[36] Observations with missing values or subjects answering „don’t know, not applicable“ were dropped from the analysis. This included 14.4% of the sample for turnover development, 11.8% for profitability, and 1.2% for employment development.

allows to get detailed insights into the effects of different kinds of innovation and technological development status on financial performance, employment effects, and firm growth. All models follow the same basic structure, they are only different in the dependent variable.

The advantage of this type of qualitative data is that it provides information about dynamic developments which are independent of the size of each firm, although only one cross-section is observed. Information about absolute turnovers and the number of employees in the survey are only useful to identify the size of a firm, but they do not provide any information about dynamic developments and performance if no true panel data are available. Alternatively, one could survey firms about the absolute size of changes (Δ_t), but such detailed information are usually not obtainable in telephone interviews.

In addition to the above questions that related to the performance of enterprises, the survey also contained questions that related to different kinds of innovative activities of firms. In particular, the following two questions were asked:

- Has your company introduced new or substantially improved products or services to your customers during the past 12 months? (yes / no / don't know, not applicable)
- Has your company introduced new company internal processes during the past 12 months? (yes / no / don't know, not applicable)

A particular goal of the survey was to find out the share of innovative activity that is directly related to or enabled by Internet-based technology. Therefore, companies that indicated in the introductory questions that they had conducted innovations in the past 12 months were asked two follow up questions:

- Has any of your product / service innovations over the past 12 months been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)
- Has any of your company internal process innovations been directly related to or enabled by Internet-based technology? (yes / no / don't know, not applicable)

96% of the survey respondents (N = 7,302) provided valid responses on the product / service innovation questions, and 96.5% on the process innovation questions. The relative frequencies of these questions are displayed in Figure 11.

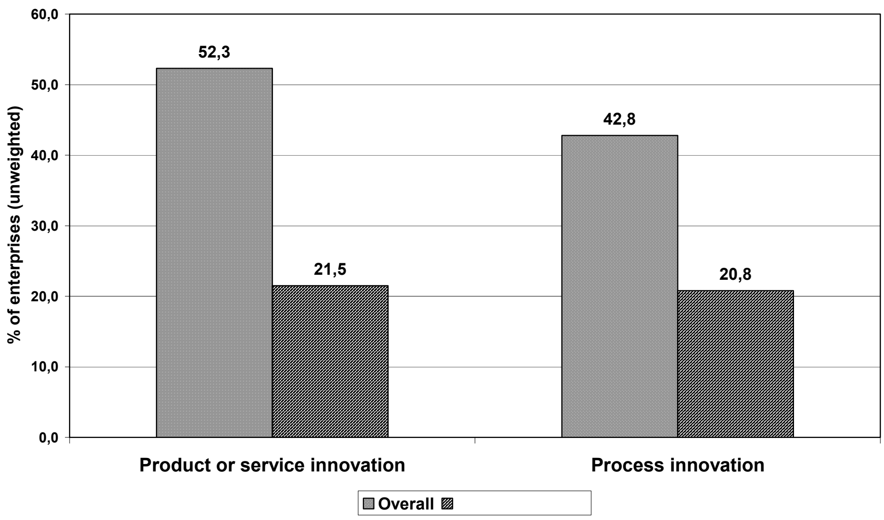


Figure 11 – Innovative activities of companies 2002-2003

Note: Unweighted survey results, e-Business Market W@tch Nov/Dec 2003

52.3% of enterprises in the sample introduced substantially improved products or services to their customers in 2003. 41.1% of these product or service innovations has been directly related to or enabled by Internet-based technology. This corresponds to 21.5% of enterprises in the sample that have introduced Internet-based product or service innovations in 2003. The importance of the Internet is even more pronounced for process innovations:

42.8% of enterprises say that they introduced new internal processes in 2003. About one half of these process innovations were directly related to or enabled by Internet-based technology.

Thus, it can be concluded that a substantial amount of innovative activity in the European Union was related to or enabled by IT and Internet-based technologies in 2003.

Another interesting finding is reported in Table 28: There is a strong significant positive correlation between product innovations and process innovations that are Internet-related. Similarly, non-Internet-enabled product and process innovations are also positively correlated at a high level of significance. On the other hand, Internet-enabled innovations are negatively associated with non-Internet-related innovations. Hence, it appears that there are three clusters of firms: Those that use IT and the Internet extensively to conduct both product/service and internal innovations, and those that also innovate in both domains, but without using the Internet. The third cluster of firms comprises of firms that do not innovate or only innovate in one domain. The correlations suggest that many companies make a conscious decision about whether they want to rely on IT to conduct innovation, or not.

Table 28 – Pearson correlations of innovative activity indicators

	Product innovation – general	**Product innovation – Internet enabled**
Process innovation - general	0.2897**	-0.1190**
Process innovation - Internet enabled	-0.1730**	0.4858**
N = 6,879. e-Business Market W@tch Nov/Dec 2003. ** denotes significance at the 99% confidence level.		

Table 29 shows the descriptive summary statistics for the dependent variables. 44.3% of enterprises in the sample experienced increasing turnover from 2002-2003, 82% report profitability for this period, and 23.3% report increasing employment. Less than one fifth of the sample recorded decreasing turnover, decreasing employment or no profits.

Table 29 – Performance indicators of companies 2002-2003

	Relative frequency	**N**
Turnover: comparison last financial year with year before		
increased	44.3%	6,253
decreased	20.4%	
roughly stayed the same	35.3%	
Has your company been profitable over the last 12 month?		
yes	82%	6,443
No. of employees: comparison last financial year with year before		
increased	23.2%	7,218
decreased	17.5%	
roughly stayed the same	59.3%	
Note: Unweighted survey results from Nov/Dec 2003.		

Table 30 shows the correlation coefficients of the performance indicators. Not surprisingly, we find that firms that experience turnover growth are significantly more likely to be profitable and to increase employment and vice versa. Noticeably, the development of turnover and employment are measures indicating whether a company is growing, declining, or stagnating. According to Table 30, growth is positively related to profitability, however it is not a pre-requisite of profitability. A significant proportion of firms in the sample are profitable although they did not increase employment. Also, some firms (not a significant part) are profitable although they experience decline.

Table 30 - Pearson correlations of performance indicators

	Profit	Employment (increase)	Employment (unchanged)	Employment (decrease)
Turnover (increase)	0.2215* (N=5,887)	0.3439* (N=6,226)	-0.1239* (N=6,226)	-0.2144* (N=6,226)
Turnover (unchanged)	0.007 (N=5,887)	-0.1886* (N=6,226)	0.1940* (N=6,226)	-0.0425* (N=6,226)
Turnover (decreased)	-0.2825* (N=5,887)	-0.2001* (N=6,226)	-0.0776 (N=6,226)	0.3147* (N=6,226)
Profit				
Employment (increase)	0.1126* (N=6,408)			
Employment (unchanged)	0.0894* (N=6,408)			
Employment (decrease)	-0.2391* (N=6,408)			
e-Business Market W@tch Nov/Dec 2003. * denotes significance at the 99% confidence level.				

The error component model of (7.3) was estimated using these data. Table 31 reports the regression results for turnover development. Table 32 shows the results for profit and employment development.

Table 31 – Fixed effect logistic regression results on turnover development

Co-variables	**Turnover increase**	**Turnover unchanged**	**Turnover decreased**
Product or service innovations last year:			
Internet-related	0.402**	-0.205*	-0.293**
general	0.439**	-0.280**	-0.219**
Internal process innovations last year:			
Internet-related	0.395**	-0.342**	-0.136
general	0.331**	-0.219**	-0.181
10-49 empl.	0.257**	-0.024	-0.307**
50-249 empl.	0.274**	0.127	-0.592**
>250 empl.	0.409**	-0.196	-0.347*
Market share:			
< 1%	-0.294**	-0.128	0.502**
1%-5%	-0.059	-0.153	0.285*
6%-10%	0.233*	-0.061	-0.283
11%-25%	0.122	-0.077	-0.071
> 25%	0.144	-0.092	-0.087
% empl. w. university degree	0.001	0.001	-0.002
# e-business technologies	0.152**	-0.125**	-0.064
Model diagnostics			
N obs	5,697	5,697	5,697
N groups	101	101	101
Log-likelihood	-3,355	-3,328	-2,453
Sign. (Prob>chi2)	0.000	0.000	0.000

** denotes significance at the 95% confidence level, * denotes significance at 90% confidence.
Reference categories: no innovations last year, 1-9 empl., market share unknown

Table 32 - Fixed effect logistic regression results on profit and employment development

Co-variables	**Profit**	**Employment increase**	**Employment unchanged**	**Employment decreased**
Product or service innovations last year:				
Internet-related	0.351**	0.409**	-0.196*	-0.165
general	0.238**	0.379**	-0.155*	-0.171*
Internal process innovations last year:				
Internet-related	0.026	0.579**	-0.400**	-0.093
general	0.048	0.495**	-0.402**	0.063
10-49 empl.	0.046	0.885**	-0.726**	0.228**
50-249 empl.	-0.079	0.876**	-0.881**	0.495**
>250 empl.	-0.097	0.860**	-1.241**	0.988**
Market share:				
< 1%	-0.536**	-0.098	-0.198*	0.388**
1%-5%	-0.039	-0.026	-0.157	0.274*
6%-10%	-0.007	0.172	-0.201	0.126
11%-25%	0.347*	0.319**	-0.350**	0.172
> 25%	0.229*	0.075	-0.100	0.083
% empl. w. university degree	0.000	0.001	0.000	-0.001
# e-business technologies	0.033	0.034	-0.085**	0.081*
Model diagnostics				
N obs	5,796	6,415	6,415	6,415
N groups	100	101	101	101
Log-likelihood	-2,320	-2,905	-3,783	-2,586
Sign. (Prob>chi2)	0.000	0.000	0.000	0.000
** denotes significance at the 95% confidence level, * denotes significance at 90% confidence. Reference categories: no innovations last year, 1-9 empl., market share unknown				

The regression results indicate that all four kinds of innovation are positively associated with turnover and employment growth and negatively associated with stagnating turnover and employment development. This supports **Hypothesis 6** and **Hypothesis 8**, which stated that innovators are more likely to grow and to expand their employment than non-innovators, independent from their ability to achieve excess profits. This is in line with related empirical evidence by Mansfield (1968), who reported that innovators in the steel and petroleum industries grew more rapidly than other firms in those industries during the years after an innovation. Also, this supports the finding that firms innovating in products, but also in processes, are more likely to expand their employment than non-innovative firms, because they grow faster in their respective markets (Pianta 2004, Pasinetti 1981).

However, there are also some differences between product and process innovations: While product innovations are positively associated with profitability, internal process innovations do not show a significant interrelation with profits. Also, product innovations are negatively associated with decreasing turnover and non-Internet-enabled product innovations are negatively associated with decreasing employment. Thus, firms that conduct product or service innovations are less likely to be in the group of firms experiencing decline. However, this does not hold for internal process innovations. Enterprises engaged in improving internal processes are not less likely to exhibit decreasing employment or turnover levels. This corresponds with the view that process innovations are a defensive strategy, whereas product innovations are an offensive, growth-oriented strategy. Also, it implies that process innovations are more likely to have a labor-substituting effect at the firm level than product innovations, i.e., firms facing a decline might invest into a labor-saving process innovation to reduce costs.

An interesting finding is that differentiating between Internet- and non-Internet related innovations reveals only small differences in estimated coefficients, i.e. whether firms use the Internet or not to conduct innovations is less important than whether they innovate at all. Also, the differences between process- and product-innovations are greater than the differences between Internet- and non-Internet related innovations.

In addition, it is interesting to observe that firms being more advanced in the use of IT (i.e. firms having adopted a higher number of Internet-based technologies) have a greater chance to exhibit increasing turnover. However, no significant effect can be reported for profitability. Thus, the empirical evidence on **Hypothesis 5** is ambiguous. **Hypothesis 5** claimed that early movers enjoy excess returns. A possible reason why there is no clear support for this hypothesis is that the theories suggesting this claim are based on the assumption that there is only moderate or no improvement in the technology over time and that the technological risk is limited or null. These are arguably tough assumptions for analyzing e-business technologies because there continues to be both a rapid decline in the price for computer hard- and software and ongoing improvements in the technologies (Moore’s law). Thus, the early mover advantages could be limited to assist firm’s growth strategies due to ongoing innovative activities rather than reflecting actual superior profitability.

In addition, the regression results show that firms who are more advanced in using e-business technologies show a higher chance of being in the group of firms that decrease employment, suggesting that e-business technologies might – after all – have a labor substituting effect. This supports Hypothesis 7.

The results also support standard economic predictions: Small firms with little market share are less likely to be profitable, and they are also less likely to exhibit increasing turnovers[37]. On the other hand, firms with high market shares are significantly more likely to be profitable, suggesting that they can exploit a certain degree of market and price setting power. Firms with low market shares have a higher chance to exhibit shrinkage in turnover and employment development, suggesting a decline of enterprises that were not able to capture larger shares of their respective markets.

In all regressions, the proxy variable for human resources (% of employees with a university degree) did not turn out to be significant, possibly suggesting that it was an improper proxy to measure the relevant types of human resources required in different kinds of firms.

[37] This obviously must not hold for enterprise start-ups, i.e. it is a „ceteris paribus“ prediction.

7.5. Discussion

There are five key messages arising from the empirical analysis:

1. Internet-based technologies are currently important enablers of innovation.
2. All four types of innovation are positively associated with turnover and employment growth at the firm level.
3. Only product/service innovations are positively associated with profitability. Process innovations do not show a significant interrelation with profits.
4. Internet-enabled innovations are at the very least not "inferior" to other kinds of innovations in terms of positive correlation with performance indicators.
5. More important than the technologies themselves (the number of e-business technologies they have installed) is what firms do with them (whether they are used to conduct innovations or not).

Although the direction of the causality between innovative activities and performance is ambiguous, it may appear surprising to find that only product/service innovations are positively associated with profitability, while process innovations are not. However, the results can be rationalized, assuming that performance follows innovation: A simple explanation could be that process innovations take longer to generate positive returns than product innovations. Process innovations are organizationally embedded and have to be routinized. Such lagged effects are obviously not observable in this cross-sectional dataset. Also, process innovation might be interdependent with other technologies and firm-specific resources and may there-fore not yield optimal returns if those complementary assets are not available or not advanced enough.

In addition, from a theoretical point of view it can be argued that strategic advantages of conducting process innovations are only sustainable (thus leading to excess profits) if direct rivals have not imitated the innovation yet (Reinganum 1981b, Götz 1999). According to this view, the adoption of generic "best practice" solutions or technology, often suggested by process re-engineering consultants and standard business software packages, generate only temporary excess returns at best, as long as competitors did not successfully copy the same practice. To a certain extent, the invention and implementation of a "best practice" solutions bears the public good problem of information (Geroski 1995): A "best practice" or standardized technological solution may be non-rivalrous in the sense that its invention and use by one firm does not automatically preclude the use by another. It may also be non-excludable if the producer of the new knowledge is unable to effectively prevent non-payers from using it. Thus, a successful process innovator may involuntarily create a positive externality for the market without being able to get a private benefit from the investment. Such externalities might be desirable from a social welfare point of view, but their existence limits the incentives of firms to invest in such activities. This theoretical appropriability problem is alleviated if the costs of conducting the process innovation or implementing the new technology is not zero, if the process and the associated technology is complex, and if it relates to other complementary or specialized assets of the firm that cannot be easily copied by rivals. Thus, sustainable advantages arising from process innovations and new production technologies can only be achieved if the innovation cannot be perfectly copied by rivals. Note that this argument does not only apply to IT-based process technologies, but to process innovations in general.

The public good problem of innovation, and hence the associated appropriability problems are not as severe for product/service innovations than for process innovations. Naturally, it is much easier to claim property rights and charge for an innovation if it can be embodied in an output sold as a new product or service. Often, products or services can be differentiated vis-à-vis competitors offers, making perfect imitation less likely and hence increasing the chance of appropriating private returns from the investment. The empirical result that product innovations are positively associated with profitability, but process innovations are not could suggest that firms in a given industry are more successful in differentiating their products and services than their production processes. Yet, the successful diffusion of a new "best practice" in an industry may still lead to higher productivity in the firms adopting the "best practice". This leads to lower production costs of the more productive firms, which makes it optimal for them to increase their output levels at a given market price. Thus, this process leads to growth of the process innovating firms and the entire industry. However, as more industry players imitate the new process and output grows, the equilibrium price in the market will fall, to the benefit of consumers and social welfare (Reinganum 1981b, Götz 1999). Via this mechanism, consumers might be the actual winners of wide-spread process innovations within an industry. The empirical evidence presented in this study is consistent with this theory.

From this perspective, the results suggest that adopting generic “best practice” solutions, often associated with standard business software and process re-engineering, do at best generate temporary excess returns, as long as competitors did not successfully copy the same practice. This suggests that sustainable advantages that are due to IT can only be achieved in two ways: (1) if the technology triggering a process innovation can be customized, complementing some other scarce resource of the firm, thus limiting imitation; or (2) if the technology can be used to innovate a new product or service offer that is valuable to customers and cannot be perfectly copied by competitors.

Assuming a reverse causality, i.e. if innovation follows performance and not the other way around, the empirical results also have an interesting implication: It would suggest that profitable firms are more likely to invest in product than in process innovation, which would imply that profitable firms are generally more customer oriented, focusing on new products and services to satisfy customer needs rather than on cost leadership.

In any case, the results emphasize the strategic importance of information technology. IT matters because it is an important enabler of innovation. Information technology and e-business tools in particular enable process innovations, if the implementation of the new technology succeeds, the routines are changed, and the new system is actually utilized. Also, IT and e-business tools can enable product or service innovations, if the new technology is successfully used to offer a new service or deliver products to customers in a way that is new to the enterprise. Depending on how the new technologies are used, the strategic objectives and consequences of IT can be quite different: The primary objective of process innovations is to reduce costs for a given output, i.e. to improve productivity, involving appropriability problems if the same process and the same technology can be perfectly copied by rivals. Yet, even in the case that firms cannot gain excess profits from their IT-enabled process innovation, increased efficiency often leads to growth and higher chances of survival in a given market, which can also be a strategic objective. On the other side, if IT is used to create new product and service offers, the strategic objective can be to explore new markets and to differentiate services and delivery modes from competitors, which can result in sustainable advantages. Especially this last point is often overlooked in the discussion about the relevance of IT, though this study demonstrates the empirical relevance of IT as an enabler of product and service innovations.

However, once the innovative potentials of IT in general and Internet-based technologies in particular will be exhausted, further investments will lose their strategic relevance and IT will become an infrastructure like streets or railways, just like Nicolas Carr (2003) suggested. However, according to the evidence presented here, which is based on 2003 data, we are still far away from such a point. Also, the development of new IT applications for business purposes is still thriving. This suggests that IT will maintain its strategic importance, simply because new IT applications will facilitate further process and product/service innovations among the adopters of these new technologies. Yet, the ability of firms to successfully transfer IT into innovation is still not a sufficient condition for superior performance and sustainable competitive advantage because performance also depends on the behavior of customers and competitors. However, the results of this study suggest that firms using IT to innovate are – at the very least – not less successful than firms using other ways to innovate. Also, innovative firms in our sample are clearly more likely to be successful than non-innovative firms.

Limitations

It should be recalled that appropriability methods vary greatly in their kind and effectiveness among industries (Levin et al. 1987, Cohen et al. 2000). Thus, the empirical results of this study with respect to profitability could be sensitive to the industries included in the sample. Consequently, the result of this study that process innovation (whether IT-enabled or not) does not correspond to higher profitability should not be generalized.

Furthermore, although the data used for this analysis are unique and interesting in various ways, they also have shortcomings. Obviously, it would be desirable to have panel data to observe the causality of innovation on firm performance, as well as the effects of past performance and other lagged variables. In addition, panel data would enable to control for unobserved heterogeneity at the firm level. Also, quantitative instead of qualitative performance variables would be desirable because they contain a greater amount of information. In addition, given that the data were collected via computer-aided telephone interviews with firm executives and IT managers, one might question the precision of their answers, especially with regard to financial performance measures. Yet, as long as the potential imprecision of their answers is not systematically related with the explanatory variables, the direction of the regression results will remain unaffected. For most variables, this seems to be a plausible assumption. However, there is one exception: It could be argued that the profitability variable in this dataset is not an objective variable (indicating whether a firm has made a positive profit in the last financial year), but a subjective variable, measuring the profit of a firm vis-à-vis some aspiration level that depends on past performance. For example, firms that experience growth could have higher aspiration levels regarding their profits than firms that experience a decline. Thus, it could be that some firms that were actually objectively profitable did not report it as such and vice versa, because they were making reference to their aspiration levels, which are unobservable in the data. If past growth is positively associated with current growth and innovative activities, and also with higher aspiration levels for profitability, the results could be biased, underestimating the positive relation between innovative activity and profitability. Thus, if such a bias exists indeed, the main messages of this study would be unaffected, with the possible exceptions that a significant positive relation between process innovation and profitability might exist after all.

PART III

8. Summary

This thesis argued that the diffusion of e-business technologies among firms is part of the ongoing process of technological change and economic development. The adoption of a new e-business technologies by firms creates opportunities to conduct innovations, either to reduce the costs for a given output, to create a new service, or to deliver products to customers in a way that is new to the enterprise. Depending on how firms utilize the technologies, the consequences can vary substantially, both at the level of the individual firm, at the market level, and at the aggregate level. Thus, it was argued that at least as important as the technologies themselves is how firms utilize them to change their business.

Part I of the thesis provided a comprehensive overview of what we currently know about the diffusion of new technologies among firms and the consequences of the diffusion process. It was emphasized that the diffusion of new technologies among firms is an essential part of the dynamics of technological development and change. An attempt was made to bridge the gap between the management and the economics literature on these topics on various occasions, with the purpose to identify complementarities between the fields and to draw conclusions for both audiences. E-business technologies were placed in perspective to the existing literature and a set of hypotheses were derived that could be empirically tested in Part II of the thesis. While Part I was taking stock of the existing theories and empirical findings, Part II presented original research results providing new theoretical arguments and empirical tests of theoretical predictions that contribute to the existing literature in a number of ways.

The new empirical results suggest that Internet-based technologies are currently important enablers of both process and product/service innovations. Chapter 7 shows that innovative firms are more likely to experience turnover and employment growth than firms that do not innovate. Also, Chapter 7 provides evidence that e-business related innovations are not inferior to other kinds of innovations in terms of positive interrelation with performance indicators. However, in contrast to process innovations, only product/service innovations exhibit a positive relationship with profitability. This indicates difficulties of firms to appropriate private returns from investments into productivity-enhancing technologies and process innovations.

The presented evidence also suggests that e-business technologies are currently an important part of technological competition among firms: They present both opportunities for profitable investments and for strategic advantages, which can be generated either by increasing market shares due to improved productivity, or through the exploration of new markets by means of product innovation and differentiation. Chapter 7 suggests that the resource-based view of the firm, which focuses on firm-internal factors influencing performance differences, can be complemented by the conceptual link between IT adoption and innovation that is proposed in this study: Firm-specific resources such as managerial skills, know-how, experience, the presence of technical experts and prior technological investments may influence the ability of firms to transfer IT investments into innovation. If no innovation is triggered, the investment will be written off. If the investment is successfully transferred into an innovation, the performance outcome will be determined in a market process. The payoff explicitly depends on the type of the innovation that was carried out and the reaction of other agents, such as customers, competitors and suppliers. Thus, there is a strong strategic dimension to the decision to adopt a new technology. In particular, the timing of the decision is important and has an influence of the ability of competitors to copy the innovation and hence on the ability of the innovator to appropriate private rents.

The empirical results also indicate that investments into IT and e-business technologies are a two-edged sword with respect to employment dynamics. On the one hand, there is evidence for a compensation effect: Firms that invest into IT-enabled innovation are more likely to grow, and therefore more likely to increase employment. However, there is also evidence for a substitution effect both on the market and within firms: The most advanced firms in terms of e-business usage are more likely to decrease employment, which suggests that labor is partially substituted by e-business technology. Also, firms that do not innovate are more likely to reduce employment, which suggests that innovative firms grow at the expense of their non-innovative rivals. The aggregate employment effect is yet unknown, but crucially depends on the dynamics of aggregate demand.

The two chapters studying the adoption and diffusion of multiple related e-business technologies revealed important insights about technological change in general: With the emergence of a new technological paradigm, firms are often confronted with the opportunity to invest into numerous, related technologies that belong to that paradigm. The theory and the empirical evidence presented here suggests that a particular pattern will emerge: Provided that the related technologies do not substitute another in their functionalities, there can be increasing returns to adoption. In this case, the probability to adopt is an increasing function of the number of previously adopted, related technologies. Thus, history matters for the technological development of a firm. An adoption decision today affects the expected value of any other related technology in the future. Hence, technological development can be viewed as a path dependent process that exhibits an endogenous acceleration mechanism. Provided that not all firms start to adopt the new technologies at the same time, a growing divergence in technological endowment among firms is a logical consequence of this mechanism. This technological divergence in the early periods after the emergence of a new paradigm will continue to grow until the most advanced firms have exhausted the potentials of the new paradigm and stop making progress. Only then will the follower firms be able to "catch up", and technological endowments will begin to converge again.

Table 33 summarizes the empirical results of Part II. There was empirical support for 8 of the 11 developed hypotheses regarding the diffusion and implications of e-business technologies. One hypothesis was rejected, and two hypotheses yielded ambiguous results. The strongest empirical support was found for **Hypothesis 10**, which suggested that the development upon the e-business trajectory can be subject to an endogenous acceleration mechanism. Support for this was found using two different datasets and four different econometric approaches.

Table 33 – Overview of empirical results

	Chapter				
Hypothesis	5.2	5.3	5.4	6.2	7.3
1 – Diffusion varies across sectors	+		+		
2 – Sectors with high concentration ratios and high technological competition are more likely to adopt	-				
3 – Large firms are more likely to adopt	+			+	
4 – Firms with medium degree of market power are more likely to adopt				+	
5 – Early movers enjoy excess returns					?
6 – Innovators are more likely to grow					+
7 – Firms that are advanced in using e-business are more likely to reduce employment					+
8 - Firms that recently used technology to innovate are more likely to increase employment					+
9 – The probability to adopt e-business technologies strictly increases with time				+	
10 – The probability to adopt any e-business technology increases with the number of previously adopted e-business technologies	+	+	+	+	
11 – Industries with high ICT competence are more likely to adopt e-business technology	?				
Legend + : empirically supported - : empirically rejected ? : ambiguous empirical results					

On the methodical side, a few new empirical methods have been applied in this study. In Chapter 7, an error component model of firm performance is introduced that controls for unobserved market specific effects. Chapter 6 featured a discrete time hazard rate model that controls for unobserved firm-specific heterogeneity to study the diffusion of multiple related technologies. The model avoided the implausible assumption that all firms will eventually adopt by specifying a flexible piece-wise constant baseline hazard rate. In Chapter 5, a simultaneous equation model of technology adoption was introduced to distinguish between the direct influence of technologies on another and exogenous factors that drive adoption decisions. Finally, Classification and Regression Trees (CART) have been introduced to study innovation adoption. The CART results have a very appealing practical value for technology providers, consultants, and marketers of new products and technologies because they enable to identify clusters that differ significantly in their probability to adopt. Provided that the collected data are fairly recent, the identified clusters can help to optimize marketing and sales strategies. For example, a technology provider might decide to focus his marketing activities on those clusters that have been identified as showing high probability to adopt. Also, a technology provider who is already conducting business with a client might use the CART results to make an "educated guess" about what will be a likely future investment of the client. This knowledge could be used to increase the chances of getting a follow-up job. In a similar way, CART can generally be used as a market research instrument for any kind of product, service or technology where recent and preferably large datasets are available.

9. Implications and further research

The theoretical considerations and empirical results of this thesis emphasize the strategic importance of new technologies in general, and IT in particular.

The observation of an endogenous acceleration mechanism of technological development along a given paradigm suggests that early mover advantages can exist that are sustainable until the early mover has exhausted the possibilities of the paradigm, and competing followers begin to catch up (if they still exist then). In addition, early mover advantages can be sustainable even in the long run if there is free entry and exit in the market, 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 competing followers, it might be less profitable for late movers to adopt at all. Also, some firms might "pre-emptively" adopt to capture strategic advantages, even if this would not be justified on ROI considerations alone.

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. "Betting on the wrong horse" could put the very existence of the firm at stake. In this case, 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, firms still need to assess how substantial the technological uncertainty is and how probable rapid technological improvements are in the future. Both of these effects make it more attractive to delay the investment. 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. Confronted with such a situation of Knightian uncertainty, firms might benefit from the knowledge of industry experts and consultants to choose their path of action.

The particular importance of e-business as a technological paradigm arises from its very general scope of application and from the fact that its underlying technology (the Internet) is subject to network effects and has already reached critical mass. The technological problem that all e-business solutions try to solve is to optimize the exchange of commercially relevant information, which is essential for running and controlling any business. They do so by providing specific software solutions that run on non-proprietary computer communication networks with a universally standardized protocol (TCP/IP). The “normal problem solving tools” of e-business technologies are applicable in various regions, sectors, firms, and functional areas. In many sectors, certain e-business applications are already the new standard for exchanging commercially relevant information and firms that are not able to keep up with this technological development face the risk of losing out to the competition (*e-Business Market W@tch* 2004).

Yet, the results of this study also imply that the strategic implications of technology investments arise less from the technologies themselves than from the way the technologies are utilized to conduct innovation on the side of the user. Theory suggests that technology-induced innovations can lead to sustainable advantages, but only if not all rivals are able to perfectly copy the improved production process or product. In any case, even if firms are not able to appropriate private excess returns from the technology-induced innovation, conducting the innovation may still have a strategic value because it may help to defend market shares against competitors who also engage in innovations. Thus, technology-induced innovation may help to increase the chances of survival in a given market.

The presence of an endogenous acceleration mechanism also has some important implications for the suppliers and marketers of e-business technologies and ICT in general: Firms that have previously invested into related technologies are more likely to make additional investments into such technologies. Thus, 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 the existence of technological interdependencies.

From an economic point of view, it was pointed out that innovation and technological change may effect various important areas, such as the development of market structure, productivity, growth, and employment dynamics. The provided empirical evidence implies that IT and e-business technologies are currently important enablers of innovative activity in Europe. Related research has demonstrated that IT investments in conjunction with complementary investments into human resources and organizational change does have positive effects on firm-level productivity and growth.

The results of this study also suggest that firms that successfully conduct innovations using e-business technologies will grow faster than non-innovating firms. However, they will probably do so at the expense of non-innovating firms, especially considering the currently stagnating demand dynamics in many markets in Europe. This might have consequences for the development of market structures. Also, there is evidence that technological advanced firms have a tendency to reduce employment, which suggests that e-business technologies can be used to substitute labor. Hence, a possible implication of this finding is that e-business technologies can be an instrument for firms to rationalize and restructure, leading to productivity growth at the expense of total employment in a low GDP growth scenario. Also, we may expect that the diffusion of e-business technologies will have a skill-biased effect on labor demand, favoring well-educated workers with ICT skills.

The finding that technological development at the firm level can be subject to increasing returns could be transferred to the aggregate level. If firms in a specific country get a head start in adopting technologies from a new paradigm, this might generate a technology gap vis-à-vis firms in other countries. This would provide an interesting alternative explanation why some countries become technological leaders and some followers, with possible consequences for productivity and per-capita income differences among countries (Barro and Sala-I-Martin 1997).

From a policy perspective, it is interesting to note that investments into innovation and new technologies might be subject to market failure, which can result in either too much or too little investment in technology compared to the social optimum. However, it is also not clear a-priori which scenario is likely to occur, if market failure will occur at all, or what the social optimum would actually be in reality. Metcalfe (1995) and Mowery (1995) provide good surveys on these issues. Some empirical studies have also analyzed the effect of government intervention in the diffusion process. Evidence suggests that governmental intervention rarely speeds up the diffusion process and government-controlled firms do not move faster than privately owned companies (Hannan and McDowell 1984, Oster and Quigley 1977, Rose and Joskow 1990).

Numerous important questions regarding the dynamics of technology diffusion still remain open and present potential for future research. For example, a panel data analysis incorporating technology investment decisions *and* performance parameters (such as profits or market share) over time would provide valuable new insights into the dynamics of market structure development and technological change. From a policy perspective, many important questions still remain open that require further theoretical and empirical research: Does intense technological competition lead to higher concentration ratios or monopoly market outcomes, and is such a scenario desirable from a social welfare perspective? What is the socially optimal level of investment into new technology and what role can policy makers play in reaching that optimum?

Also, the strategic dynamics of new technology diffusion, as proposed by stock and order effect models, need a more rigorous empirical analysis. How do real decision makers behave in such situations of strategic uncertainty? Furthermore, the role of risk with regards to the properties of technologies need to be disentangled from the role of ambiguity and the process of information acquisition about the new technology. As theory suggests, these are different concepts with different impacts on the diffusion process. Also, the rapidly emerging field of behavioral economics provides manifold evidence that actual human behavior in risky and ambiguous situations is very complex and only badly described by the standard assumptions of risk aversion or expected utility theory (see for example Kahneman and Tversky, 1979; Thaler et. al., 1997; Fox and Tversky, 1995; Schade et al., 2002). It has not yet been analyzed how these psychological phenomena influence the behavior of real decision makers in the specific context of technology investments in firms. Thus, we do not yet know how different information conditions and levels of uncertainty actually influence the spread of new technologies among firms in the real world where perceptions and risk attitudes of decision makers do matter. Empirical studies with real world data clearly have limitations to answer these questions. Instead, laboratory experiments might provide useful new insights because they allow to control and to manipulate risk, ambiguity, and information conditions in explicit ways. This could be subject to interesting future research.

References

Abel, A.B. and Blanchard, O. 1986. The present value of profits and cyclical movements in investment. Econometrica. *54* 249-273.

Acemoglu, D. 2002. Technical change, inequality and the labor market. Journal of Economic Literature. *40(1)* 7-72.

Acs, Z.J. and Audretsch, D.B. 1987. Innovation, market structure, and firm size. Review of Economics and Statistics. *67* 567-574.

Aghion, P. and Howitt, P. 1992. A model of growth through creative destruction. Econometrica. *60(2)* 323-351.

Ahire, S.L. and Ravichandran, T. 2001. An innovation diffusion model of TQM implementation. IEEE Transactions on Engineering Management. *48(4)* 445-464.

Allen, T.J. 1977. Managing the Flow of Technology. MIT Press, Cambridge.

Antonucci, T. and Pianta, M. 2002. The employment effects of product and process innovations in Europe. International Review of Applied Economics. *16(3)* 295-308.

Atrostic, B.K., Gates, J. and Jarmin, R. 2003. Measuring the electronic economy at the U.S. Census Bureau - Proceedings of the Statistics Canada Symposion. 12/29/2003, http://www.statcan.ca/english/conferences/symposium2002/session10/s10d.pdf.

Armour, H.O. and Teece, D.J. 1978. Organizational structure and economic performance: A test of the multidivisional hypothesis. Bell Journal of Economics and Management Science. *9* 106-122.

Arrow, K.J. 1962. Economic welfare and the allocation of resources for invention. in NBER: The Rate and Direction of Innovative Activity. Princeton University Press, Princeton.

Arrow, K.J. 1962a. The economic implications of learning by doing. Review of Economic Studies. *29(3)* 155-173.

Arrow, K.J. 1964. Economic welfare and the allocation of resources for innovation. in: Nelson, R.R. The Rate and Direction of Innovative Activity. Princeton University Press, Princeton.

Arrow, K.J. and Debreu, G. 1954. Existence of an equilibrium for a competitive economy. Econometrica. *22(3)* 265-290.

Arthur, B. 1989. Competing technologies, increasing returns, and lock-in by historical events. Economic Journal. *99(394)* 116-131.

Audretsch, D. 1995. Innovation, growth and survival. International Journal of Industrial Organization. *13* 441-457.

Bailey, E.E. and Friedlaender, A.F. 1982. Market structure and multiproduct industries. Journal of Economic Literature. *20* 1024-1048.

Bailey, E.E. and Lawrence, R.Z. 2001. Do we have a new economy? NBER Working Paper. *No W8243*. Cambridge, Massachusetts.

Bain, A. 1964. The Growth of Television Ownership in the UK since the War: A Lognormal Model. Cambridge University Press, Cambridge.

Bain, J.S. 1956. Barriers to New Competition. Their character and consequences in manufacturing industries. Augustus M. Kelly Publishers.

Baldwin, W.L. and Scott, J.T. 1987. Market Structure and Technological Change. Harwood Academic Publishers, Chur and New York.

Baltagi, B. 2001. Econometric Analysis of Panel Data.: John Wiley & Sons.

Barnett, H.G. 1953. Innovation: The Basis of Cultural Change. McGraw-Hill, New York et al.

Barney, J. 1991. Firm resources and sustained competitive advantage. Journal of Management. *17(1)* 99-120.

Barro, R.J., Mankiw, N.G. and Sala-i-Martin, X. 1995. Capital mobility in neoclassical models of growth. American Economic Review. *85(1)* 103-115.

Bass, F.M. 1969. A new product growth model for customer durables. Management Science, *15*, 215-27.

Baumol, W.J. 2002. The Free-Market Innovation Machine. Princeton University Press, Princeton and Oxford.

Baumol, W.J., Willig, R.D. and Panzar, J.C. 1982. Contestable Markets and the Theory of Industry Structure. Harcourt Brace Jovanovich, San Diego.

Barro, W.J. and Xavier Sala-I-Martin. 1997. Technological diffusion, convergence, and growth. Journal of Economic Growth. *2* 1-27.

Beath, J., Katsoulacos, Y. and Ulph, D. 1987. Sequential product innovation and industry evolution. Economic Journal (Supplement). *97* 32-43.

Beath, J., Katsoulacos, Y. and Ulph, D. 1995. Game-theoretic approaches to the modelling of technological change. in: Stoneman, P. Handbook of the economics of innovation and technological change. Blackwell, Oxford and Cambridge. 132-181.

Beck, J., Grajek, M. and Wey, C. 2005. The diffusion of barcode scanning in European retailing. Mimeo.

Becker, B. 1965. A theory of the allocation of time. Economic Journal. *75* 493-517.

Becker, G. 1975. Human Capital. NBER, New York.

Becker, S.W. and Whisler, T.L. 1967. The innovative organization: a selective view on current theory and research. Journal of Business. *40(4)* 462-469.

Besen, S. and Farrell, J. 1994. Choosing how to compete : Strategies and tactics in standardization. Journal of Economic Perspectives. *8* 117-131.

Bertschek, I. and Kaiser, U. 2004. Productivity effects of organizational change: Microeconometric evidence. Management Science. *50(3)* 394-404.

Baradwaj, A.S. 2000. A resource-based perspective on information technology capability and firm performance: An empirical investigation. MIS Quarterly. *24(1)* 169-196.

Black; S.E. and Lynch, L.M. 2004. What's driving the new economy? The benefits of workplace innovation. Economic Journal. *114(493)* 97-116.

Blair, J. 1972. *Economic Concentration*. Harcourt Brace Jovanovich, New York.

Blundell, R., Griffith, R. and Van Reen, J. 1999. Market structure, market value and innovation in a panel of British manufacturing firms. Review of Economic Studies. *66* 529-554.

Bolton, M.K. 1993. Organizational innovation and substandard performance: When is necessity the mother of innovation? Organization Science. *4(1)* 57-75.

Breiman, L., Friedman, J.H., Olshen, R.A. and Stone, C.J. 1984. Classification and Regression Trees. Belmont, Wadsworth International Group.

Burmeister, K. and Schade, C. 2005. Status quo bias versus variety seeking: An experimental investigation into situational and individual moderators. Marketing Journal of Research and Management. *1* 14-25.

Burnett, N. 1997. Gender economics courses in liberal arts colleges. Journal of Economic Education. *28(4)* 369-377.

Breshnahan, T.F. and Trajtenberg, M. 1995 General purpose technologies: 'Engines of growth'? Journal of Econometrics. *65* 83-108.

Brynjolfsson, E. and Hitt, L.M. 1996. Paradox lost? Firm-level evidence on the returns to information systems spending. Management Science. *42(4)* 541-558.

Brynjolfsson, E. and Hitt, L.M. 2000. Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives. *14(4)* 23-48

Brynjolfsson, E. and Hitt, L.M. 2002. Information technology, workplace organization and the demand for skilled labor: Firm-level evidence. Quarterly Journal of Economics. *117* 339-376.

Brynjolfsson, E. and Hitt, L.M. 2003. Computing productivity: Firm level evidence. Review of Economics and Statistics. *LXXXV(4)* 793-808.

Carr, N. 2003. IT doesn't matter. Harvard Business Review. *May* 5-12.

Caves, R.E. 1989. International differences in industrial organization. in: Schmalensee, R. (ed.). Handbook of Industrial Organization. North-Holland, Amsterdam. 1225-1246.

Cefis, E. and Marsili, O. 2003. Survivor: The role of innovation in firms' survival. E.A.R.I.E. 2004 Conference Paper. DIW Berlin, Berlin.

Chamberlain, G. 1980. Analysis of covariance with qualitative data. Review of Economic Studies. *47(1)* 225-238.

Chan, Y. 2000. IT value: The great divide between qualitative and quantitative and individual and organizational measures. Journal of Management Information Systems. *16(4)* 225-261.

Chari, V. and Hopenhayn, H. 1991. Vintage human capital. Journal of Political Economy. *99* 1142-1165.

Christensen, R. 1990. Log-linear models. Springer, New York et al.

Church, J. and Gandal, N. 1993. Complementary network externalities and technological adoption. International Journal of Industrial Organization. *11* 239-260.

CIS. 2004. Community Innovation Survey. 07/26/05. http://www.dti.gov.uk/iese/cis.htm or http://europa.eu.int/pol/rd/index_en.htm.

Cohen, W.M. and Klepper, S. 1996. Firm size and the nature of innovation within industries: The case of process and product R&D. Review of Economics and Statistics. *78* 232-243.

Cohen, W.M., Levin, R. and Mowery, D.C. 1987. Firm size and R&D intensity: A re-examination. Journal of Industrial Economics. *35* 543-565.

Cohen, W.M. and Levinthal, D.A. 1989. Innovation and learning: The two faces of R&D. Economic Journal. *99(397)* 569-596.

Cohen, W.M., Nelson, R. and Walsh, J. 2000. Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). National Bureau of Economic Research. Working paper *7552*.

Cohen et al. 2001. Tools: The drivers of e-commerce. BRIE-IGCC E-conomy Project Task Force - Tracking a Transformation: E-Commerce and the Terms of Competition in Industries. Brookings Press, Washington DC.

Comanor, W.S. 1967. Market structure, product differentiation, and industrial research. Quarterly Journal of Economics. *81* 639-657.

Curry, B. and George, D. 1983. Industrial concentration: A survey. Journal of Industrial Economics. *31* 203-255.

Czarnitzki, D. and Kraft, K. 2004. Innovation indicators and corporate credit ratings: Evidence from German firms. Economics Letters. *82* 377-384.

Damanpour, F. 1991. Organizational innovation: a meta-analysis of effects of determinants and moderators. Academy of Management Journal. *34* 555-590.

Dasgupta, P. and Stiglitz, J. 1980. Industrial structure and the nature of innovative activity. Economic Journal. *90* 266-293.

Dasgupta, P. 1986. The theory of technological competition. in: Binmore, K. and Dasgupta, P. (eds). Economic Organizations as Games. Basil Blackwell, Oxford.

David, P.A. 1969. A contribution to the theory of diffusion. Center for Research in Economic Growth Research Memorandum, *71*, Stanford University.

David, P.A. 1985. Clio and the economics of QWERTY. American Economic Review. *75(2)* 332-337.

David, P.A. 1990. The dynamo and the computer: A historical perspective on the modern productivity paradox. American Economic Review Papers and Proceedings. *1(2)* 355-361.

David, P. 1991. Behind the Diffusion Curve. Westview Press, Oxford.

Davies, P.A. 1979. The Diffusion of Process Innovations. Cambridge University Press, Cambridge.

DeCanio, S., Dibble, C. and Amir-Atefi, K. 2000. The importance of organizational structure for the adoption of innovations. Management Science. *46(10)* 1285-1299.

Deutsches Patentamt. 2004. Richtlinien für die Prüfung von Patentanmeldungen. Abs. 3.3.3. 11/08/2004, http://www.dpma.de/formulare/p2796.pdf.

Devaraj, S. and Kohli, R. 2000. Information technology payoff in the healthcare industry: A longitudinal study. Journal of Management Information Systems. *16(4)* 41-67.

Devaraj, S. and Kohli, R. 2003. Performance impacts of information technology: Is actual usage the missing link? Management Science. *49(3)* 273-289.

Dewar, R.D. and Dutton, J.E. 1986. The adoption of radical and incremental innovations: an empirical analysis. Management Science. *32(11)* 1422-1433.

Dixit, A.K. and Pindyck, R.S. 1996. Investment under uncertainty. 2nd printing. Princeton University Press, Princeton.

Dosi, G. 1982. Technological paradigms and technological trajectories. Research Policy. *11* 147-162.

Dosi, G. 1997. Opportunities, incentives and the collective patterns of technological change. Economic Journal. *107* 1530-1547.

Easton, G.S. and Jarrell, S.L. 1998. The effects of total quality management on corporate performance: An empirical investigation. Journal of Business. *71(2)* 253-307.

Economides, N. 1996a. The economics of networks. International Journal of Industrial Organization. *14(6)* 673-699.

Economides, C. 1996b. Network externalities, complementarities, and invitations to enter. European Journal of Political Economy. *12* 211-232.

Edquist, C., Hommen, L. and McKelvey, M. 2001. Innovation and Employment. Edward Elgar, Cheltenham and Northampton.

EITO. 1999. European Information Technology Observatory 1999. Eggebrecht-Presse, Frankfurt/M.

EITO. 2003. European Information Technology Observatory 2003. Eggebrecht-Presse, Frankfurt/M.

Ettlie, J.E. and Vellenga, D.B. 1979. The adoption time period for some transportation innovations. Management Science. *25(5)* 429-443.

European e-Business Market W@tch. 2003. E-Biz Concepts. European Commission, DG Enterprise. 11/08/2004, http://www.ebusiness-watch.org.

European e-Business Market W@tch. 2004a. The European e-Business Report 2004. Office of Official Publications of the European Communities, Luxembourg.

Evangelista, R. and Savona, M. 2002. The impact of innovation on employment and skill in services – evidence from Italy. International Review of Applied Economics. *16(3)* 309-318.

Evangelista, R. and Savona, M. 2003. Innovation, employment and skills in services – firm and sectoral evidence. Structural Change and Economic Dynamics. *14(4)* 449-474.

Farrell, J. and Saloner, G. 1986. Installed base and compatibility: innovation, product preannouncement, and predation. American Economic Review. *76(4) 940-955.*

Farrell, J. and Saloner, G. 1992. Converters, compatibility, and the control of interfaces. Journal of Industrial Economics. *40(1) 9-36.*

Fogel, R. 1964. Railroads and American Economic Growth. Johns Hopkins University Press, Baltimore.

Fox, C.R. and Tversky, A. 1995. Ambiguity aversion and comparative ignorance. Quarterly Journal of Economics. *110 585-603*.

Fudenberg, D. and Tirole, J. 1985. Pre-emption and rent equalization in the adoption of new technology. Review of Economic Studies. *52 383-401*.

Gandal, N., Kende, M. and Rob, R. 2000. The dynamics of technological adoption in hardware / software systems: The case of CD players. Rand Journal of Economics. *31(1) 43-61*.

Gatignon, H., Tushman, M.L., Smith, W. and Anderson, P. 2002. A structural approach to assessing innovation: construct development of innovation locus, type, and characteristics. Management Science. *48(9) 1103-1122*.

Gemünden, H.G. and Walter, A. 1996. Förderung des Technologietransfers durch Beziehungspromotoren. Zeitschrift Führung Organisation. *65(4) 237-245*.

Geroski, P., Machin, S. and Van Reenen, J. 1993. The profitability of innovating firms. Rand Journal of Economics. *24(2) 198-211*.

Geroski, P. 1994. Market Structure, Corporate Performance and Innovative Activity. Clarendon Press, Oxford.

Geroski, P. 1995. Markets of technology: Knowledge, innovation and appropriability. in: Stoneman, P. Handbook of the economics of innovation and technological change. Blackwell, Oxford and Cambridge.

Glynn, M.A. 1996. Innovative genius: a framework for relating individual and organizational intelligences to innovation. Academy of Management Review. *21(4)* 1081-1111.

Gordon, R.J. 2000. Does the 'new economy' measure up with the great inventions of the past? Journal of Economic Perspectives. *14(4) 49-77*.

Gordon, R.J. 2002. Comments to 'Productivity growth and the new economy' by Nordhaus (2002). Brookings Papers on Economic Activity. *2002:2 245-253*.

Götz, G. 1999. Monopolistic competition and the diffusion of new technology. Rand Journal of Economics, *30(4) 679-693*.

Green, S.G., Gavin, M.B. and Aiman-Smith, L. 1995. Assessing a multidimensional measure of radical technological innovation. IEEE Transaction on Engineering Management, *42(3) 203-214*.

Greene, W.H. 2003. Econometric Analysis. 5th international edition. Prentice Hall, Upper Saddle River (NJ).

Greenwood, J. 1997. The Third Industrial Revolution: Technology, Productivity, and Income Inequality. AEI Press, Washington D.C.

Greenwood, J. and Jovanovic, B. 1998. Accounting for growth. NBER Working Paper. *No. 6647*. Cambridge, Massachusetts.

Griliches, Z. 1957. Hybrid corn: An exploration in the economics of technological change. Econometrica. *48 501-22*.

Griliches, Z. 1981. Market value, R&D, and patents. Economics Letters. *7 183-187*.

Grossman, G.M. and Helpman, E. 1991. Innovation and Growth in the Global Economy. MIT Press, Cambridge.

Grossman, G.M. and Helpman, E. 1994. Endogenous innovation in the theory of growth. Journal of Economic Perspectives. *8(1) 23-44*.

Gruber, H. and Verboven, F. 2001. The diffusion of mobile telecommunications in the European Union. European Economic Review. *45 577-588*.

Hagen, E. 1971. Traditionalismus, Statusverlust, Innovation. in: W. Zapf. Theorien des sozialen Wandels. Kiepenheuer and Witsch, Koeln.

Hambrick, D. 1987. Top management teams: Key to strategic success. California Management Review. *30 88-108*.

Hannan, T.H. and McDowell, J.M. 1984. The determinants of technology adoption: The case of the banking firm. Rand Journal of Economics. *15 328-335*.

Hannan, T.H. and McDowell, J.M. 1990. The impact of technology adoption on market structure. Review of Economics and Statistics. *72 164-168*.

Harabi, N. 1995. Appropriability of technical innovations: An empirical analysis. Research Policy. *24 981-992*.

Harris, S.E. and Katz, J.L. 1991. Organizational performance and information technology investment intensity in the insurance industry. Organization Science. *2(3) 263-295*.

Hatch, N.W. and Mowery, D.C. 1998. Process innovation and learning by doing in semiconductor manufacturing. Management Science. *44(11) 1461-1477*.

Hauschildt, J. 1997. Innovationsmanagement. 2nd edition. Vahlen, Muenchen.

Hauschildt, J. 1999. Promotors and champions in innovations – development of a research paradigm. in: The Dynamics of Innovation – Strategic and Managerial Implications. Springer, Berlin. *167-182*.

Hay, D.A. and Morris, J. 1991. Industrial Economics and Organization –Theory and Evidence. Oxford University Press, Oxford.

Helpman, E. 1998. General Purpose Technologies and Economic Growth. MIT Press, Massachusetts.

Hempell, T. 2002. Does experience matter? – Innovations and the productivity of ICT in German services. ZEW Discussion Paper. *No. 02-43*. Mannheim.

Hitt, L. and Brynjolfsson, E. 1996. Productivity, business profitability, and consumer surplus: Three different measures of information technology value. MIS Quarterly. *20(2) 121-142*.

Horsky, D. 1990. A diffusion model incorporating product benefits, price, income and information. Marketing Science. *9(Fall) 342-385*.

Hubbard, G.R. 1990. Introduction. in: Hubbard, G.R. (ed): Asymmetric Information, Corporate Finance, and Investment. University Chicago Press, Chicago.

Hubbard, R.G. and Kashyap, A.K. 1992. Internal net worth and the investment process: An application to U.S. agriculture. Journal of Political Economy. *100(3) 506-534*.

Huber, P.J. 1967. The behavior of maximum likelihood estimation under non-standard conditions. In L.M. LeCam and J. Neyman, eds. Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. University of California Press. *221-233*.

Huisman, K.J.M. 2001. Technology Investment: A Game Theoretical Real Options Approach. Kluwer Academic Publishers, Boston et al.

Hurley, R.F. and Hult, T.M. 1998. Innovation, market orientation, and organizational learning: an integration and empirical examination. Journal of Marketing. *62 42-54*.

IDC – International Data Corporation. 2000. Corporate eLearning: market forecast and analysis. www.idc.com.

Ireland, N. and Stoneman, P. 1985. Technological diffusion, expectations and welfare. Oxford Economic Papers. *June 283-304*.

Ittner, C.D., Larcker, D.F. and Rajan, M.V. 1997. The choice of performance measures in annual bonus contracts. Accounting Review. *72(2) 231-255*.

Jenkins, S. 2004. Survival Analysis. Lecture notes, University of Essex. http://www.iser.essex.ac.uk/teaching/stephenj/ec968/index.php#_Toc520705913, viewed Sept. 19th 2004.

Jones, C. 1998. Introduction to Economic Growth. W.W. Norton & Co., New York.

Jorgenson, D.W. 2001. Information technology and the U.S. economy. American Economic Review. *91(1) 1-32*.

Jorgenson, D.W. and Stiroh, K.J. 2000. U.S. economic growth and the industry level. American Economic Review. *90(2) 161-167*.

Jovanovic, B. and Nyarko, Y. 1996. Learning by doing and the choice of technology. Econometrica. *64(6) 1299-1310*.

Jovanovic, B. and Stolyarov, D. 2000. Optimal adoption of complementary technologies. American Economic Review. *90(1) 15-29*.

Kahneman, D. and Tversky, D. 1979. Prospect theory: An analysis of decisions under risk. Econometrica. *47 262-291*.

Kamakura, W.A., Kossar, B.S. and Wedel, M. 2004. Identifying innovators for the cross-selling of new products. Management Science. *50(8) 1120-1133*.

Kamien, M.I. and Schwartz, N.L. 1982. Market structure and innovation. Cambridge University Press, Cambridge et al.

Karshenas, M. and Stoneman, P. 1993. Rank, stock, order and epidemic effects in the diffusion of new process technology. Rand Journal of Economics. *24(4) 503-28*.

Karshenas, M. and Stoneman, P. 1995. Technological diffusion. in: Stoneman, P. (ed). Handbook of the Economics of Innovation and Technological Change. Blackwell, Oxford and Cambridge. *265-297*.

Katsoulacos, Y.S. 1986. The Employment Effect of Technical Change. Wheatsheaf, Brigthon.

Katz, M. and Shapiro, C. 1985. Network externalities, competition, and compatibility. American Economic Review. *75(3) 424-440*.

Katz, M. and Shapiro, C. 1986. Technology adoption in the presence of network externalities. Journal of Political Economy. *94(4) 822-841*.

Katz, M. and Shapiro, C. 1992. Product introduction with network externalities. Journal of Industrial Economics. *40(1) 55-83*.

Katz, M. and Shapiro, C. 1994. Systems competition and network effects. Journal of Economic Perspectives. *8(2) 93-115*.

Kauermann, G. and Carroll, R.J. 2001. The sandwich variance estimator: efficiency properties and coverage probabilities of confidence intervals. Journal of the American Statistical Association. *97 482-493*.

Kelley, M.R. and Brooks, H. 1991. External learning opportunities and the diffusion of process innovations to small firms. Technological Forecasting and Social Change. *39 103-125*.

Kiefer, N. 1990. Econometric methods for grouped duration data. In: Hartog, J, Ridder, G., and Theeuwes, J. (eds), Panel Data and Labor Market Studies. North Holland, Amsterdam.

Knight, K.E. 1967. A descriptive model of the intra-firm innovation-process. Journal of Business. *40 478-496*.

Kohli, R. and Devaraj, S. 2003. Measuring information technology payoff: A meta-analysis of structural variables in firm-level empirical research. Information Systems Research. *14(2) 127-145*.

Köllinger, P. 2001. E-Learning: Eine Marktanalyse für Deutschland. Symposion Publishing, Duesseldorf.

Köllinger, P. 2002. E-Learning - vom Modethema zur Unternehmenspraxis. in: Köllinger, P. E-Learning in deutschen Unternehmen. Symposion Publishing, Duesseldorf.

Köllinger, P. 2003. The dynamics of turnover and e-business development – a virtuous circle? in: The European e-Business Report 2003. Office for Official Publications of the European Communities, Luxembourg. *215-220*.

Köllinger, P. and Schade, C. 2004. Adoption of e-business: patterns and consequences of network externalities. Center of Applied Statistics and Economics. Discussion paper 04/2004. Humboldt-Universität, Berlin.

Krueger, A. 1993. How computers have changed the wage structure: Evidence from microdata, 1984-1989. Quarterly Journal of Economics. *110 33-60*.

Kuhn, T. 1962. The Structure of Scientific Revolutions. Chicago University Press, Chicago.

Kuznets, S. 1972. Innovations and adjustments in economic growth. Swedish Journal of Economics. *74 431-451*.

Lancaster, T. 1979. Econometric methods for the duration of unemployment. Econometrica. *47 939-956*.

Lancaster, T. 1990. The Econometric Analysis of Transition Data. Cambridge University Press, Cambridge.

Landes, D. 1969. The Unbound Prometheus. Cambridge University Press, Cambridge.

Lawless, M.W. and Anderson, P.C. 1996. Generational technological change: Effects of innovation and local rivalry on performance. Academy of Management Journal. *39(5) 1185-1217*.

Lenz, R.T. 1981. ‚Determinants' of organizational performance: An interdisciplinary review. Strategic Management Journal. *2(2) 131-154*.

Levin, R., Klevorick, A., Nelson, R., and Winter, S. 1987. Appropriating the returns from industrial research and development. Brookings Papers on Economic Activity. *1987(3) 783-820*.

Levin, S.G., Levin, S.L. and Meisel, J.B. 1987. A dynamic analysis of the adoption of a new technology: the case of optical scanners. Review of Economics and Statistics. *69 12-17*.

Liang, K.Y., Zeger, S.L. and Qaqish, B. 1992. Multivariate regression analysis for categorical data. Journal of the Royal Statistical Society, Series B. *54 3-40*.

Lieberman, M.B. 1984. The learning curve and pricing in the chemical processing industries. Rand Journal of Economics. *15(2) 213-228*.

Litfin, T. 2000. Adoptionsfaktoren - Empirische Analyse am Beispiel eines innovativen Telekommunikationsdienstes. DUV, Wiesbaden.

Lloyd-Ellis, H. and Roberts, J. 2002. Twin engines of growth: Skills and technology as equal partners in balanced growth. Journal of Economic Growth. *7 87-115*.

MacDonald, G. and Ryall, M.D. 2004. How do value creation and competition determine whether a firm appropriates value? Management Science. *50(10) 1319-1333*.

Machlup, F. 1980. Knowledge: Its Creation, Distribution and Economic Significance – Vol. 1: Knowledge and Knowledge-Reproduction. Princeton University Press, Princeton.

Maddala, G. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press, New York.

Mahajan, V., Muller, E. and Bass, F.M. 1990. New product diffusion models in marketing: A review and directions for research. Journal of Marketing. *54 1-26*.

Malone, T. and Rockart, J. 1995 Computers, networks and the corporation. Scientific American. *265(3) 128-136*.

Mamer, J.W., and McCardle, K.F. 1987. Uncertainty, competition, and the adoption of new technology. Management Science. *33(2) 161-177*.

Mankiw, G.N., Romer, D. and Weil, D.N. 1992. A contribution to the empirics of economic growth. Quarterly Journal of Economics. *107(2) 407-437*.

Mankiw, G.N., Phelps, E.S. and Romer, P.M. 1995. The growth of nations. Brookings Papers on Economic Activity. *1995(1) 25th Anniversary Issue*, 275-326.

Mansfield, E. 1964. Industrial research and development expenditures: Determinants, prospects, and relation to size of firm and inventive output. Journal of Political Economy. *72 319-340*.

Mansfield, E. 1968. Industrial Research and Technological Innovation: An Econometric Analysis. Norton, New York.

Mansfield, E. (ed.) 1977. The Production and Application of New Industrial Technology. Norton, New York.

Mansfield, E. 1983. Technological change and market structure: An empirical study. American Economic Review, Papers and Proceedings. *73 205-209*.

Mansfield, E. 1985. How rapidly does new industrial technology leak out? Journal of Industrial Economics. *34 217-23*.

Mansfield, E. 1993. The diffusion of flexible manufacturing systems in Japan, Europe and the United States. Management Science. *39(2) 149-159*.

March, J.G. and Sutton, R.I. 1997. Organizational performance as a dependent variable. Organization Science. *8(6) 698-706*.

Mas-Colell, A., Whinston, M.D. and Green, J. 1995. Microeconomic Theory. Oxford University Press, New York and Oxford.

Masuch, M. 1985. Vicious circles in organizations. Administrative Science Quarterly. *30(1) 14-33*.

McCardle, K.F. 1985. Information acquisition and the adoption of new technology. Management Science. *31 1372-1389*.

McFadden, D. 1974. Conditional logit analysis of qualitative choice behavior. in: Zarembka, P. (ed). Frontiers in Econometrics. Academic Press, New York.

Melville, N., Kraemer, K.L. and Gurbaxani, V. 2004. Information technology and organizational performance: An integrative model of IT business value. MIS Quarterly. *28(2) 283-322*.

Merriam-Webster. 2003. dictionaryonline edition. 12/09/2003. www.m-w.com/home.htm

Mesenbourg, T.L. 2003. Measuring electronic business. U.S. Bureau of the Census. 12/29/03. http://www.census.gov/eos/www/papers/ebususa.pdf.

Metcalfe, S. 1995. The economic foundations of technology policy: equilibrium and evolutionary perspectives. in: Stoneman, P. (ed.). Handbook of the Economics of Innovation and Technological Change. Blackwell Publishers, Oxford.

Meyer, A.D. and Goes, J.B. 1988. Organizational assimilation of innovations: a multilevel contextual analysis. Academy of Management Journal. *31(4) 897-923*.

Milgrom, P. and Roberts, J. 1990. The economics of modern manufacturing: technology, strategy, and organization. American Economic Review. *80(3) 511-528*.

Milgrom, P., Qian, Y. and Roberts, J. 1991. Complementarities, momentum, and the evolution of modern manufacturing. American Economic Review. *81(2) 84-88*.

Moore, G.E. 1965. Cramming more components onto integrated circuits. Electronics. *38(8) 114-117*.

Mowery, D.C. 1983. The relationship between intrafirm and contractual forms of industrial research in American manufacturing, 1900-1940. Explorations in Economic History. *20 351-374*.

Mowery, D.C. 1995. The practice of technology policy. in: Stoneman, P. (ed.). Handbook of the Economics of Innovation and Technological Change. Blackwell Publishers, Oxford.

Nault, B.R., Wolfe, R.A. and Dexter, A.S. 1997. Support strategies to foster adoption of interorganizational innovations. IEEE Transactions on Engineering Management. *44(4) 378-389*.

Nelson, R.R. 1959. The simple economics of basic scientific research. Journal of Political Economy. *67 297-306*.

Nepelski, D. 2003. The impact of innovation on market structure – the case of e-business in the automotive industry. Unpublished Diploma Thesis. Humboldt-University, Berlin.

Nilakanta, S. and Scamell, R.W. 1990. The effect of information sources and communication channels on the diffusion of innovation in a data base development environment. Management Science. *36(1) 24-40*.

Nordhaus, W.D. 2002. Productivity growth and the new economy. Brookings Papers on Economic Activity. *2:2002 211-244*.

OECD. 1999. Defining and measuring e-commerce: a status report. 12/29/03. http://www.oecd.org/dataoecd/12/55/2092477.pdf.

OECD. 2004. Information technology outlook. 01/25/05. http://www.oecd.org/document/57/0,2340,en_2649_201185_33950905_1_1_1_1,00.html.

Oliner, S. and Sichel, D. 2000. The resurgence of growth in the late 1990s: Is information technology the story? Journal of Economic Perspectives. *14(4) 3-22*.

Oliva, T.A. 1991. Information and profitability estimates: modeling the firm's decision to adopt a new technology. Management Science. *37(5) 607-623*.

Oster, S. 1982. The diffusion of innovations among steel firms: The basic oxygen furnace. Bell Journal of Economics. *13 45-56*.

Oster, S. and Quigley, J. 1977. Regulation and the diffusion of innovation: Some evidence from building codes. Bell Journal of Economics. *8 361-377*.

Pagano, M. and Gauvreau, K. 1993. Principles in Biostatistics. Duxbury Press, Belmont.

Panzar, J.C. 1989. Technological determinants of firm and industry structure. in: Schmalensee, R. (ed.) Handbook of Industrial Organization. North Holland, Amsterdam, *3-59*.

Panzar, J.C. and Willig, R.D. 1981. Economies of scope. American Economic Review. *71 268-272*.

Papadakis, V. and Bourantas, D. 1998. The chief executive officer as corporate champion of technological innovation: an empirical investigation. Technology Analysis and Strategic Management. *10(1) 89-109*.

Parente, S. 1994. Technology adoption, learning-by-doing, and economic growth. Journal of Economic Theory. *63 346-369*.

Parente, S. and Prescott, E. 1994. Barriers to technology adoption and development. Journal of Political Economy. *102(2) 298-321*.

Pasinetti, L. 1981. Structural Change and Economic Growth. Cambridge University Press, Cambridge.

Pavitt, K. 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Research Policy. *13 343-373*.

Pawlina, G. and Kort, P.M. 2001. Investment under uncertainty and policy change. CentER discussion paper. *2001-05*. Tilburg University, CentER, Tilburg, The Netherlands.

Pennings, J. and Harianto, F. 1992. The diffusion of technological innovation in the commercial banking industry. Strategic Management Journal. *13 29-46*.

Phillips, A. 1966. Patents, potential competition, and technical progress. American Economic Review. *56 301-310*.

Pianta, M. 2000. The employment impact of product and process innovation. in: Vivarelli, M. and Pianta, M. (eds). The Employment Impact of Innovation: Evidence and Policy. Routledge, London.

Pianta, M. 2001. Innovation, demand and employment. in: Petit, P. and Soete, L. (eds). Technology and the Future of European Employment. Edward Elgar, Cheltenham.

Pianta, M. 2004. Innovation and employment. in: Fagerberg, J., Mowery, D. and Nelson, R. (eds). The Oxford Handbook of Innovation. Oxford University Press, Oxford.

Porter, M. 2001. Strategy and the Internet. Harvard Business Review. *March 63-78.*

Prasad, B. and Harker, P.T. 1997. Examining the contribution of information technology toward productivity and profitability in U.S. retail banking. Wharton School Working Paper. *No. 97-07*. University of Pennsylvania, Philadelphia.

Preissl, B. 2003. E-business in service industries, usage patterns and service gaps. DIW Discussion Paper. *373*. DIW Berlin, Berlin.

Quirmbach, H. 1986. The diffusion of new technology and the market for an innovation. Rand Journal of Economics. *17 33-47*.

Reinganum, J.F. 1981a. On the diffusion of new technology: a game theoretic approach. Review of Economic Studies. *48 395-405*.

Reinganum, J.F. 1981b. Market structure and the diffusion of new technology. Bell Journal of Economics. *12 618-624*.

Richardson, V.J., Subramani, M. and Zmud, R.W. 2003. Benefiting from information technology investments: The role of IT conversion capability. Mimeo. 05/15/05. http://ids.csom.umn.edu/Faculty/Mani/Homepage/Papers/IT%20Conversion%20Capabilities_july15.pdf.

Rickards, T. 1985. Stimulating Innovation - A Systems Approach. Palgrave Macmillan, London.

Rivera-Batiz, L.A. and Romer, P.M. 1991. Economic integration and endogenous growth. Quarterly Journal of Economics. *106(2) 531-555*.

Roberts, E.B. 1987. Introduction: managing technological innovation - a search for generalizations. in: Roberts, E.B. Generating Technological Innovation. Oxford University Press, New York / Oxford.

Robinson, W.T. and Chiang, J. 1996. Are Sutton’s predictions robust? – Empirical insights into advertising, R&D, and concentration. Journal of Industrial Economics. *44 389-408*.

Rogers, E.M. 2003. Diffusion of Innovations. 5th edition. Free Press, New York et al.

Romeo, A. 1975. Interindustry and interfirm differences in the rate of diffusion of an innovation. Review of Economics and Statistics. *5(3) 311-319*.

Romeo, A. 1977. The rate of imitation of a capital embodied process innovation. Economica. *44 63-69*.

Romer, P.M. 1986. Increasing returns and long-run growth. Journal of Political Economy. *94(5) 1002-1037*.

Romer, P.M. 1987. Crazy explanations for the productivity slowdown. in: Fischer, S. (ed). NBER Macroeconomics Annual 1987. MIT Press, Cambridge.

Romer, P. 1990. Endogenous technological change. Journal of Political Economy. *98 S71-S102*.

Romer, D. 1996. Advanced Macroeconomics. McGraw Hill, New York et al.

Rose, N. and Joskow, P. 1990. The diffusion of new technologies: Evidence from the electric utility industry. Rand Journal of Economics. *21 354-373*.

Rosenberg, N. 1972. Technology and American Economic Growth. Harper and Row, New York.

Rosenberg, N. 1982. Inside the Black Box. Cambridge University Press, Cambridge / New York.

Ruttan, V.W. 1997. Induced innovation, evolutionary theory and path dependence: sources of technical change. Economic Journal. *107 1520-1529*.

Ruttan, V.W. 2001. The computer and semiconductor industries. Technology, Growth, and Development. Oxford University Press, New York.

Santhanam, R. and Hartono, E. 2003. Issues in linking information technology capability to firm performance. MIS Quarterly. *27(1) 125-153*.

Sarkar, S. 2000. On the investment-uncertainty relationship in a real options model. Journal of Economic Dynamics and Control. *24 219-225*.

Scherer, F.M. 1967. Market structure and the employment of scientists and engineers. American Economic Review. *57 524-531*.

Schade, C., Kunreuther, H. and Kaas, K.P. 2002. Low probability insurance decisions: The role of concern. Wharton Risk Center Working Paper. *02-10-NK*. Wharton School, University of Pennsylvania.

Scherer, F.M. 1980. Industrial market structure and economic performance. 2nd edition. RandMcNally, Chicago.

Scherer, F.M. and Ross, D. 1990. Industrial market structure and economic performance. 3rd edition. Houghton Mifflin Company.

Schmalensee, R. 1988. Industrial Economics: An Overview. Economic Journal. *98 643-681*.

Schmookler, J. 1966. Invention and Economic Growth. Harvard University Press, Cambridge.

Schröder, A. and Schade, C. 2002. Bounded rationality in three-player simultaneous market entry games. Proceedings of the 2001 IEEE EMS International Engineering Management Conference. *213-218*.

Schumpeter, J.A. 1934. The Theory of Economic Development. 8th printing, 1968. Harvard University Press, Cambridge.

Schumpeter, J.A. 1942. Capitalism, Socialism & Democracy. 5th edition, reprinted 1968. Routledge, London and New York.

Segerstrom, P.S. and Zolnierek, J.M. 1999. The R&D incentives of industry leaders. International Economic Review. *40(3) 745-766*.

Shaked, A. and Sutton, J. 1986. Relaxing product competition through product differentiation. Review of Economic Studies. *49 3-13*.

Shapiro, C. and Varian, H. 1999. Information Rules: A Strategic Guide to the Network Economy. Harvard Business School Press, Boston.

Sheshinski, E. 1967. Tests of the “learning by doing” hypothesis. Review of Economics and Statistics. *49(4) 568-578*.

Sinha, R.K. and Chandrashekaran, M. 1992. A split hazard model for analyzing the diffusion of innovations. Journal of Marketing Research. *29 116-128*.

Singh, J.V. 1986. Performance, slack, and risk taking in organizational decision making. Academy of Management Journal. *29(3) 562-585*.

Solow, R.M. 1956. A contribution to the theory of economic growth. Quarterly Journal of Economics. *70(1) 65-94*.

Solow, R.M. 1957. Technical change and the aggregate production function. Review of Economics and Statistics. *39(3) 312-320*.

Souitaris, V. 2002. Technological trajectories as moderators of firm-level determinants of innovation. Research Policy. *31 877-898*.

Spence, M.A. 1981. The learning curve in competition. Bell Journal of Economics. *12(1) 49-70*.

Srinivasan, R., Lilien, G.L. and Rangaswamy, A. 2002. Technological opportunism and radical technological adoption: an application to e-business. Journal of Marketing. *66 47-60*.

Sutton, J. 1991. Sunk Costs and Market Structure - Price Competition, Advertising, and the Evolution of Concentration. MIT Press, Cambridge.

Sutton, J. 2001. Technology and Market Structure: Theory and History. MIT Press, Cambridge.

StataCorp. 2001. Stata Reference Manual – Release 7, Volume 4. Stata Press, College Station (TX).

Stoneman, P. 1980. The rate of imitation, learning, and profitability. Economic Letters. *6 1179-1183*.

Stoneman, P. 1981. Intra-firm diffusion, Bayesian learning and profitability. Economic Journal. *91 375-388*.

Stoneman, P. 1995. Handbook of the Economics of Innovation and Technological Change. Blackwell Publishers, Oxford and Cambridge.

Stoneman, P. 2000. Path dependency and reswitching in a model of multi technology adoption. Center for Economic Policy Research. *June*. Presented at a Festschrift in honor of Paul David, Stanford University.

Stoneman, P. 2002. The Economics of Technological Diffusion. Blackwell Publishers, Oxford.

Stoneman, P. and Kwon, M.J. 1994. The diffusion of multiple process technologies. Economic Journal. *104 420-431*.

Stoneman, P. and Kwon, M.J. 1996. Technology adoption and firm profitability. Economic Journal. *106(437) 952-962*.

Sueyoshi, G.T. 1995. A class of binary response models for grouped duration data. Journal of Applied Econometrics. *10(4) 411-431*.

Tabak, F. and Barr, S.H. 1999. Propensity to adopt technological innovations: the impact of personal characteristics and organizational context. Journal of Engineering and Technology Management. *16 247-270*.

Taylor, C. and Silverstone, A. 1973. The Economic Impact of the Patent System. Cambridge University Press, Cambridge.

Teece, D. 1987. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Research Policy. *15 285-305*.

Thaler, R.H., Tversky, A., Kahneman, D. and Schwartz, A. 1997. The effect of myopia and loss aversion on risk taking: An experimental test. Quarterly Journal of Economics. *112 2 647-661*.

Thijssen, J.J.J., Huisman, K.J.M. and Kort, P.M. 2001a. Strategic investment under uncertainty and information spillovers. Working Paper - Tilburg University - Department of Econometrics and CentER. Tilburg.

Thijssen, J.J.J., van Damme, E.E.C., Huisman, K.J.M. and Kort, P.M. 2001b. Investment under vanishing uncertainty due to information arriving over time. CentER discussion paper. *2001-14*. Tilburg University, CentER, Tilburg, The Netherlands.

Thomas, L.A. 1999. Adoption order of new technologies in evolving markets. Journal of Economic Behaviour and Organisations. *April 453-482*.

Tilton, J.H. 1971. International Diffusion of Technology: The Case of Semiconductors. Brookings Institution, Washington D.C.

Tirole, J. 1988. The Theory of Industrial Organization. 7th printing, 1994. MIT Press, Cambridge.

Tushman, M. and Moore, W.L. 1982. Readings in the management of innovation. 2nd edition. Pitman Publishing, Boston.

van Ark, B. 2002. Measuring the new economy: An international comparative perspective. Review of Income and Wealth. *48(1) 1-14*.

van den Goorbergh, R.W., Huisman, K.J.M. and Kort, P.M. 2001. Investment under uncertainty and risk aversion in incomplete markets. Working Paper – Tilburg University – Department of Finance and CentER. Tilburg.

Varian, H. 1992. Microeconomic Analysis. 3rd edition. Norton & Company, New York and London.

Vivarelli, M. 1995. The Economics of Technology and Employment: Theory and Empirical Evidence. Edward Elgar, Aldershot.

Vickers, J. 1986. The evolution of industry structure when there is a sequence of innovations. Journal of Industrial Economics. *33 515-529*.

Weill, P. 1992. The relationship between investment in information technology and firm performance: A study of the valve manufacturing sector. Information Systems Research. *3(4) 307-333*.

White. H. 1982. Maximum likelihood estimation of misspecified models. Econometrica. *56 997-1019*.

Wiseman, R.M. and Bromiley, P. 1996. Toward a model of risk in declining organizations: An empirical examination of risk, performance and decline. Organization Science. *7(5) 524-543*.

Witte, E. 1998. Das Promotoren-Modell. in: Hauschildt, J. and Gemünden, H.G. (eds). Promotoren. Gabler, Wiesbaden.

Wooldridge, J.M. 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge.

Young, A. 1993. Invention and bounded learning by doing. Journal of Political Economy. *101(3) 443-472*.

Zettelmeyer, F. and Stoneman, P. 1993. Testing alternative models of new product diffusion. Economics of Innovation and New Technology. *2 283-308*.

Zhang, H. and Bracken, M. 1995. Tree-based risk factor analysis of preterm delivery and small-for-gestational-age birth. American Journal of Epidemiology. *141 70-78*.

Zhang, H. and Singer, B. 1999. Recursive Partitioning in the Health Sciences. Springer, New York et al.

Zmud, R.W. 1982. Diffusion of modern software practices: influence of centralization and formalization. Management Science. *28(12) 1421-1431*.

Appendix 1 – CART

Splitting nodes

A number of methods have been proposed to define the best split (Breiman, 1984, chapter 4). Entropy impurity is used for the study in Chapter 5.4. The entropy criterion is related to the likelihood function. It tends to look for splits where as many levels as possible are divided perfectly or near perfectly. As a result, entropy puts more emphasis on getting rare characteristics right than e.g. Gini or Twoing.

Consider the following split, where a, b, c, and d are the number of subjects in the two daughter nodes:

Table 34 – Cross table for two daughter nodes

	Predictor	Adopter	Non-Adopter	
Left node	$s_i = 1$	*a*	*b*	*a+b*
Right node	$s_i = 0$	*c*	*d*	*c+d*
		a+c	*b+d*	*n = a+b+c+d*

Following Breiman et. al. (1984, pp. 94-102), the entropy impurity in the left daughter node is

(1) $$i(t_L) = -\frac{a}{a+b}\log\left(\frac{a}{a+b}\right) - \frac{b}{a+b}\log\left(\frac{b}{a+b}\right).$$

Likewise, the entropy impurity in the right daughter node is

(2) $$i(t_R) = -\frac{c}{c+d}\log\left(\frac{c}{c+d}\right) - \frac{d}{c+d}\log\left(\frac{d}{c+d}\right).$$

The impurity of the parent node consequently is

(3) $$i(t) = -\frac{a+c}{n}\log\left(\frac{a+c}{n}\right) - \frac{b+d}{n}\log\left(\frac{b+d}{n}\right).$$

The goodness of a split, s, is then measured by

(4) $$\Delta I(s,t) = i(t) - P\{t_L\}i(t_L) - P\{t_R\}i\{t_R\}.$$

The goodness of a split is calculated for all available predictor variables, and the best predictor, which is the one with the highest $\Delta I(s,t)$, is selected.

This recursive partitioning process continues until the tree is saturated in the sense that the offspring nodes subject to further division cannot be split any further (e.g. when there is perfect homogeneity in the node). The resulting saturated tree is called T_0.

Pruning

The purpose of pruning is to find the right-sized tree, which should be a nested sub-tree of T_0. The right-sized tree should not be subject to over-fitting and insignificant splits, but detailed enough to exhibit a good classification performance. To begin, we need to define a concept to measure classification performance. Recall that CART predicts the outcome (e.g. adoption or non-adoption) based on the group membership of a subject. In the tree, each subject falls into exactly one terminal node. We choose a class assignment rule that assigns a class to every terminal node $t \in \tilde{T}$. In our application, node *t* is assigned "adopter {Y=1}" if $P\{Y=1|t\} \geq 0.5$ and vice versa. In this simple case, the expected cost resulting from any subject within a node is given by

$$(5) \quad r(t) = 1 - P(i \mid t),$$

where $P(i \mid t)$ is the percentage of correctly classified subjects in a node.

Note that r(t) becomes smaller for any additional split. The formal proof is given by Breiman et. al. (1984, p. 95-96). Thus, r(t) is minimal for the saturated tree.

The classification performance of the entire tree is given by the quality of its terminal nodes

$$(6) \quad R(\mathrm{T}) = \sum_{t \in \tilde{T}} P(t) r(t) \ ,$$

where $R(\mathrm{T})$ is the misclassification cost of all terminal nodes in the tree, $\tilde{\mathrm{T}}$ the set of terminal nodes, and $\mathrm{P}(t)$ the probability of a subject to fall into the terminal node t.

We are now ready to turn to the main idea of cost-complexity pruning (Breiman et. al., 1984, pp. 66-71): For any subtree $\mathrm{T} \leq \mathrm{T}_0$, define its complexity as $|\tilde{\mathrm{T}}|$, the number of terminal nodes in T. Let $\alpha(\geq 0)$ be a real number called the complexity parameter and define the cost complexity of the entire tree as

$$(7) \quad R_\alpha(\mathrm{T}) = R(\mathrm{T}) + \alpha |\tilde{\mathrm{T}}|.$$

For any value of $\alpha(\geq 0)$, there is a unique smallest subtree of T_0 that minimizes $R_\alpha(\mathrm{T})$. The formal proof is in Breiman et. al. (1985, chapter 10). Thus, by gradually increasing α, a sequence of nested essential subtrees of T_0 can be constructed by pruning off the weakest branches at each threshold level of α. Note that T_0 minimizes $R_\alpha(\mathrm{T})$ if $\alpha = 0$. If α becomes large enough, the root node becomes the optimal solution.

Selection of the best pruned tree using cross-validation

The classification performance $\mathrm{R}(\mathrm{T})$ as specified in (6) is obviously biased and results in severe over-fitting. To select the best pruned tree, we need a more honest estimate of the true misclassification cost of the tree. Using cross-validation (Breiman et. al., 1984, pp. 75-78), we estimate $\hat{\mathrm{R}}(\mathrm{T})$ by growing a series of V auxiliary trees together with the main tree grown on the learning sample Λ. The V auxiliary trees are grown on randomly divided, same sized subsets, $\Lambda_\mathrm{V}, \mathrm{v} = 1,..,\mathrm{V}$, with the v-th learning sample being $\Lambda^{(\mathrm{v})} = \Lambda - \Lambda_\mathrm{V}$ so that $\Lambda^{(\mathrm{v})}$ contains the fraction $(\mathrm{V}-1)/\mathrm{V}$ of the total data cases. For each v, the trees and their pruning sequence are constructed without ever seeing the cases in Λ_V. Thus, they can serve as an independent test sample for the tree $\mathrm{T}^{(\mathrm{V})}(\alpha)$. The idea now is that for V large, $\mathrm{T}^{(\mathrm{V})}(\alpha)$ should have about the same classification accuracy as $\mathrm{T}(\alpha)$. If unit misclassification costs are used, and priors are data estimated as in Chapter 5.4, the estimated misclassification costs $\hat{\mathrm{R}}(\mathrm{T})$ equal the proportion of misclassified test set cases in the V auxiliary trees. The best pruned tree is the one with the smallest $\hat{\mathrm{R}}(\mathrm{T})$.

Significance of splits

Finally, the significance of each individual split in the selected tree can be tested following Sheskin (2000; section 16.6): Recall the notation from table 8. The resubstitution risk is defined as

$$(8) \quad r = \frac{\frac{a}{a+b}}{\frac{c}{c+d}}.$$

The calculation of the confidence interval of r requires to compute the standard error of the two daughter nodes, which is given by

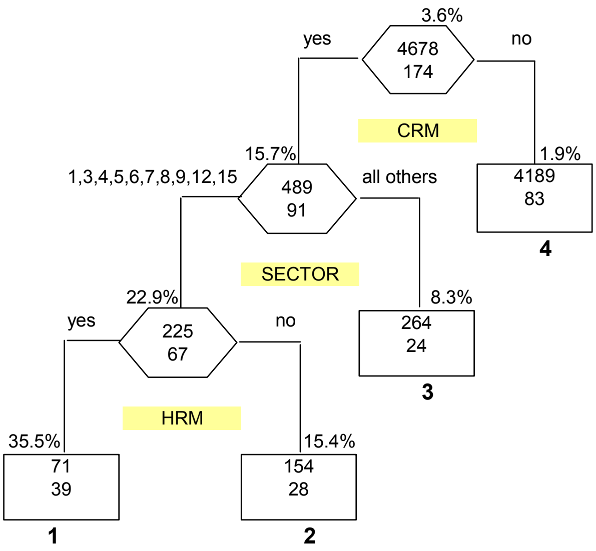
$$(9)\quad SE_r = \sqrt{\frac{1}{a}+\frac{1}{b}+\frac{1}{c}+\frac{1}{d}}\,.$$

Since the sampling distribution of the resubstitution risk is positively skewed, a logarithmic scale transformation is employed in computing the confidence interval (Christensen, 1990; Pagano and Gauvreau, 1993). The α -confidence level is obtained by

$$(10)\quad \left\{e^{\left[\ln(r)-SE\bullet z_\alpha\right]};e^{\left[\ln(r)+SE\bullet z_\alpha\right]}\right\}\ ,$$

where z_α is the tabled two-tailed z value for the $(1-\alpha)$ confidence level. For the 95% confidence level, the relevant .05 value is $z_{.05} = 1.96$. This test is computed for all splits in the tree that was selected from the pruning sequence after the cross-validation procedure.

Appendix 2 – Additional CART results



SECTOR:

1 Food	9 Tourism
2 Publishing	10 Monetary Services
3 Chemicals	11 Insurances
4 Metal Products	12 Real Estate
5 Machinery	13 Business Services
6 Electronics	14 ICT
7 Transport Equipment	15 Health Services
8 Retail	

Figure 12 – CART for SCM

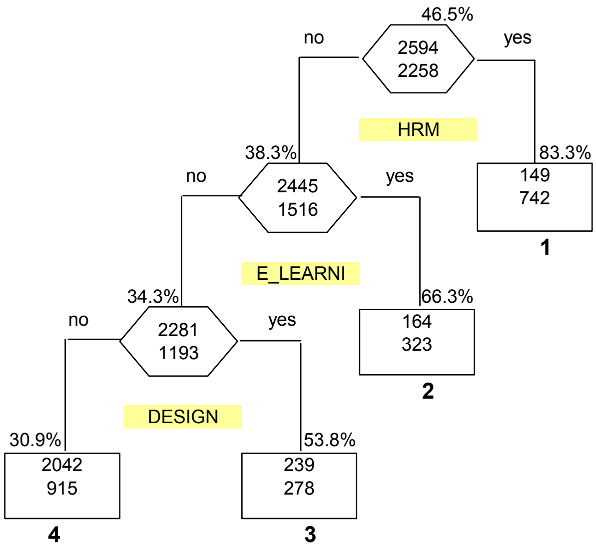


Figure 13 – CART for sharing documents online (Share_doc)

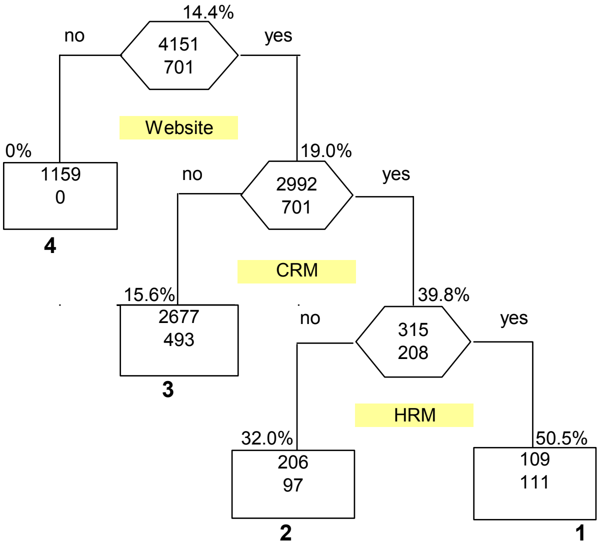


Figure 14 – CART for CMS

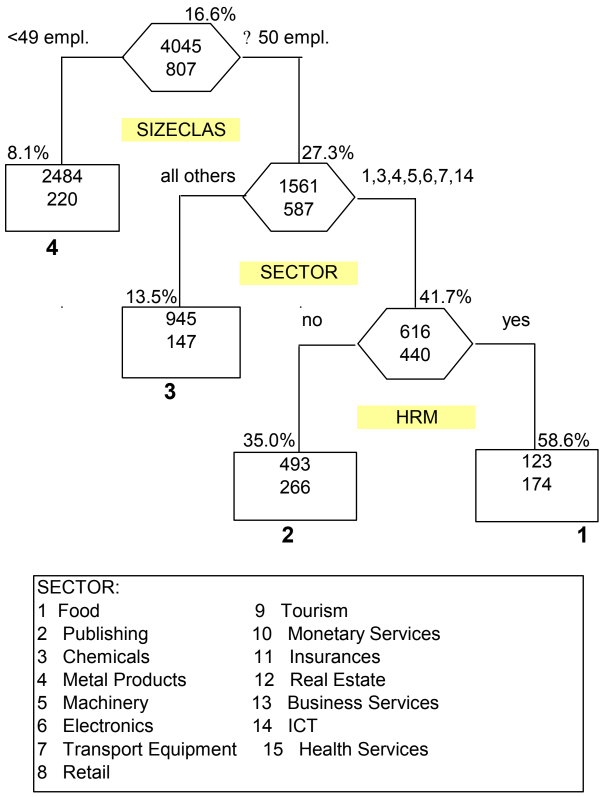


Figure 15 – CART for ERP

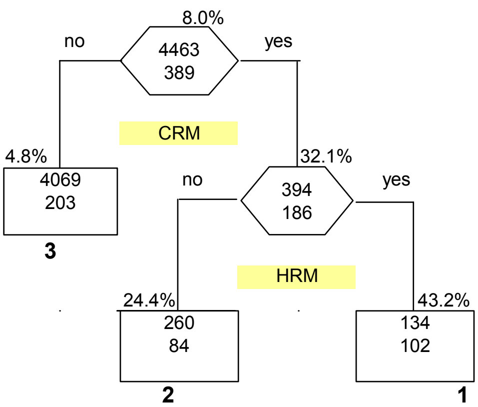
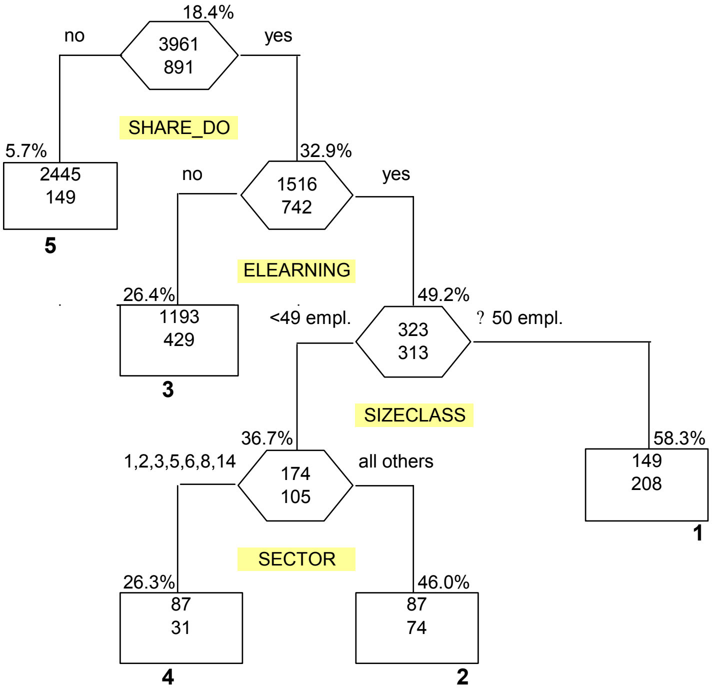


Figure 16 – CART for KMS



SECTOR:

1 Food	9 Tourism
2 Publishing	10 Monetary Services
3 Chemicals	11 Insurances
4 Metal Products	12 Real Estate
5 Machinery	13 Business Services
6 Electronics	14 ICT
7 Transport Equipment	15 Health Services
8 Retail	

Figure 17 – CART for HRM

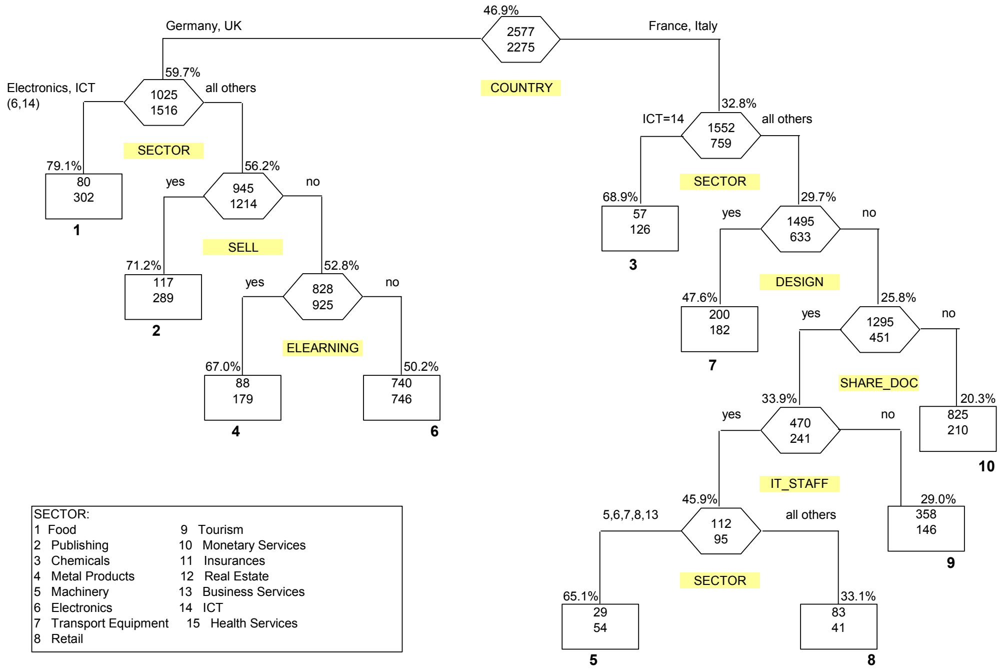
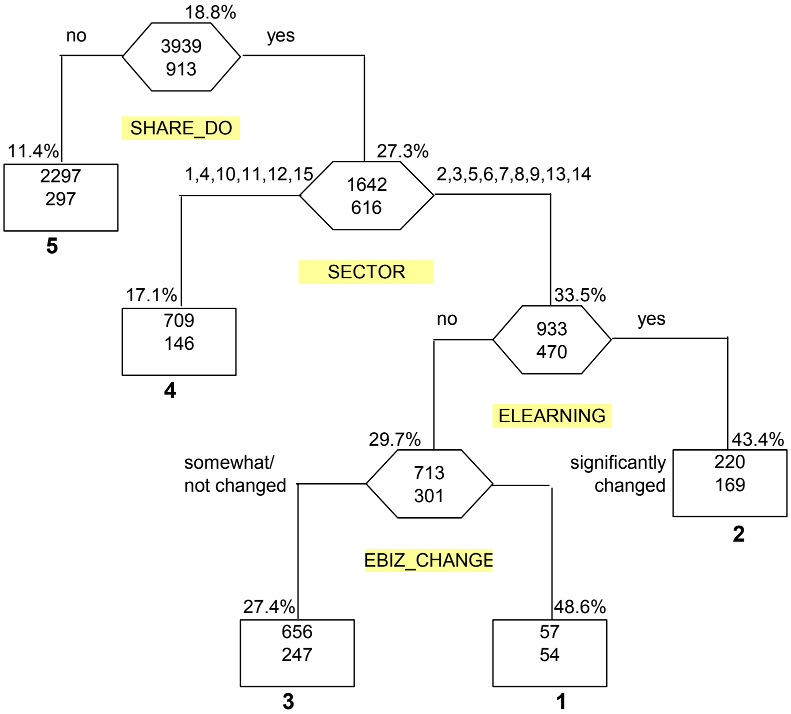


Figure 18 – CART for online purchasing (Purch)



SECTOR:

1 Food	9 Tourism
2 Publishing	10 Monetary Services
3 Chemicals	11 Insurances
4 Metal Products	12 Real Estate
5 Machinery	13 Business Services
6 Electronics	14 ICT
7 Transport Equipment	15 Health Services
8 Retail	

Figure 19 – CART for Design

Selbstständigkeitserklärung

Hiermit versichere ich, dass ich die vorliegende Arbeit ohne fremde Hilfe selbständig verfasst und nur die aufgeführten Quellen und Hilfsmittel benutzt habe. Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt.

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