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INNOVATIONS AND ECONOMIC CHANGE – THE ROLE OF GENERAL PURPOSE TECHNOLOGIES

A Methodological and Empirical Analysis

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To Vio and Ela

Author's Declaration

Unless otherwise indicated in the text or references, or acknowledged below, this thesis is entirely the product of my own scholarly work. Any inaccuracies of fact or faults in reasoning are my own and accordingly I take full responsibility. This thesis has not been submitted either in whole or part, for a degree at this or any other university or institution. This is to certify that the printed version is equivalent to the submitted electronic one.

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Acronyms

AH Aghion and Howitt (model)

AMC Absorbing Markov chain

GDP Gross domestic product

GNP Gross national product

GPT General purpose technology

HT Helpman and Trajtenberg (model)

ICM ICT manufacturing industries

ICS ICT related services

ICT Information and communication technologies

ISCO International standard classification of occupations

IT Information technology

LPG Labor productivity growth

NACE Statistical classification of economic activities in the European Community

OECD Organisation for Economic Co-operation and Development

R&D Research and development

SDA Structural decomposition analysis

TEP Technoeconomic paradigm

Chapter 1

Introduction

Economic history has been defined by innovations. This is particularly true for general purpose technologies (GPTs) spurring sustained growth as a result of their pervasive use in the economy. Typical examples include the steam engine, electricity and information and communication technology (ICT). GPTs can be broadly characterized by the following three features (Bresnahan, 2010; Jovanovic and Rousseau, 2005a; Lipsey et al., 2005):

1. *Pervasiveness*: The technology affects a broad range of sectors throughout the economy and disposes of a wide variety in application.
2. *Scope of improvement*: Advances in the GPT reduce costs in the user industries.
3. *Technological complementarities*: Its utilization requires the design of new or the re-design of existing products and processes.

The present thesis revolves around the first characteristic, the notion of pervasiveness, as *the* crucial feature that distinguishes a general purpose technology from other radical innovations, and proposes methods to trace its trajectory at the sector level.

Introduced by Bresnahan and Trajtenberg (1995), the concept of GPTs drew strong scientific attention in the late 1990s, during the rise of the IT era and in the aftermath of the strong productivity slowdown in the U.S. In an attempt to understand these trends in productivity, a new growth narrative developed around GPTs (see, e.g., Aghion and Howitt (1998a); Helpman and Trajtenberg (1998a,b)) that strongly focused on innovational spillovers between the sector providing this technology and its application sectors: Technical progress in the first sector increases R&D activities in the latter industries, as complementary inputs need to be developed for the efficient utilization of the technology. Nevertheless, even though the impact of a GPT is inherently attributed to its pervasive use throughout the economy, technical complementarities in the production process are little accounted for in these models. Moreover, the heterogeneous nature of technological change is reduced to a simple productivity parameter that increases with each arrival of a new GPT.

On an empirical level, historical studies have offered rich insights into the evolution of GPTs. For instance, David and Wright (2003) investigate the different diffusion paths of electricity in the U.S., U.K. and Japan, and draw conclusions regarding the future evolution of ICT. Rosenberg and Trajtenberg (2004) examine the positive effects of the Corliss engine on economic growth in the U.S. in the late 19th century. Lipsey et al. (2005) undertake an extensive historical survey on general purpose technologies in the Western world, covering the time span from 10,000 BC until 2010.

The few quantitative studies in this field have also centered on innovational spillovers between the GPT and other technologies. Feedback effects have primarily been examined by use of patent and patent citations data (see, e.g., Hall and Trajtenberg (2004); Moser and Nicholas (2004)). In this context, an innovation (protected by a patent) is conceived as 'general', if it spurs innovation activities in a broad range of other technological fields (as measured by patent citations). However, as Bresnahan (2010, 781) points out, knowledge flows are not able to capture technological complementarities that occur through the *application* of the respective GPT in production.

The minor consideration of the role of a GPT in the production chain, on the one hand, and the focus on innovation spillovers, on the other hand, serve as the main motivation for this dissertation. Centering on the pervasive character of a GPT and its diffusion process, complementarities between the GPT-providing sector and the application sectors are studied in the marketplace instead of at the innovational level. The project therefore addresses the research problem within a multi-sector framework, in which a general purpose technology is examined in the following way:

1. Rather than modeling a GPT as a process innovation that spawns product innovations in form of complementary inputs, the GPT is treated as a product innovation which is produced by a specific sector by means of other commodities and triggers changes in production methods throughout the economy.
2. Reverting to commodity flows instead of intangible knowledge assets, a GPT is investigated in the form of technology embodied in intermediates and capital goods.
3. The study of vertical integration of industries allows tracing the diffusion and effects of GPTs through the intersectoral network.
4. By analyzing the linkages between the GPT-producing sector and the user sectors over time, we take on an evolutionary perspective, stressing the carrier population – not the single carrier of a technology – as a crucial object of study.

Based on this framework, different concepts are developed that allow tracking general purpose technologies over the long term and on the meso level. The elaborated methods are applied to input-output tables and capital flow data for Denmark from 1966 until 2009 in order to trace the evolution of the current GPT at work, ICT. Denmark was chosen due to its leading innovator role within the European Union.[1] This top position comes largely as a result of cutting-edge engineering in the field of biotechnology and wind power generation, whereas

[1] Denmark ranks second behind Sweden and above Germany and Finland among the four innovation leaders in the European Union (European Commission, 2014).

with regard to information and communication technologies, Denmark relies to a large extent on imports. This fact allows us to study the consequences of ICT for economic growth primarily via its impact on the production network and less through final demand. Furthermore, the empirical findings feed a stylized growth and diffusion model which analyzes the changes triggered by the emergence of a GPT in an evolutionary multi-sector framework.

Regarding the structure of the thesis, all chapters are self-contained and can be read separately. However, they appear in chronological order of their writing; reading in this way therefore also sheds light on the development of the arguments underlying the present work.

Chapter 2 serves as an introduction into the topic, as it surveys the theoretical literature on general purpose technologies and distinguishes the concept from other approaches on radical technological change. In this regard, it gives a critical overview of the way that mechanisms behind this form of innovation-driven growth have been modeled.

Part I, considered as the core of this dissertation, contains three essays on uncovering GPTs and their role for economic development from a mesoeconomic perspective: Chapter 3, co-authored by A. Rainer[†], analyzes the impact of this type of technological change on labor productivity growth. An evolutionary multisectoral framework is presented as an alternative to the concepts discussed in chapter 2. The Sraffian static model is extended by the replicator dynamics of evolutionary game theory to describe how the increasing population of carriers of the new technology on the firm level causes changes in the production method on the sectoral level. The theoretical framework lays the ground for a structural decomposition analysis, assessing the impact of ICT on aggregate and sectoral labor productivity growth. Social consequences of a GPT are discussed on the example of skill-induced wage dispersion during the rise of the IT-era.

Given the empirical evidence that ICT became consequential only after the diffusion rate had slowed down, chapter 4 proceeds with the notion of pervasiveness in the context of input-output analysis. We argue that conventional linkage analysis is not concise enough to comprise the case of general purpose technologies since the density, but not the structure of the inter-industry network is taken into account. An extended linkage indicator is therefore proposed that captures the widespread use of a commodity in production as a descriptive tool for studying pervasive technological change. The method allows deriving a ranking of industries according to their pervasive role in the economy. Additionally, we examine the diffusion path of ICT throughout the economic system.

Chapter 5 represents a continuation of this work in so far as a tool is developed which maintains the industry ranking without losing the information on the intersectoral level. In this context, we analyze structural change by means of a social network approach where the production system is represented in a hierarchical order, as a so-called 'technical tree', and explore the characteristics and dynamics of this evolving technical tree over time. The application to the Danish

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economy underscores the capability of the method for detecting general purpose technologies by the locus of their production.

The results presented in part I are supplemented by a statistical companion containing further tables and figures.

The empirical evidence gathered throughout this work serves subsequently as an input for modeling growth and diffusion in the presence of GPTs (see chapter 6 in part II, also co-authored by A. Rainer[†]). The classical multisectoral approach introduced in chapter 3 is further elaborated for the model to be able to reconstruct the retarded diffusion process of a GPT, technical progress in the GPT-producing sector, as well as skill-induced wage disparities. It is shown that the characteristics of a GPT and the corresponding empirical findings can be theoretically explained in a multi-sector evolutionary framework.

Chapter 2

Modeling Major Technological Change: A Survey on General Purpose Technologies

The present chapter deals with theoretical concepts centered around general purpose technologies (GPTs), a term introduced by Bresnahan and Trajtenberg (1995). GPTs are characterized by the following features: (1) wide range of applicability: by affecting most sectors; (2) scope of improvement: advances in this technology lower the costs of its users over time; (3) technological complementarities: GPTs stimulate the new design or redesign of other products and processes. Before discussing the models that explicitly deal with GPTs other theories related to major technological change will be briefly reviewed.

2.1 Introduction

Ever since, economic development has shown an uneven path: Periods represented by high growth rates and booming sectors have been followed by an overall downswing in the economy and depression. Joseph A. Schumpeter identified innovative activities as the heart of his theory on business cycles (Schumpeter, 1997). Innovations, coming in swarms, boost at first those industries in whose production they are utilized. Gradually, these new technologies diffuse throughout other sectors so that in the end, the whole economy grows at a greater pace than before. The more radical and all-encompassing an innovation is, the bigger the change in the overall production system.

Technologies which affect all sectors and foster innovative activities throughout the whole socio-economic system are called general purpose technologies (GPTs henceforth). Prominent examples include the steam engine, electricity, and more recently information and communication technology (ICT). New generation technologies, and specifically nanotechnology (Youtie et al., 2008), have high potential to become GPTs in the near future.

The term itself was introduced into the economic literature by Bresnahan and Trajtenberg (1995). In their seminal paper they stress the important role of GPTs in causing 'innovational complementarities,' i.e. raising the R&D productivity in user sectors. In a decentralized economy, however, increasing returns to scale and the generality of purpose also generate coordination problems among up- and downstream sectors. As a conclusion, not only the industrial organization of inventing industries has to be examined more closely, but it is also crucial to analyze sectoral interrelations more carefully, since “the locus of technical change” matters (Bresnahan and Trajtenberg, 1995, 85). In a first attempt, the authors restrict their analysis to a partial equilibrium framework, in which one sector supplies the GPT at a specific technology level (or quality) to a set of application sectors. The producer of the GPT is assumed to have monopoly power in setting the price of the GPT as well as its quality level. Subsequently, the downstream sectors determine how much to invest in their own level of technology in order to maximize the rents related to the use of the GPT. Due to these ‘strategic complements’ (Bulow et al., 1985), a dual inducement mechanism sets in: Quality improvements in the GPT sector lead to rising R&D activities in the application sectors, which in turn increase the payoff for the GPT producer and gives him an incentive for further improvements. The generality of purpose also creates horizontal externalities between the user industries, in so far as the more sectors operate the GPT (and thereby enhance their own technology level), the higher the investments in the GPT itself become and hence the rise in its quality. Despite this mutual dependence, the GPT-providing sector and the application sectors nevertheless stand in a hierarchical order to one another, as the key technology together with the induced product and/or process innovations downstream form a technology tree.

Bresnahan and Trajtenberg show that when no technological information is exchanged among up- and downstream sectors, each Nash-equilibrium results in a lower GPT level and less innovative activities within the application sectors, compared to the social optimum. Coordination between the agents in form of technological contracting would reduce the level of underprovision of the GPT. Extending the analysis from a static Cournot-game to a model of dynamic oligopoly as proposed by Maskin and Tirole (1987), the authors study the role of informational flows, which increase the predictability of technological enhancements and lead to higher technological progress in both producer and user sectors of the GPT.

Even though Bresnahan and Trajtenberg concentrate on the incentive mechanisms for innovations and the role of industrial organization in this context, their concept of general purpose technologies has given rise to a bunch of dynamic theories emphasizing the complementary nature of major technological change. Given the generality of purpose, the GPT requires subtechnologies to facilitate its efficient employment in production. These spillovers can be captured by the term of technological complementarities, which arise “in any situation in which the past or present decisions of the initiating agents that alter the technologies under their control (a) alters the value of other existing technologies and/or (b) creates the opportunity to alter the nature of other existing technologies and/or (c) creates opportunities for developing new technologies” (Lipsey et al., 2005, 103). Technological complementarities thus subsume both innovational and technical externalities between the GPT-providing sector and the application sectors.

The present paper attempts to discuss the body of literature on existing GPT-models. It thereby extends previous reviews on this topic (most notably by Lipsey et al. (1998, 2005)) without claiming completeness. The chapter is organized as follows: Section 2.2 distinguishes the notion of GPT from related theories in the economics of technological change. Section 2.3 reviews the most prominent models of GPTs. Section 2.4 entails concluding remarks and suggests specific aspects towards which future models of GPTs could be directed.

2.2 Related Theories

The concept of general purpose technologies is not the only approach that captures radical technological change; there exists a variety of theories that center around drastic technological breakthroughs. The present section briefly summarizes the most important ones.

Technoeconomic Paradigms

Introduced by Dosi (1982) and Perez (1983), technoeconomic paradigms (TEPs) have become a core notion in evolutionary economics (see, e.g., Freeman and Perez, 1988; Freeman and Soete, 1994; Perez and Soete, 1988). A TEP entails a much broader concept than the GPT, as it is defined as a "systemic relationship among products, processes, organizations, and institutions that coordinate activity" (Lipsey et al., 2005, 372). Changes in the TEP, generated by a set of radical innovations and some new technological systems, thus not only lead to new products or processes, but create whole new industries and organizational forms. They can be understood as the "creative gales of destruction" in Schumpeter's long wave theory (Freeman, 1991).

Similar to Kuhn's concept of paradigm shifts, each era is characterized by certain phases: A new TEP comes up within the old era, provided that the current structure has generated an innovation-sympathetic environment. However, it does not immediately break up the existing regime; it rather takes a long period of gestation in which it competes with the incumbent TEP. In this time, the core innovation is being used in some industries and bit-by-bit takes over the whole economy, initiating a 'structural crisis of adjustments', in which capital equipment and skill profile get adapted, and the firm management, the industrial organization and the institutional landscape change. This process takes some time, since, on the one hand, the present environment may be resistant to the new technological breakthrough, and on the other hand the different parts of the system do not change in a coordinated fashion. Furthermore, one or a set of new key inputs evolve, which are available in abundance and show a wide range of applicability, and whose prices continuously fall alongside with the evolution of the new paradigm. The path-dependent, irreversible transformation of the system is based on an evolutionary approach. As Freeman points out, only the persistent search for minimum costs resembles neoclassical economics (Freeman, 1991, 225).

In their later book *As Time Goes By: From the Industrial Revolutions to the Information Revolution* (2001), Freeman and Louca go further by describing the Western economic history from 1750 up to now as a sequence of five technoeconomic paradigms, each generating a long wave (industrial revolution; railroads, steam and mechanization; steel, electricity and minerals; mass production, the automobile and oil; information and communication technology). Again, a systemic approach is at the core of the theory, distinguishing five subsystems within the society: science, technology, economy, politics and culture. As each of the parts evolves along its own trajectory, the arrival of a new TEP triggers off a structural crisis due to maladjustment. Certain social mechanisms ensure that the subsystems become synchronized again. Since these coordination processes are specific to each wave, no common characteristics can be derived and therefore, as Lipsey et al. criticize, the approach is an "*ex-post* rationalization of whatever happens" (Lipsey et al., 2005, 376), rather than a whole theory.

Relating the concept at hand to general purpose technologies, there are certainly many similarities; both assume that economic regimes are technologically constrained and eventually run into diminishing returns. Like the TEP theory, the subsequently described macroeconomic models of GPT explain long waves where growth is rejuvenated by drastic technological change; however, in the theory of technoeconomic paradigms the breakthrough is even more invasive, since adjustment processes are not only dealt with on the firm and industry level, but also encompass the organizational, institutional and political structure. However, understanding the concept of general purpose technologies as a lean version of the TEP theory would not do justice to the former. As Lipsey et al. (2005) points out, due to the holistic perspective the framework is not able to capture the technology tree as modeled by Bresnahan and Trajtenberg; while one TEP era is characterized by a set of co-evolving (major and minor) techniques, GPT models entail a strict hierarchy between the actual key technology and complementary technologies. Thus, the piece-meal treatment of major technical change in GPT models allows for a more detailed examination of a technological paradigm, focusing on the production side.

Macroinventions

In his book *The Lever of Riches: Technology and Economic Progress*, Mokyr (1990) strongly emphasizes the difference between minor innovations and radical technical change and its importance for the study of economic growth. Denying the adequacy of the Newtonian equilibrium approach in this context, he follows an analogy-as-heuristic concept in the field of evolutionary economics (Mokyr, 1990). In contrast to Boulding (1981) and Nelson and Winter (1982), who defined the commodity or the firm as the analogon to a species, the technique itself is the unit upon which selection occurs, and technological change is nothing else than the successive emergence of new techniques.

Just as biological evolution shows periods of stasis interrupted by periods of drastic evolutionary changes, technological history has been all but smooth. Mokyr borrows Richard Goldschmidt's distinction between micro- and macromutations (1940) to explain this uneven path of technological change: Microinventions thereby refer to incremental changes that improve, adapt or streamline existing techniques, reduce costs, material and energy use, improve form and function and increase durability (Mokyr, 1990, 13). When they cumulate, they are able to cause technological change, i.e. generate a technique that can be sufficiently discriminated from previous ones.[1] Macroinventions, on the other hand, are able to explain the phases of radical change. They emerge *ab nihilo*, and have no clear antecedent (Mokyr, 1990, 13). Moreover, they are mostly not location-specific, i.e. they do not depend on particular climatic or topographic conditions.

While microinventions represent an improvement within a species, macroinventions are *per se* the new species. However, they can only sustain the selection process if they are economically as well as technically feasible and fit into the institutional setting. The potential of this new technology lies in its impact on subsequent innovations, as it stimulates the emergence of further adaptive microinventions and raises their productivity.[2] Mokyr emphasizes the complementary character of both types of innovations: Without the emergence of macroinventions, microinventions would finally reach a technological ceiling, and without subsequent microinventions, macroinventions would fail to be profitable. Based on an extensive historical survey, Mokyr concludes that technological breakthroughs tend to cluster: For example, the Middle Ages and the Industrial Revolution are both characterized by a large number of macroinventions, while in between these eras evolution was driven by microinventions and gradual change. This can partly be explained by critical-mass models where one agent after the other jumps on the bandwagon of innovation. Drastic institutional or organizational changes might also increase the receptiveness of the economy to macroinventions (Mokyr, 1990, 298). An important difference between both lies in the fact that microinventions can be (and have already been) examined by traditional economic tools: They react on price signals and market imbalances and are by-products of learning-by-doing and learning-by-using;[3] thus, given the socio-economic environment, the direction of technical change and the probability of success is more or less explicable. In contrast, a macroinvention – the rise of a genius idea – is by all means unpredictable. Just as genetics in evolutionary biology fails to unravel the mystery of mutation, economic analysis can never fully explain the phenomenon of macroinventions. It can only postulate a certain framework of social, economic and political factors that tend to promote their emergence.

Mokyr's distinction between micro- and macroinventions has faced some criticism, the most severe of which concerns the presumption that inventions of the first type are a matter of intention, whereas technologies of the latter can only be created by an act of genius or serendipity (see, for example, Lipsey et al. (2005) and Sokoloff (1991)). Likewise, the idea that technological breakthroughs have no clear-cut parentage has been contested.

Macroinventions and general purpose technologies are evidently very similar concepts: The strong interrelation between micro- and macroinventions is basi-

[1] As an example, Mokyr mentions the gradual evolution of a sailing ship to a steamship over a period of five decades.

[2] This idea can already be found in Usher (1920).

[3] The importance of learning-by-doing for incremental innovations was also stressed in Lundvall (1988).

cally reflected by the notion of technological complementarities. In both theories, the new technology is under continuous improvement over its lifetime. Interestingly, they also share the idea that technology is supply-constrained. But whereas Mokyr argues that demand is not able to generate innovations, Bresnahan and Trajtenberg do not consider the demand side just for the sake of simplicity. What is not explicitly stated in the approach at hand is the pervasive character of the new innovation; while the dynamo and the steam engine diffused throughout the whole economy, the screw propellers or the hot-air balloon, also classified as macroinventions, were not so widely used. Moreover, Mokyr assigns most of the productivity gains to microinventions, simply because they dominate in number. In contrast, general purpose technologies are perceived as the real engines of economic growth. Even more, growth eventually ceases in most of the GPT models without the arrival of a new big innovation. Whatever the differences, the two concepts unite in proposing radical technological change as the true 'lever of riches'.

General Technological Change

A further approach dealing with major technological progress is the model by Antonelli (2003). The author distinguishes between technical and technological change, where the latter can be further differentiated between general and contingent technological change. According to Antonelli (2003, 80), the type of change is mainly determined by four criteria: (1) technological vs. scientific opportunities; (2) internal vs. external sources of new knowledge; (3) learning-by-doing vs. learning-by-using; (4) switching costs regarding fixed (tangible and intangible) capital, and the degree of irreversibility. Whenever scientific opportunities are broadly available and easy to access, when learning-by-doing takes place and the switching costs and irreversibility are low, then entrepreneurs are likely to act in favor of general technological change rather than contingent technological change.

The ideas unfold in a neoclassical equilibrium framework with bounded rationality and myopic expectations, where innovations cause and are fed by out-of-equilibrium conditions.[4] This disequilibrium is a direct result of a change in demand and, most relevant, in relative factor prices. In this case, technological change necessarily has to occur in order to adjust to the new market situation. The decision whether to invest in the introduction of a new general technology or a contingent (biased) technology is taken against the background of a specific factor market.

The argument is the following: If a firm operates close to the technology frontier, with a technique that already considers the specific endowments of labor and capital (both being available in abundance), it will introduce a new general technology in order to remain competitive. This general technology is most often only locally neutral, so that if the factor market diverges to a large extent from

[4] Technical and technological change can both be explained in the same local space. Whereas the first means a change in factor intensity, i.e. a movement along the same isoquant, the latter is reflected by a shift of the isoquant.

the original one, firms are likely to shift their research activities to the development of a contingent technology which improves the performance of an existing innovation. They do so by adjusting the general technology to the specific local factor market, instead of inventing a totally new production method. Thus, the approach emphasizes the interplay between adoption (of a new general technology) and adaption (the generation of a contingent technology) and can be used to model general purpose technologies alongside with its complementary innovations as a sequence of new general technologies and contingent technologies. The relative factor prices determine the external path dependence (Arthur, 1989; David, 1985), while the irreversibility of capital affects the internal path-dependence. Moreover, it allows for cross-country comparisons, in so far as it can explain, given specific factor endowments, why some economies always push the technology frontier, while others are more likely to imitate. Given that factor markets differ across economies, the new technology diffuses at a higher rate, the more similar the factor endowments are between the place of origination and the place of adoption.

Furthermore, Antonelli (2003) examines the horizontal and vertical effects, i.e. the effects among different application sectors and between up- and downstream industries. The horizontal effect differs with regard to the type of innovation: Contingent technological change can prevent other firms from imitation, as the innovation is specific to local factor endowments, whereas a general technology evolves over an epidemic diffusion path. When relative price changes matter, it is also important to investigate the vertical relationship between the industry which supplies the intermediary input that is strategic in the implementation of the new technology and those sectors which introduce the new GPT. Together with the industrial dynamics of monopolistic competition, barriers of entry and exit, etc., the pattern and time path of diffusion can be derived on the basis of absolute and relative factor prices. Assuming that the market for the new intermediate input is monopolistically organized, the production costs in downstream sectors may rise after the introduction of the GPT, whereas the suppliers of capital goods complementary to the old technology face declining demand and decreasing prices for their products. Gradually, they get driven out of the market, while entries in the new intermediary sector lower the price for the new capital good and thus increase the adoption rate of the new technology in the downstream sectors (due to rising profitability). The result is a sigmoid diffusion path as a sequence of probit diffusion processes that generate Schumpeterian growth cycles.

Antonelli's concept is an attempt to link economics of technological change to economics of innovation. His model of induced technical change is a broader concept than the theory of GPTs in so far as it also deals with the type of and ground for innovation. It thus endogenizes the arrival of a technology by linking it to the demand side, an assumption which has seriously been questioned since Hick's induced innovation approach (most noteworthy by Schumpeter). In the present concept, the change in relative prices rules economic development, and it is not clear in which way it actually depends on the size of the technological innovation.

2.3 Models of General Purpose Technologies

The theory of general purpose technologies is very much linked to explaining the long waves in economic history. It was only during the mid-90s that pervasive technologies became a widely-debated issue in economics, not least because of the rising impact of ICT, and because of the fact that the existing theories could explain neither the changing productivity pattern of this technology throughout its lifetime nor its diffusion path over the whole economy. Since the possible output slump featured in these models is the ultimate consequence of the "gales of creative destruction", Verspagen (2004) calls them the American counterpart of Schumpeterian economics.

While methodological approaches of technological change due to incremental innovations are amply available, the theoretical literature on GPTs is relatively sparse. The present section reviews the existing approaches that exemplify the channels through which a GPT affects economic growth: either through the creation of new (intermediate) products or through upgrades in the quality of the products, in the light of Schumpeterian growth theory; or through knowledge accumulation modeled in an evolutionary framework.

Expanding Product Variety

Models in this line treat a new technology as a process innovation that triggers product innovations in other sectors: The GPT cannot be operated until compatible components have been developed for it, hence technological complementarities are eminent. In contrast to innovations that represent a quality-improvement over a product, in this approach the invented good bears a horizontal, and not a vertical relation to the existing one, because it is the product variety that increases.

Model by Helpman and Trajtenberg (HT) Helpman and Trajtenberg (1998a) lift the concept of GPTs by Bresnahan and Trajtenberg (1995) from the partial analysis to a full-fledged model, by incorporating the technology tree into a general equilibrium framework, in which growth is linked to successive improvements in the operation of the GPT. The technology can only be used successfully in the production process after a critical mass of complementary inputs have been produced which render the switch from the old to the new technique possible. Thus, a recession period characterized by declining output and incomes can precede the phase of productive utilization of the GPT. This becomes manifest in recurrent growth cycles in the long run, where productivity slows down in the first phase due to adoption problems and then increases at a higher rate, until the diffusion process comes to a standstill and the technology is replaced by a new one. In Helpman and Trajtenberg (1998b), the existing model is extended in order to analyze the diffusion of a GPT over heterogeneous final good sectors and to deduct its impact on macro aggregates. Since the technique is adopted gradually, a cyclical growth pattern is again established, whose length depends on the diffusion rate over the different sectors. As soon as growth is fading out in the second phase, the firms start anew to invest in R&D, so that growth is rejuvenated.

The formal approach is based upon an endogenous growth model of expanding product variety, developed by Grossman and Helpman (1991, ch. 3) and entailing Romer's concept of monopolistic competition (Romer, 1990). In order to keep the model simple, it is assumed that one general purpose technology after the other arrives at pre-determined time intervals. Thus, the authors abstract from dealing with the generation of the new technical rule itself, and basically build their framework upon three activities: the final good sector producing a homogeneous commodity by means of a specific GPT alongside with compatible inputs, the so-called components; (in-house) research units developing blueprints for the new components; the latter are subsequently produced by the firms operating in the manufacturing sector. The demand for components is specified by a Dixit-Stiglitz consumption index (Dixit and Stiglitz, 1977) which imposes an equal and constant elasticity of substitution between any two components, independent of the technology in use. The GPT itself enters the production function only in the form of a productivity parameter, whereby those GPTs that arrive later also perform better. Together with the number of different components available, total final output is determined. All firms in the component-manufacturing sector operate under monopolistic competition: Each firm owns the blueprint for a specific component which is produced by one unit of labor only. As the specification of factor demand values all components equally, profit maximizing behavior results in a single price for all intermediate products. As a consequence, each component is used in equal quantity. Thus, having once successfully introduced the blueprint, entrepreneurs share the market power equally among them and the value of each firm is determined by the future profits from manufacturing the blueprint. Assuming perfect foresight, the development of the new blueprint will take place whenever the expected profit stream covers at least the research costs. Then, the entrepreneur reallocates the only primary production factor, homogeneous labor, from manufacturing to developing components. Constant returns to scale together with free entry ensures that the entrepreneur cannot gain extra profits by undertaking R&D. The more components are available for a specific GPT, the higher is its productivity in the final good production.

When a new GPT arrives, it cannot be immediately operated, as the available components are not compatible with it; hence prior to its utilization, the number of components developed and manufactured for it has to exceed a certain threshold that makes the new technology superior to the incumbent one. Only then does the switch from one GPT to the next take place. However, a technology cannot be infinitely improved, as its average productivity is decreasing with every further product development. The economy moves from one static equilibrium to the next, in each of which cost minimization of the final good producers leads to the utilization of the most productive technology; profit maximization among firms in the application sector determines the optimal labor-allocation; and intertemporal utility maximization of consumers actuates the demand path for the final good.

Analyzing long-term economic growth implies studying the equilibrium trajectory correlated with the arrival of a GPT until the introduction of the next one. Depending on whether the technology has already been exploited to its full potential or not before the arrival of a new one, the overall cycle assigned to the lifetime of a technology can be divided either into three or just two phases (the latter is indicated in figure 2.1). Phase 1 is the period where a new GPT enters the stage; perfect foresight makes the firms shift labor resources to the development of new components, while the final good sector still operates with the incumbent technology and the corresponding inputs. This phase is characterized by constant profits (due to the constant supply of old components), rising nominal wage rates and an increasing product variety. As soon as the number of available components has reached a critical mass, the economy enters phase 2 of the cycle, in which production takes place under the new technology, and labor is divided between manufacturing new components and continuing the development of blueprints. In this period, suppliers of new components can gain profits while the wage rate is declining again. In the case that the meanwhile established GPT cannot be further improved before the end of its lifetime, a third phase indicates the subperiod, where the final good is still produced with the incumbent technology, but all research activities have ceased and await the arrival of the next GPT. It follows that the wage rate, profits and the number of components are constant. Since the efficiency parameter of the GPT and the arrival rate are exogenous, both phases are of constant length in a stationary equilibrium, i.e. each technology evolves along the same time interval. Real GDP falls at the beginning of each cycle and keeps decreasing throughout the first phase, on the one hand because profits immediately jump to zero (see figure 2.1), and on the other hand because of the negative correlation with the wage rate (which is increasing) as labor resources are redirected to R&D. In phase 2 the growth trend is reversed and output is continuously rising. Thus, the model perceives the slump as an “integral feature” (Helpman and Trajtenberg, 1998a, 71) of a GPT which results from the necessity of complementary investments and the deployment of resources.

The model is subsequently extended to skill-induced wage differentials[5] and a continuum of final good sectors each producing with the same set of components, but at different productivity levels. In this case, there is no abrupt switch from one GPT to the other at the beginning of phase 2; rather, the new technology disperses over time across the final good sectors, while the incumbent technology is operated in the remaing sectors (and components for it keep being manufactured), and the adoption rate increases with the number of manufactured components.

In Helpman and Trajtenberg (1998b), the authors study further the growth process induced by a GPT by investigating the relation between the order of adoption

[5]A more stylized model that seeks to explain wage inequality between different skills by the emergence of a GPT is presented in Jacobs and Nahuis (2002). Within this neoclassical framework, output declines upon arrival of the GPT because skilled workers leave production and start engaging in R&D activities, in order to raise the firm-specific knowledge stock. This in turn increases productivity (and output) over time. Wage inequality occurs immediately after the emergence of the new technology, since the productivity in R&D increases the skill premium, while wages of unskilled workers drop as skilled labor is directed to knowledge accumulation.

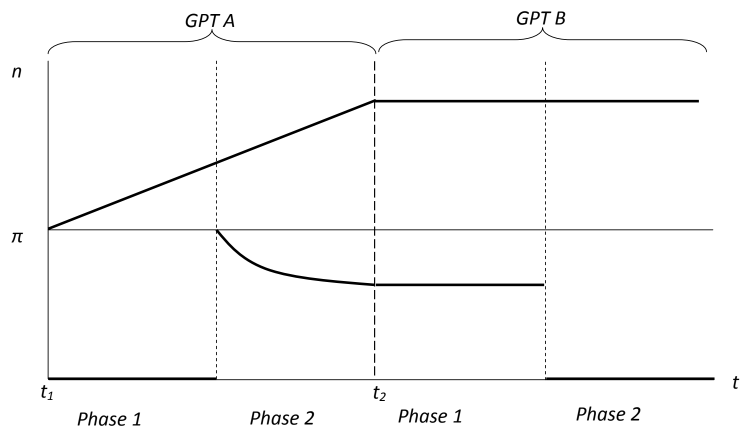

Figure 2.1: Phases of two successive GPTs (π denotes profits, n the number of components). Source: Helpman and Trajtenberg (1998a, 66)

and the pace of diffusion. The existing framework is modified so as to allow for a variety of final good sectors, each of which utilizes tailor-fit components. Every sector is specified by a set of four parameters that defines the order of adoption: (1) a productivity parameter that gives the comparative advantage of the new GPT over the old one; (2) the stock of available inputs compatible with the old GPT; (3) a demand parameter; and (4) an R&D parameter that reflects the costs of new product development. Thus, the sectors are exogenously ranked according to their potential of being early adopters or laggards. Correspondingly, the technology will be adopted sooner by a final good sector, the better the new GPT fits into the current production structure; the less components have been developed for the old GPT so far (so that the required "critical mass" is rather small); and the lower the spending share for intermediate products and research costs.

As before, two GPTs may well co-exist, so that the only primary input labor has to be allocated among manufacturing old as well as new components and the development of new sector-specific blueprints. The mathematical framework is such that not more than one sector engages in R&D at the same time; as a consequence, one final good sector after the other undergoes the two-phase cycle, where prior to the technology switch, the number of new sector-specific components developed in the first phase has to exceed a certain threshold. Thus, the diffusion process over the economy can be described by a sequence of sectoral waves whose length is, in contrast to the former model, endogenously determined by resource allocation. In the basic approach of a single final good sector, the cycle refers to the time period between the arrival of a technology and its replacement by the next one, while in the present model it is determined by the speed of diffusion of one and the same technology over different sectors. As soon as all final good sectors have adopted the new GPT and the economy approaches the steady state, each sector except for the last one enters a further round of product development, triggering a second R&D wave (see figure 2.2). The evolution of real wages also occurs in sectoral waves, in each of which the real wage stagnates in the phase prior to the technology switch and rises thereafter. Like in the previous model, real GDP declines in the first phase and rises in the second, and this pattern is repeated for each subsequent sector introducing the new GPT. However, throughout the whole cycle, the average growth rate and real wages are increasing.

To summarize, the model is able to embed the concept of general purpose technologies as proposed by Bresnahan and Trajtenberg into a (formally complex) general equilibrium framework. It thus provides a basis for investigating the diffusion process of a pervasive technology across all sectors of the economy and allows deducing its impact on prices of the final commodity and of capital and labor inputs, on the stock market, on the variables of distribution and on GDP. Helpman and Trajtenberg (1998b) further showed that the basic model can be extended to cope with skill-induced wage differentials (which spread with the appearance of a GPT such as in the course of the ICT revolution). However, the present framework still lacks explaining externalities between component-manufacturing sectors and excludes feedback effects from the application sectors (i.e. the final good sectors) to the GPT: Innovational spillovers are one-way, reflected by the productivity of the technology rising with the number of supporting components. Assigning to each GPT a constant productivity parameter, the major technological breakthrough itself remains in the black box, while the model focuses on the complementary inputs which facilitate its implementation. Moreover, the arrival rates are exogenously determined, so that the model cannot explain why and when a new technology is introduced. Successive GPTs always have the same lifetime and just differentiate according to the pre-determined productivity parameter, thus the performance of one technology is an upscale copy of the preceding one. In this perspective, the history of technological change is a sequence of identically evolving technologies each arriving in equal time intervals. A drawback of the model is the predicted slump of the economy immediately upon the emergence of a new GPT. The feature of the formal framework that real GDP declines whenever one sector, whatever its size and relevance, starts introducing the new technology, cannot be defended empirically, and has stimulated further research in the theory of GPTs.

Model by Aghion and Howitt (AH) On the basis of the model by Helpman and Trajtenberg (HT-model hereafter), Aghion and Howitt (1998a) elaborate a simple Schumpeterian approach comprising three evolution stages of a GPT: innovation, complementary component-building and technological spillovers. This model does not only allow for endogenizing the timing of introduction regarding the GPT, but also considers the important fact that the adoption of the GPT by a firm does not take place in isolation, but by imitating other firms that have already implemented the technology successfully.

According to Aghion and Howitt, the HT-model bears two inconsistencies concerning the predicted slow-down after the arrival of a new GPT: First, the

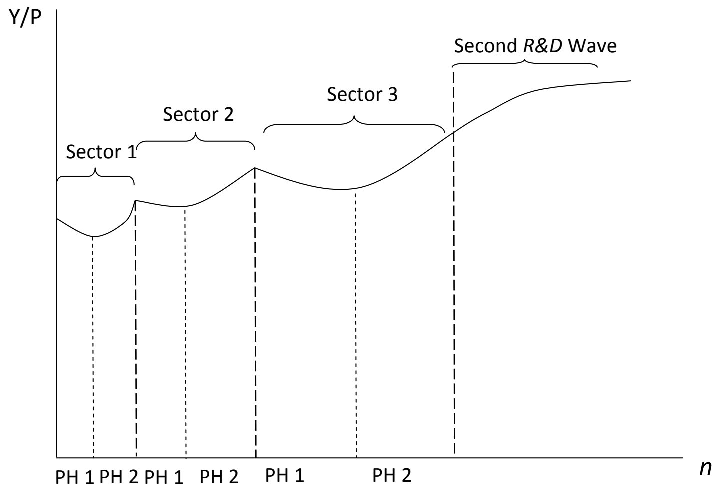

Figure 2.2: Diffusion of a single GPT over three sectors (Y/P denotes real income, n the number of components). Source: Helpman and Trajtenberg (1998b, 105)

size of a possible productivity slump cannot be explained simply by the shift of labor from manufacturing to R&D, as the research sector is in reality too small to induce a fall in output; and second, slumps do not occur *immediately* upon the emergence of a new technology; controversially, historical studies show a lag of several decades from the point of its arrival, until its far-reaching effects are actually measurable (David, 1990). The first problem can be explained by risky experimentation on a large scale (Atkeson and Kehoe, 2008), increased temporary unemployment, or obsolescence of physical and human capital (Howitt, 1998). As concerns the second question about the timing of the slowdown, the authors argue that most notably technological spillovers play a critical role, i.e. firms learn from each other how to adopt the new technology. In their view, the experience of other entrepreneurs with the introduction of a technology serves as a template upon which firms can start developing their own adoption process. Over all sectors, this type of social learning may – or may not – cause a slump during the first phase of implementation, depending on the speed of diffusion of the new technology.

In order to model technological spillovers, Aghion and Howitt revert to their basic Schumpeterian growth model with a continuum of sectors each producing a share of the aggregate output by means of the GPT currently at work.[6] The discovery of a new technology is subject to a Poisson process with a constant arrival rate. A short time interval between successive GPTs thereby discourages research, as monopoly rents can only be reaped over a few periods; whereas a decrease in the arrival rate ensures the diffusion of the technology over the whole

[6]This generalized version in Aghion and Howitt (1998b, ch. 2) deals with endogenous technological change and Schumpeter's notion of creative destruction. Within this model it is possible to analyze GPTs, but not exclusively. It also abstracts from endogenizing the arrival times.

economy. After a GPT arrived, each sector has to invent its own intermediate input in order to use the new technology successfully. However, in contrast to the HT-model, developing a blueprint now requires the afore-mentioned template which prevents the researchers starting from point zero again.

After the successful introduction, a new GPT simply scales up the production function of the consumption good; thus, as in the HT-model, the technology directly enters the final good sector(s) as a constant efficiency parameter, so that the increase in productivity along the lifetime of the GPT is driven by the number of supporting components.

Analogous to the three stages of the innovation process, the authors differentiate between three states each sector has to undergo: Throughout the first state, the old GPT is in use and no change in output with respect to the new technology occurs. The second state denotes the phase when a new template has already been discovered either independently (given by a Poisson arrival rate equal for each sector) or by imitating similar firms, but still the old technology is operated; and the third state refers to the successful implementation of the new GPT with a corresponding increase in productivity. As concerns the time path, the rate of independent discovery is very low, so that the emergence of a GPT does not have an immediate effect on the economy; rather, agents wait until others have already gained experience with the unknown technology. The probability of a firm moving from the first to the second state thereby increases with the number of its observations of successful firms. Once the template is achieved, the firm has to invest labor in the development of components (the process of which is also subject to a certain success rate), in order to finally reach the last state of introducing the new technology. During this transition phase, no output is produced at all. Since a fixed number of workers are devoted to R&D, the endogenous allocation of labor only concerns the manufacturing of the old and new components respectively, since both technologies are simultaneously operated in the economy. Differential equations give the evolution of the sectors in the second and third state of the innovation process. Figure 2.3 presents both paths on the basis of the simulations carried out in Aghion and Howitt (1998a). Social learning thereby prevents the firms from engaging in experimentation instantly after a new GPT appears. Instead, entrepreneurs wait until they can benefit from the experience of others with the new technology, and the likelihood of imitation increases with the pool of successful adopters. Hence, the fraction of sectors with templates rises slowly, peaks in the middle, and diminishes as more and more sectors have succeeded in installing the new GPT. This results in the diffusion path of the new GPT evolving along a logistic curve. These dynamics subsequently determine the growth of aggregate output. In contrast to the HT-model, the slump does not occur immediately upon arrival of the new GPT, but starts delayed due to the externalities of experimentation. If social learning does not take place, if the labor resources required for developing the template are low and uncertainty in this experimentation phase is ruled out, output grows at a constant rate and no slump occurs at all. As can be seen in figure 2.4, technology diffusion over the whole economy causes one entire cycle of GDP growth, while in the HT-model

GDP develops in waves where each sectoral adoption induces a fall in output. However, the reason for the slowdown is the same: The higher the number of sectors engaged in R&D, the lower the output. The magnitude of the recession thereby also depends on the efficiency gains brought on by the new technology and the degree of substitutability between the components.

In fact, many further characteristics of the HT-model are inherent in the present framework: The demand function for intermediate goods is also of Stiglitz-Dixit type, so that inputs are assumed to substitute each other at a constant rate, while in reality, many components (e.g. soft- and hardware) complement each other in the production process. Technical externalities among application sectors are still not considered, as sectoral spillovers only occur regarding innovative activities. Again, the increase in productivity can be traced back to the emergence of a new GPT itself accompanied by the rising number of compatible inputs; while the nature of technological change is totally abstracted from and replaced by a constant efficiency parameter. Furthermore, the arrival of a GPT occurs at pre-determined time intervals which are long enough to let (almost) all sectors adopt the incumbent technology before.

Accounting for the size of the slump, Aghion and Howitt (1998a) further extend the basic model to deal with skill differentials, costly job search and obsolescence of capital. If skilled labor is necessary to introduce the new technology, but not elsewhere, then the economy takes longer to overcome the recession, due to short supply of qualified workers. Unemployment is explained as a side-effect of creative destruction, i.e. workers in the manufacturing sector temporarily lose their jobs when the new GPT is introduced as they do not possess the essential skills to produce the new component. Moreover, not everybody suceeds in finding a new job and structural unemployment increases the size of the slowdown, as manufacturers of new components run out of labor. Creative destruction also refers to both human and physical capital and means the partial irreversibility of tailor-fit inputs in the course of the arrival of a new technology. Sunk costs enlarge the slump at the peak of experimentation.

Rise in Product Quality

Quality-ladder models consider the vertical relation between the invented good and the existing one. An entrepreneur is willing to invest in R&D to improve the state-of-the-art good, i.e. to enhance the spectrum of services to the consumer. If the innovation process is successful, the firm is able to drive the supplier of the lower-quality good out of the market and to set up limit (or quality-adjusted) pricing. However, the stream of monopoly profits lasts only until somebody else comes up with a product of better quality. Step by step, the product thereby climbs up the quality ladder and the size of the jump reflects the extent of improvement.

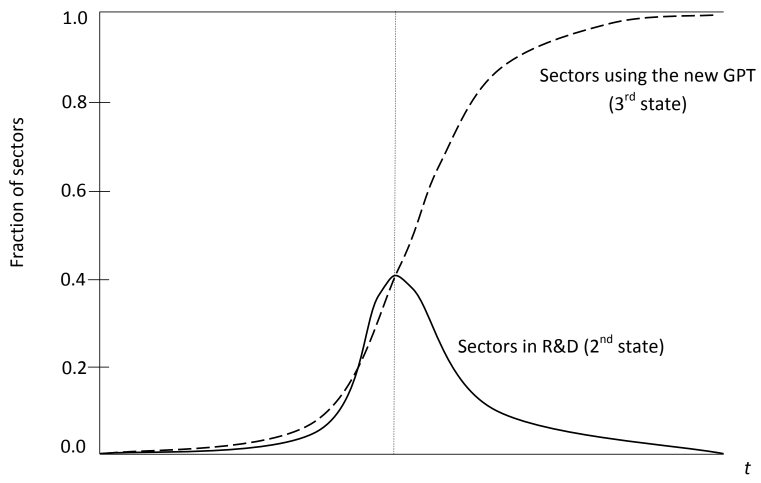

Figure 2.3: Diffusion of a GPT and related R&D activities (t denotes time, the vertical line shows the peak in research activities). Source: Aghion and Howitt (1998a, 132)

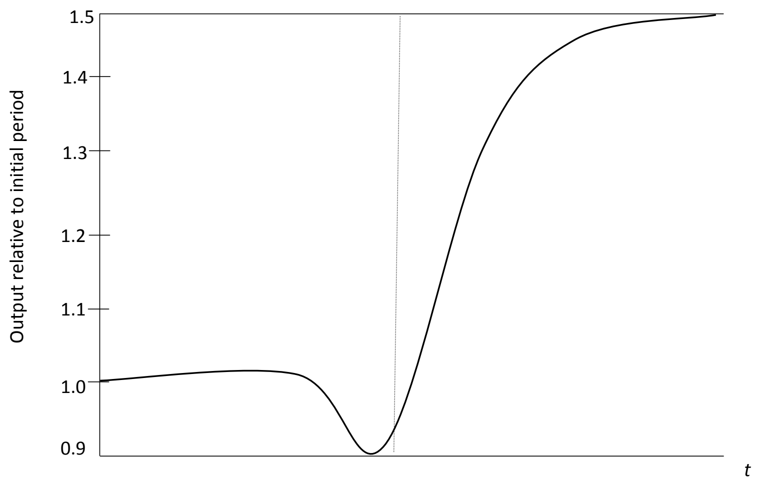

Figure 2.4: Evolution of output (the vertical line corresponds to the peak in research activities of figure 2.3). Source: Aghion and Howitt (1998a, 134)

Model by Petsas Opposed to the previous models of expanding goods variety in intermediate goods, the model by Petsas (2003) features the rising product quality of final consumption goods that channels the impact of a new GPT throughout the economy. The technology itself shows the typical sigmoid diffusion path, however, the rate of diffusion among firms is exogenous to the model. The economy converges to a long-run steady state equilibrium, but during the transition, in which per capita consumption rate falls and the interest rate increases, output growth (measured in GNP) exhibits again a cyclical evolution. The novelty in the approach lies in the fact that population growth is taken into account and leads to diminishing returns with regard to research activities, i.e. with the growing size (or scale) of the market it gets more and more difficult to substitute old goods for new products (Petsas, 2003, 580).[7] Thus, neither the rate of innovation nor long-run output growth follow the same exponential path of population growth, so that the economy converges again to a steady state.[8]

The framework by Petsas basically features the same setup as the quality-ladder model by Grossman and Helpman (1991, ch. 4): Final goods are produced by a continuum of industries; and each sector has to allocate the only resource input labor between manufacturing of the goods of highest quality and R&D, in order to foster the innovation of the next generation of final commodities. Households are modeled as dynastic families that maximize intertemporal utility. Each member supplies labor in exchange for wages, consumes only top-of-the-line products and saves by holding assets of innovative firms (Petsas, 2003, 584). The GPT unexpectedly enters the economy in a steady state with constant output growth rates and constant R&D expenditures, where only the old technology is in use; and affects all firms in each sector by increasing (1) the size of all future innovations, and (2) labor productivity in research and thus the arrival intensity of innovations, which in turn enhances the long-run growth rate of the industry. Analogously to Aghion and Howitt (1998a), an epidemic model gives the sigmoid diffusion path of the GPT over all industries at a predetermined rate. As to the industry structure, firms in a sector operate under perfect foresight in an imperfectly competitive market and can be differentiated according to the quality of their product. In order to improve the state-of-the art commodity, the agents have to redirect labor resources to R&D, where free entry applies and production takes place under constant returns to scale. The winner of the R&D race defines and produces the new state-of-the-art good. Each industry follows the same memoryless Poisson process of technical innovation, where the research output is dependent on the GPT under use and the number of workers devoted to R&D. However, with the rising scale of the economy, undertaking research becomes more difficult. Hence, the probability of successful innovation increases with the adoption of the new technology, but falls over time due to population growth. As a consequence, the long-run growth rate is affected by the rate of innovation as well as the sigmoid diffusion pattern of the GPT, and the economy converges to a new steady state after all industries have switched to the new technology. In contrast to the model by Helpman and Trajtenberg and the model by Aghion and Howitt, a positive growth rate prevails even in the absence of a new GPT.

As a conclusion, the approach at hand is a noteworthy contribution to the body of literature on GPT, in so far as it tackles with the scale effects present

[7] As argued, this absence of scale effects matches historical evidence better (see for example Jones (1995)).

[8] On the contrary, implementing positive population dynamics in the HT-model (1998a) or the model by Aghion and Howitt (1998a) would let the GDP cycle disappear in the long-run.

in all other models. Clearly, rising product quality is just the other side of the coin: the formal framework and the results are similar to the models based on expanding goods' variety. The big difference lies in the channels through which the GPT is supposed to act in this approach: A technical breakthrough has a direct impact on the productivity of R&D workers and the size of innovations, and therefore it is possible to deduce its overall effect on the economy. So the model is able to capture the pervasiveness of a GPT, but not the feedback effects from the user sectors to the technology, so that once more general purpose technologies fall – from time to time – like manna from heaven and stay as they are until the end of their life-cycle. Since there is no intermediate goods sector, innovational complementarities consist in 'improving the improvements' in quality, i.e. in increasing the magnitude of innovations in the consumer goods sector. In comparison to the other models, where new components necessarily have to be discovered in order to make use of the new technology, the essentialness of GPT is missing here: Product quality would rise nevertheless over time, though slower in the absence of a new technology, and the economy would still grow, but at a lower rate.

Model by Schaefer, Schiess and Wehrli A quality-ladder model of Schumpeterian growth is also used in a recent article by Schaefer et al. (2014) to examine the effects of a *sequence* of GPTs on long-term growth. Each new technology lifts the economy from one steady state to another and induces oscillating cycles during the transition. Additionally, the model features two stylized facts in the history of radical technological change: (1) New GPTs draw on existing technologies (thus the arrival is endogenized), and (2) the interval between successive GPTs has been decreasing over time, due to the ever rising stock of knowledge (Carlaw and Lipsey, 2011).

The approach shares a similar framework with Petsas (2003), however, the likelihood of success in R&D does not depend on the market size, but on the location of the specific firm on the quality ladder: The higher the quality improvement attained, the more difficult it becomes to succeed in research. Once having achieved a better quality of the product, the leading firm in each industry produces and supplies the sectoral output to the final good sector. Aggregating over all companies engaged in the intermediate and final good sector, respectively, allows deriving a macroeconomic quality index, which reflects the cumulated applied knowledge stock. As for the winner of the quality race, the flow of monopoly rents ends with the next successful innovation in the respective industry. The higher the rate of innovation, i.e. the probability of research success, the sooner the incumbent firm is replaced by a challenger and the shorter is the profit stream. The arrival and evolution of a new GPT depends on the applied knowledge stock currently available, as well as on the degree of complementarity with the incumbent GPT. Thus, structural breaks in the evolution path occur whenever old and new technologies are fairly incompatible, i.e. the knowledge acquired in the past is of little use for the operation of the new GPT; and because the lack in experience with the new GPT leads to a drop in the average level of knowledge. Along its lifetime, the efficiency of the GPT evolves along a logistic curve, driven by an increase in R&D expenditures for the development of complementary inputs. The arrival of a GPT is determined by a Poisson process and thus contains an element of uncertainty, but also – in contrast to the other models – depends positively on the level of applied knowledge. Given a continuous increase in this stock over time, the period between any two GPTs therefore becomes shorter and shorter.

As the authors argue, the assumption of the path dependence of successive GPTs reflects the history of innovations way better. Regarding the characteristics of general purpose technologies, the concept is able to capture the notion of innovational complementarities between the technology and the application sectors, where the GPT enters the production of the final good sector only indirectly over its impact on intermediate products. The diffusion of the GPT is modeled by the number of quality improvements in the different intermediate goods: The technology is nevertheless *ad hoc* pervasive, because all industries instantaneously start the quality race upon arrival, and no *a priori* changes in the production structure are required. As a consequence, just one GPT is operated at any point in time. Finally, the technology itself does not undergo any further improvements while in use.

All in all, Schaefer et al. (2014) enhance the existing literature on GPTs by the important aspect that the time interval between pervasive innovations has been decreasing over time. In their model, however, the history of technological change resembles a sprint relay where one GPT passes the torch of economic development on to the next breakthrough technology, each of which runs an increasingly shorter distance than its predecessor. Moreover, there is no coevolution of GPTs taking place. But this is an essential, likewise stylized, fact of innovative activities: The development of technologies can be strongly interwoven (see, for example, the ongoing discussion of the relation between ICT and clean technology as of 'greening ICT' and 'ICT for green').

Increase in Knowledge Stock

In a series of articles, Lipsey, Bekar and Carlaw model GPTs in an evolutionary framework covering the notion of uncertainty and path dependence inherent in technological change (Carlaw and Lipsey, 2011, 2001, 2003, 2006). Since the methodological concept differs profoundly from the previous ones, it represents the second generation of GPT models, drawn more from historical evidence. In this regard, the approach allows for successive implementations of different GPTs that are endogenously developed and whose creation bears uncertainties concerning arrival times and performance. Agents act on bounded rationality, while in all other models the individuals are able to foresee the whole performance of the GPT already at its arrival. Furthermore, sustained growth does not necessarily imply the invention of a new GPT, which is the case for the first generation of models. On the methodological level, while previous approaches use dynamically stationary equilibrium concepts, the model by Lipsey et al. does not imply any concept of equilibrium or balanced growth. In each period a different transitional competitive equilibrium is achieved, and the economy never ends in a steady state.

At about the same time as Bresnahan and Trajtenberg (1995), Lipsey and Bekar (1995) dealt with pervasive technical change under the notion of enabling technologies, which indicates the power of radical innovations in triggering structural breaks. On the basis of extensive historical studies the authors identify two important features of these technologies, both also imminent in the concept of GPTs, namely the wide range of applicability and the need of complementary products. Nevertheless, Lipsey and Bekar argue that not all GPTs necessarily have far-reaching effects on the economy in the sense that they induce deep structural adjustments upon the economic system. Though this first approach has been brought more in line with the existing concept of GPTs, it still retains a more holistic view of technological progress and its impact on structural change. The authors analyze technological change induced by a GPT not only by focusing on its own performance, but with regard to other technologies in use, the facilitating structure and public policy. Thus, examining in great detail the effects on each class of this so-called structuralist-evolutionary system, Lipsey et al. (2005) differentiate between two types of new GPTs, complementary and transforming technologies, the latter being assigned the motor of drastic structural change. As each of this kind of GPT, such as electricity and ICT, shows similarities in performance and diffusion, a stylized evolution path for a new transforming technology is deducted and embedded into a formal model.

The formal model (Carlaw and Lipsey, 2011; Lipsey et al., 2005) consists of three different sectors, one producing a single consumption good, an R&D sector where applied knowledge is used to make the GPT feasible for the specific purpose of producing the final commodity, and one pure research sector, where the GPT itself is developed. Intersectoral relations reflect the technology structure of the economy. However, commodity and research outputs are all produced by means of one generic constrained input which has to be allocated between the three sectors, and all production functions exhibit diminishing returns to scale with regard to the resource input, and constant or diminishing returns to scale to the knowledge stock they use.

The GPT does not directly enter the production function of the final commodity, but only indirectly because the new technology (i.e. the current stock of pure knowledge), affects *ad hoc* the stock of applied knowledge, which in turn contributes to the production of the consumer good. The impact of the GPT on the marginal productivity of applied knowledge thereby evolves along a logistic efficiency curve, opposed to the linear development of components in the approaches of expanding product variety. Thus, the level of output and the growth cycle is determined by the efficiency curve and not via the diffusion process across firms and sectors. The third sector is devoted to the development of a new GPT by means of a certain stock of applied knowledge and a generic resource input, and captures the notion of uncertainty.[9]

[9] Uncertainty is introduced in the following way (Lipsey et al., 2005, 455): The flow of pure knowledge produced by a given effort is subject to random fluctuations; the arrival of a new GPT fluctuates around a typical length; and the impact of a newly introduced GPT on the

Hence it is the direct interrelatedness of the applied and the pure knowledge sector which represents technological complementarities and the feedback effects on the GPT. Under perfect competition, the generic resource is allocated across the three sectors by agents maximizing their expected payoffs to investments at each point in time. As the discount factor is set to zero, the problem is reduced to dealing with intersectoral, but not intertemporal tradeoffs: Shifting resources from the consumption to the applied knowledge sector will lower consumptive output in the current period, but will increase the future productivity in the consumption sector, thus leading to a higher average growth rate of output. Diverting inputs to the production of pure knowledge will affect the impact, but not the timing, of the new GPT. In the absence of perfect foresight, the expectations are formed upon the current marginal products and given the random variables that obstructs the correct anticipation of the future productivity, the economic system results in a non-stationary equilibrium.

Unlike all other models on GPT, the present concept addresses the problem of competing GPTs, whereby the new generation still dominates the old one in the long run, but not necessarily in the short run, as its full impact is not immediately revealed upon arrival.

In Carlaw and Lipsey (2011), the authors go further by allowing the concurrent deployment of many complementary GPTs, each assigned to a different technology class.[10] Every sector therefore covers a number of distinct activities, in the form of laboratories in the pure knowledge sector, R&D facilities in the applied knowledge sector, and the production of different commodities in the consumption good sector. Each 'lab' operates in a specific technology class and invents a new GPT every once in a while, whose productivity evolves along the logistic path. However, in order to model diffusion, the efficiency of the GPT varies across R&D facilities. As soon as a new GPT is invented, each R&D facility decides whether to stick to the old technology or switch to the new one, by comparing the productivity levels of the incumbent and the challenging GPT in the specific technology class. As long as the old GPT under use has a higher efficiency profile, the new GPT is not adopted. Given the evolution of a GPT over its lifetime, the new technology spreads through the R&D facilities at a rate that not only depends on its own productivity profile, but also on the environment to employ it.

The concept by Lipsey et al. (2005) represents a clear break with all other models, as it does not entail permanent increasing returns to knowledge and does not presume a linear relationship between resource accumulation devoted to R&D and the growth rate. The model predicts sustained growth, also in the absence of a new GPT, and differing average growth rates along the sequence of GPTs. Given its holistic view, the approach shows many parallels to the notion of

productivity of applied knowledge is determined in part endogenously by resource allocation and in part exogenously by two random factors that affect the location and the height of its efficiency curve.

[10] Based on historical evidence, the following classes are suggested as broad categories of technology: (1) materials, (2) information and communication technologies, (3) power sources, (4) transportation equipment, and (5) organizational forms.

technoeconomic paradigms: It not only distinguishes between similar phases, but also the historic specificity and the non-ergodicity of technological innovation is accounted for and unfolds in a spectrum of possible outcomes, in contrast to the stylized results inherent in the first generation of models. The loss in generality is thus outweighed by the gain in explanatory power.

2.4 Conclusion

The present chapter aimed at discussing the existing literature on major technological change, focusing on the most prominent models of general purpose technologies. The original concept by Bresnahan and Trajtenberg (1995) has been extended by the models at hand in various ways: Most importantly, the diffusion path of the GPT and its effects on macro-aggregates cannot be modeled within a partial equilibrium framework. Uncertainty was not considered in Bresnahan and Trajtenberg (1995) either, where the main focus lies on the coordination problem linked to asymmetric information and the public good character of commercial research.

In the full-fledged approaches, GPT-driven growth is modeled in different ways: Either by the switch from one technology to the next, rendering current means of production obsolete, by a jump in the quality ladder, or by a shift of the efficiency curve (table 2.1 compares the models with regard to the most important features). These concepts go beyond the hitherto existing literature on endogenous growth by taking into account the complementary structure of technologies (Carlaw and Lipsey, 2011). However, as Janssen (1998) indicates, the economic system is an undeterministic, heterogeneous, irreversible system which is in constant disequilibrium and contains evolutionary characteristics. This holds *a fortiori* true when a GPT enters the system. The approaches listed in the first section have all considered the path-dependent nature of technological change, whereas most of the models explicitly dealing with GPTs do not. Except for Lipsey et al. (2005), technical change is not studied as a phenomenon *per se*, but by presupposing Harrod-neutral technical progress to sustain a long-run steady state. Modeling the GPT as a process innovation that triggers the design of complementary inputs still does not give much of an explanation of the sources and nature of the groundbreaking innovation itself. The jump in the productivity parameter gives *a priori* credit to a technology that only exists through its components. It is thus rather a manifestation of what Lipsey et al. (2005, 99) call a 'general purpose principle', a concept that serves as the basis of many technologies, such as mechanization. Firms in the intermediate sector make use of this principle by embodying it in the production of compatible inputs. The introduction of complementary products in innovation-driven growth models match historical evidence better than the first models of endogenous growth (see Lucas, 1988; Romer, 1990), yet the technology specification is rudimentary: Components are developed and produced by labor only. In Helpman and Trajtenberg (1998a,b) and Aghion and Howitt (1998a) these intermediates are imperfect substitutes, which means that no component ever leaves the production of the consumption good. Similarly, it may be questionable if quality-ladder models are an appropriate tool for capturing GPTs, since these approaches cannot reflect their feature of generating new products that differ far more than just in quality. More precisely, the internet revolution would not have been possible simply by improving the quality of a bulb. Thus, the heterogeneity of technologies is not accounted for. More controversially, the present models are not able to encompass the broad characteristics of a GPT sufficiently. Whereas the scope of improvement is evident throughout this literature, either through the expanding variety and the increase in quality of components, or in the accumulation of applied knowledge, technological spillovers focus to a large extent on innovational complementarities. For another example of spillovers, horizontal externalities between component producers are just present in the model by Aghion and Howitt (1998a), where the number of observations of competing firms increases the probability of the successful discovery of an own template. On the other hand, the vertical feedback effects from the user sectors to the GPT itself can be fully captured only in the model by Lipsey et al. (2005). Pervasiveness, the most distinct feature of this type of radical innovations, seems to have faded into the background. The baseline model of Helpman and Trajtenberg (1998a), for example, consists of only one final good sector employing the GPT, which makes it impossible to study the diffusion process of the technology.

Given these shortcomings, modeling GPTs within an input-output framework would enrich the insights into the effects of major technological change by extending the rudimentary technology structure presented in the first generation of GPT models. Inter-industry relations allow, on the one hand, the analysis of technical complementarities, which was already outlined by Hirschman (1958); and, on the other hand, the endogenous production of the GPT itself. In this framework, a new GPT represents a product innovation that induces process innovations in the user sectors. Furthermore, the heterogeneity of industries and vertical integration of sectors offer a more nested technology tree underpinning the investigation of diffusion processes. An input-output approach in the line of classical economics and based upon the seminal work of Sraffa (1960) may serve as a reference point where commodities are produced by means of other commodities. The creation of a GPT can thereby be captured by the production of a new commodity that is subsequently used in an increasing range of sectors downstream. The efficiency of the GPT evolves differently in each sector, similar to the approach of Lipsey et al. (2005). The change in relative prices indicate the direction of technical change, just as in Antonelli (2003). The model can also explain how changes on the production side have an impact on the distribution side. A major advantage of this approach is that it offers a unified framework for the theoretical and empirical investigation of general purpose technologies.

	Expanding product variety		**Rising product quality**		**Increase in knowledge stock**
	Helpman & Trajtenberg 1998b	Aghion & Howitt 1998a	Petsas 2003	Schaefer, Schiess & Wehrli 2014	Bekar, Carlaw & Lipsey 2005
Endogeneity of GPT	no	Poisson arrival process	no	endogenous arrival of GPT	endogenous generation of GPT
Evolution of GPT	no	no	no	no	yes
Technical complementarities	between GPT and CS	between GPT and CS	no	no	between pure knowledge sector and applied knowledge sector between applied knowledge sector and consumption sector
Innovational complementarities (rising R&D productivity downstream)	yes	yes	yes	yes	yes
Primary production factors	labor	labor	labor	labor	unspecified resource input
Sectoral diffusion	yes	yes	yes	yes	yes
Uncertainty	no	arrival time, adoption	R&D race	arrival time, R&D race	arrival time, size of innovation
Monopolistic competition	CS	CS	final good sector	CS	no

Table 2.1: Comparison of GPT models (CS stands for component sector)

Part I

Essays on General Purpose Technologies and Economic Change

Chapter 3

On the Economic Purpose of General Purpose Technologies: An Evolutionary Multisectoral Framework

General purpose technologies (GPTs) are technical breakthroughs that are able to spur and sustain growth as a result of their pervasive use in the economy. This paper attempts to study the effects of these innovations on the economic system at a theoretical and empirical level. First, the diffusion process of a GPT is reconstructed by an evolutionary multisectoral framework: An input-output approach is combined with the replicator dynamics of evolutionary game theory, in order to give a rationale how the adoption of an innovation at the firm level leads to a changing production mode at the industry level. Subsequently, a structural decomposition analysis for Denmark from 1966 to 2007 tracks the impact of the current GPT, the information and communication technologies (ICT), on aggregate and sectoral labor productivity growth. Findings show that the broad diffusion of ICT affected growth significantly only after 2000, owing to skill-biased technical change and capital deepening.

Keywords | general purpose technologies, labor productivity, structural decomposition analysis, ICT, evolutionary economics, Sraffa

3.1 Introduction

History has witnessed a number of radical innovations that changed the mode of production and the structure of the economic system. Prominent examples are the steam engine, electricity or more recently, ICT. Given the pervasive use and potential for increasing the overall innovation rate, this type of major technological change can be captured by the notion of general purpose technologies (GPTs). The distinct evolution pattern of GPTs generates profound economic and social consequences: The arrival of ICT, for instance, has been associated with the productivity slowdown in advanced economies (especially in the U.S.) experienced in the 1980s; as the irreversibility of tailor-fit inputs for incumbent production processes and the obsolescence of capital, as well as the short supply of skilled labor hampered its efficient utilization right from the beginning (Helpman, 1998).

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Only after these barriers were overcome, could a phase of substantial growth be observed in the beginning of the 1990s. On an empirical level, a wide spectrum of studies have dealt with the immediate and long-term effects of ICT on productivity growth (see, e.g., Jorgenson and Timmer (2011), Jorgenson et al. (2007), Basu and Fernald (2007), Inklaar and Timmer (2007)). Most of these studies focus on Anglo-American countries, in particular the U.S., and identify IT as an important source for both capital deepening and total factor productivity growth in the late 1990s and after 2000.

Even though the ICT revolution took several decades to show up in the productivity accounts, the wages of skilled workers has risen significantly from the emergence of this GPT onward. The most common explanation is that the employment of ICT makes great demands on the qualification of the workforce: New skills are required that first need to be accomplished through investments in education and training. The relation between the emergence of a GPT and skill-biased technical change have been extensively discussed in the theoretical (Aghion and Howitt, 1998a; Aghion et al., 2002; Helpman and Trajtenberg, 1998a,b; Jacobs and Nahuis, 2002) and empirical literature. Increasing computerization has not only led to higher levels of both skills and wages in the workforce (Allen, 2001; Autor and Krueger, 1998; Berman and Griliches, 1994; Krueger, 1993; Majumdar, 2008), but also to the substitution of low-skilled by higher-skilled workers (Levy and Murnane, 1996), and rising wage inequality both among and within different education groups (Autor and Krueger, 1998; Murphy and Welch, 1992). Another strand of research investigated the effects of specific GPTs (without referring to this notion explicitly) within a dynamic input-output setting. Twenty years ago in their seminal work on the future effects of computerization on the labor force, Leontief and Duchin (1986) developed an input-output model to test four scenarios for how automation would impact the volume and composition of the workforce in the U.S. from 1980 until 2000. As evidenced by these empirical findings, rapid technical change due to advances in information and communication technologies has resulted in a differentiated qualification profile of the labor force. In a similar study for West Germany, Kalmbach and Kurz (1990) analyzed the direct and indirect effects of micro-electronics on size and structure of the labor force. In their model, strong emphasis is put on the role of private investment behavior for the diffusion process of this technological breakthrough. Pan (2006) suggests a dynamic input-output framework where R&D investments are endogenized and drive the evolving dominance of a new technology, embodied in fixed capital, in sectoral production. The approach is subsequently applied to the Chinese economy by projecting the impact of non-fossil energy on the electricity sector.

This paper aims at investigating in detail the role of GPTs for productivity growth and wage dispersion. An evolutionary, multi-sectoral approach is developed that explains the economic dynamics triggered by the emergence of a GPT on theoretical grounds. The Sraffian static model is augmented by the replicator-dynamics approach of evolutionary game theory to describe how the increasing population of carriers of the new technology at the firm level causes changes in the production method on the sectoral level. The theoretical framework lays the ground for a structural decomposition analysis, assessing the impact of ICT *ex post* on aggregate and sectoral productivity for a small open economy, Denmark, between 1966 and 2007. We revert to labor productivity growth as a measure of economic development, since ICT has had a special impact on the labor market: On the one hand, labor intensity of production decreased through automation owing to ICT-capital, while on the other hand the IT boom has increased the demand for qualified workers. Annual changes in labor productivity are decomposed into technical change, (non-investment) final demand, shifts in the employment of low and high skilled labor, factor substitution, and technical change embodied in capital goods. Furthermore, the effects of technical change within the ICT sector and capital-deepening of ICT are studied on an intersectoral level. Finally, we also discuss transitional wage disparities between low and higher-skilled labor during the rise of the IT era.

The paper proceeds as follows: Section 3.2 introduces the multisectoral evolutionary framework. Section 3.3 describes the structural decomposition analysis and the underlying data, while a detailed presentation of the decomposition and the industry classification can be found in appendix 3.A and 3.B, respectively. Section 3.4 displays the most important results with a special emphasis on the GPT at work, ICT. Concluding remarks are given in section 3.5.

3.2 Methodology

The workhorse models on general purpose technologies (Aghion and Howitt, 1998a; Helpman and Trajtenberg, 1998a,b) explain observed diffusion patterns of this type of radical innovations as a result of R&D activities. This section aims to provide a sound theoretical explanation of the micro-funded diffusion process by means of an evolutionary framework based on firm growth processes.

The model we propose centers around the vertical integration of sectors each of which produces a different commodity by a different production process. Since pervasive utilization throughout the economy is one of the major characteristics defining a GPT, analyzing the economic implications of GPTs in a multi-sector setting is inevitable. Therefore a classical input-output model developed by Sraffa (1960) serves as the basis of our investigation.

In an N-sector economy, let $a_{mn} \in (0,1)$ be the amount of good m (produced in sector m) and l_n the amount of labor to produce one unit of output in sector n. Given this state of technology, the relationship between relative prices, a general rate of profit, and the implicit wage rate can be scrutinized in the following price equation:

$$(1+r)\mathbf{p}^T\mathbf{a}_n + w\ l_n = p_n \tag{3.1}$$

r gives the uniform rate of profits, w the wage rate, and the n-th entry p_n of the price vector $\mathbf{p} \in \mathbb{R}_+^N$ denotes the price of commodity n. If more than one process for producing commodity n exists, choice of technique determines the cost-minimizing production system. It is thereby implicitly assumed that all firms operating in sector n would instantaneously use the most efficient production method. In the following, we will introduce a framework that captures the intra- and intersectoral dynamics upon the emergence of a new technology.

An Evolutionary Multisectoral Model of Technological Diffusion

The emergence of a GPT is accompanied by a newly skilled workforce necessary to operate the innovative technology. Skill diversification, including the existence of wage premia, is considered by allowing for K different skills. $l_{mk} > 0$ then denotes the quantity of skill k necessary to produce one unit of output of sector m. Suppose now, for each sector n a number I_n of processes exists to produce the respective good. At time t a fraction $q_n^{i_n}(t)$ of the output of sector n is produced by process i_n. If $a_{nm}^{i_n}$ is the input of good m and $l_{nk}^{i_n}$ the input of skill k labor to produce one unit of good n by means of process i_n, then

$$\bar{a}_{nm} = \sum_{i=1}^{I_n} q_n^{i_n}(t) a_{nm}^{i_n} \text{ and } \bar{l}_{nm} = \sum_{i=1}^{I_n} q_n^{i_n}(t) l_{nm}^{i_n}$$

are the respective input coefficients of the average technology operated in sector n at time t.

Assuming prices to be still determined by unit costs of production, one gets the following modified price equation for the commodity produced in sector n under a given rate of profit r:

$$(1+r)\mathbf{p}^T\bar{\mathbf{a}}_n + w\mathbf{u}^T\bar{\mathbf{l}}_n = p_n \tag{3.2}$$

$\mathbf{u}$= $\mathbf{u} = \mathbf{w}/w$ is the wage vector with the k-th entry w_k denoting the remuneration of skill k per unit of labor.

Intrasectoral dynamics What remains to be answered is the time development of the market shares $q_n^{i_n}(t)$ of the different technologies operated *within* a sector. Extra profits $\rho_n^{i_n}$ gained by some specific technology induce firm growth as follows:

$$(1+r+\rho_n^{i_n})\mathbf{p}^T\mathbf{a}_n^{i_n} + w\mathbf{u}^T\mathbf{l}_n^{i_n} = p_n \tag{3.3}$$

with vectors $(\mathbf{a}_n^{i_n}, \mathbf{l}_n^{i_n})$ of input coefficients of technology i_n in sector n. Firm output $x_n^{i_n}$ now grows according to extra profits. Consequently,

$$\frac{\dot{x}_n^{i_n}}{x_n^{i_n}} = \rho_n^{i_n}$$

and due to $x_n^{i_n} = q_n^{i_n} x_n$ and $\dot{x}_n = \sum_{i_n=1}^{I_n} \dot{x}_n^{i_n}$ one gets $\dot{x}_n/x_n = \bar{\rho}_n$. Here x_n denotes total output of sector n, and $\bar{\rho}_n = \sum_{i=1}^{I_n} q_n^{i_n}\rho_n^{i_n}$ is the average extra profit generated in sector n. Acknowledging $\dot{x}_n^{i_n} = \dot{q}_n^{i_n} x_n + q_n^{i_n} \dot{x}_n$, the evolution of the system in the presence of technical change is described by the replicator dynamics:[1]

$$\frac{\dot{q}_n^{i_n}}{q_n^{i_n}} = \rho_n^{i_n} - \bar{\rho}_n \tag{3.4}$$

The arrival of a new GPT Within this evolutionary multi-sector framework, a new GPT represents a product innovation and implies the emergence of a new sector producing this technological breakthrough. The adoption of this new technology by other sectors constitutes a process innovation, as old production methods are getting replaced. Thus, the emergence of a new pervasive technology triggers a phase of adjustment on the meso level, during which firms in the different sectors start one by one introducing the new GPT, which modifies the incumbent production method. This phasing-in of a new process is reflected by a continuous change in the average level of the technical coefficients $\bar{\mathbf{a}}_n, \bar{\mathbf{l}}_n$ of sector n.

In the following, we investigate the evolution of the technique empirically in a time-discrete manner, so that the system of production at time t is determined by

$$(1+r)\bar{A}(t)\mathbf{p} + \bar{L}(t)\mathbf{u} = \mathbf{p} \tag{3.5}$$

The relationship between r and w can be depicted by means of wage-profit curves:[2] Defining a fixed commodity basket $\mathbf{d} \in \mathbb{R}_+^N$ as *numéraire* by $\mathbf{d}^T\mathbf{p} = 1$ and a rate of profit r, the $w - r$ relationship

$$\bar{w}(t) = \frac{1}{\mathbf{d}^T \left(\mathbb{I} - (1+r)A(t)\right)^{-1} L(t)\,\mathbf{u}} \tag{3.6}$$

is obtained.

Equation (3.6) distinguishes from the tautological concept of real wage-profit curves (see Michl (1991)): While the first are directly derived from the production system, the latter are based on the division of total income (as stated in national accounts) into wages and profits.[3] Both approaches allow for investigating changes

[1] A more detailed derivation and explanation of equation (3.4) is provided by Rainer (2012).

[2] This system deviates from the 'normal' or long period position (Kurz and Salvadori, 1995, 46) of the economy, as characterized by viability of production and absence of extra profits (and thus choice of technique). However, it still entails a uniform rate of profits and wages, as benefits from technological change are assumed to be covered in the changing shares of the different production methods available in each sector at a specific point in time (see equation (3.4)).

[3] For recent studies see, e.g., Ferretti (2008) who derives the wage-profit frontier for a set of 18 industrialized countries over a time span of 45 years (1961–2005) in order to show technical change. Vaona (2011) analyzes profit dynamics and its impact on the direction of technical change (capital or labor-saving) by means of wage-profit curves for Denmark, Finland and Italy.

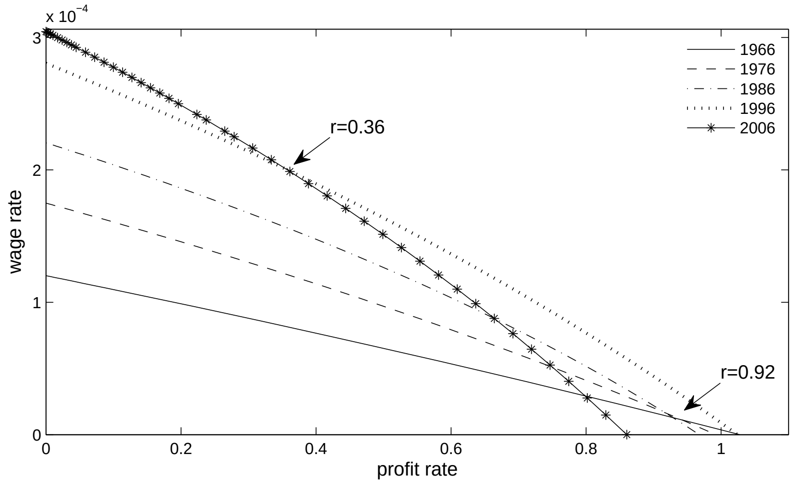

Figure 3.1: Wage-profit curve for Denmark from 1966 to 2006

in labor and capital productivity, however, equation (3.6) based on the Sraffian system also renders possible an *intersectoral* analysis.

Different kinds of technical change are pictured by the dynamics of the $w-r$ relationship: Harrod-neutral or purely labor-saving technical progress is represented by a clockwise rotation of the curve, whereas Solow-neutral or purely capital-saving technical progress corresponds to an anti-clockwise rotation. Hicks-neutral or factor-saving technical change leads to a parallel shift outwards. If two curves – related to different technologies – intersect, then technical progress is not unambiguous and one has to draw on the actual income distribution to scrutinize the sort of change (Degasperi and Fredholm, 2010).[4]

Figure 3.1 shows the corresponding wage-profit frontier for Denmark from 1966 to 2006. The intersection with the axes determines the maximum wage rate (for $r = 0$), and the maximum rate of profits (for $w = 0$), respectively. Until 1986 the curve rotates clockwise around a more or less stable maximum rate of profit in the range of 0.92, this means that in the 20 years between 1966 and 1986 labor-saving technological change took place. For 1996 the $w - r$ relationship shows unambiguous technical progress, because both intersection points moved outwards. Since then, however, the maximum rate of profits has decreased and the curves of 1996 and 2006 intersect at a rate of profit equal to 0.36. Comparing this value to the gross profit rate for 2006 which ranged around 10 percent, it is clear that the latter technique turns out to be labor-saving and capital-using relatively to the former production system.

In the case of a zero profit rate, equation (3.6) denotes the maximum wage

[4] Degasperi and Fredholm (2010) develop a method of productivity accounting and propose wage-profit frontiers based on the classical approach to show the economic evolution of several OECD countries over a period from 1970 to 2005.

rate (i.e. the vertical intercept in figure 3.1) and reads

$$\bar{w}(t) = \frac{1}{\mathbf{d}^T \bar{S}(t)\, \bar{L}(t)\, \mathbf{u}} \tag{3.7}$$

with the Sraffa inverse $\bar{S} \equiv \left(\mathbb{I} - \bar{A}\right)^{-1}$. The maximum wage rate is thus a function of physical quantities of embodied ($\bar{A}$) and commanded ($\bar{L}$) labor. Moreover, it reflects the purchasing power of one unit of labor due to the commodity basket $\mathbf{d}^T$ it is able to buy. Therefore the wage rate represents both the technical characteristics of the production system as well as consumption choices of the economy (Pasinetti, 1993, 24).

Note that the higher $\bar{w}$, the less direct and indirect labor inputs are necessary for the production of the commodity bundle. From a dynamic perspective, an increase in the maximum wage rate over time thus indicates productivity gains due to technical progress. In this regard, the relative change in the maximum wage rate from one period to the next provides a measure for annual labor productivity growth:

$$g_t^l = \frac{\bar{w}_t - \bar{w}_{t-1}}{\bar{w}_{t-1}} = \bar{w}_t \left(\frac{1}{\bar{w}_{t-1}} - \frac{1}{\bar{w}_t} \right) \tag{3.8}$$

This measure differs from the conventional indicator of labor productivity growth in so far as it considers not only the labor quantities that are directly employed in the respective sector, but also takes into account the labor input in upstream production. This means that an industry exhibits a higher labor productivity (as defined by (3.7)) whenever the supplying industries operate less labor-intensely.

Structural Decomposition Analysis

Structural decomposition analysis (SDA) has been a prominent tool in input-output analysis for associating changes in one variable, most often gross output or value added, to changes in other variables (Dietzenbacher and Los, 1997, 1998; Miller and Blair, 2009; Rose and Casler, 1996). Examples of structural decomposition analysis of labor productivity are given in Jacob (2003) for the case of Indonesia, or Yang and Lahr (2008, 2010) for the case of China.

In this paper, SDA is used to trace labor productivity growth by means of changes in the maximum wage rate, as stated in (3.7). In order to also investigate the role of final demand as driver for structural dynamics, the Leontief model is introduced into the analysis. In the latter, gross output $\mathbf{x}$ is calculated from the demand side, as opposed to the Sraffian model, where $\mathbf{x}$ is derived from the supply side[5]:

$$\mathbf{x}^T A + \mathbf{y}^T = \mathbf{x}^T \Longleftrightarrow \mathbf{x}^T = \mathbf{y}^T \;\left(\mathbb{I} - A\right)^{-1}$$

[5] In the following, the bar above variables – indicating average coefficients – is dropped for the sake of better reading.

$\mathbf{y}$ gives total final demand (from private households and government, investment and exports). Furthermore, total employment $\mathbf{l}$ can be calculated as the sum of (weighted) labor inputs $L\mathbf{u}$ embodied in the gross output vector $\mathbf{x}$:

$$\mathbf{l} = \text{diag}\,(L\mathbf{u})\;\; \mathbf{x} = \text{diag}\,(L\mathbf{u})\;\; H\;\mathbf{y} \tag{3.9}$$

$H \equiv (\mathbb{I} - A^T)^{-1} = S^T$ denotes the Leontief inverse.

Combining (3.9) with (3.7), the maximum wage rate is given by

$$\bar{w} = \frac{1}{\mathbf{d}^T\; S\; L\; \mathbf{u}} = \frac{1}{\mathbf{d}^T\; S\; \hat{\mathbf{l}}\; \hat{\mathbf{x}}^{-1}\; \mathbf{e}} = \frac{1}{\mathbf{d}^T\; S\; \hat{\mathbf{l}}\; [\text{diag}(H\mathbf{y})]^{-1}\; \mathbf{e}} \tag{3.10}$$

where the symbol $\hat{}$ indicates a diagonalized vector and $\mathbf{e} \in \mathbb{R}^N$ is a vector with coefficients $e_n = 1$ for all $n = 1, \ldots, N$. Considering two different snap shots in time, from (3.8) and (3.10) labor productivity growth g_t^l can be derived as

$$g_t^l = w_t\; \mathbf{d}^T \Big[S_{t-1}\; \hat{\mathbf{l}}_{t-1}\; [\text{diag}(H_{t-1}\mathbf{y}_{t-1})]^{-1} - S_t\; \hat{\mathbf{l}}_t\;\; \text{diag}(H_t\mathbf{y}_t)]^{-1} \Big] \mathbf{e} \tag{3.11}$$

Given (3.11), the relative change in the maximum wage rate can be decomposed into four partial factors: (1) technical change as indicated by a change in the direct input matrix A ($\Delta S \equiv S_t - S_{t-1}$), (2) change $\Delta\mathbf{l} \equiv \mathbf{l}_t - \mathbf{l}_{t-1}$ of total employment, (3) substitution effect, indicated by a change in A^T ($\Delta H \equiv H_t - H_{t-1}$) and (4) change $\Delta\mathbf{y} \equiv \mathbf{y}_t - \mathbf{y}_{t-1}$ of final demand. This initial decomposition is extended by differentiating between low and high-skilled labor, and capital flows of ICT and Non-ICT related investments. The decomposition can be found in detail in appendix 3.A.

3.3 Data

National Accounts

Denmark belongs to the innovation leaders in the European Union, ranking second (behind Sweden) in the most recent Innovation Union Scoreboard (European Commission, 2014). With regard to ICT, the country was chosen as a case study for the following two reasons: Firstly, it is a small open economy acting as a net importer of ICT products.[6] ICT can therefore be analyzed from a more general perspective, since the focus is on the impact of a GPT as an input of production and not on its impact on final demand. Economies such as the U.S., Japan or Finland – which are net exporters of ICT products – would cause a bias with regard to our research question: It is their extensive trade with these products that affects economic development, and not primarily the pervasive use of this GPT in production.

Moreover, Statistics Denmark also provides a very good database that fits the purpose of this work: Annual input-output tables for 130 sectors in NACE

[6] The only exceptions are central processing units. For a detailed analysis of Denmark's position among Europe with regard to ICT activities see Koski et al. (2002).

Rev. 1.1 classification (which largely corresponds to ISIC Rev. 3.1), in constant prices of the year 2000, entailing domestic and import flows, and covering a long period of time (1966 to 2007).[7] Applying the criterion of Jovanovic and Rousseau (2005b), whereby the emergence of a GPT can be dated to the year when the new technology reaches a one percent share in the industrial sector's stock equipment – which in Denmark's case was in 1979 – we can therefore also study the pre-arrival time.

The 130 sectors in the original classification were subsumed under 53 industries for the sake of better illustration of the results and in order to ensure the non-singularity of the system (the list of industries is given in table 3.B.1). Concerning the definition of the ICT-producing sector, a broad classification scheme is used, including not only the ICT-manufacturing sector, but also computer-related business activities and software consultancy. The following industrial and service classes comprise the notion of ICT in the scope of the present analysis: (1) Mfr. of information and communication technology (ICM): mfr. of office machinery and computers, mfr. of radio and communications equipment (2) ICT-related services (ICS): Computer activities, software consultancy and supply.[8]

Investments in ICT capital deserve a special consideration, since most ICT products are not used up within one period, but remain in the production process. Thus the analysis needs to include investment flows as well. From 1993 to 2007 real investment matrices, in constant prices of year 2000, were available in five categories: (1) buildings other than residential, (2) machinery, (3) transport, (4) software, and (5) construction. The classification of delivering sectors is identical to the one in the input-output scheme. However, the set of investing sectors corresponded to the national standard classification of 53 sectors, whereby three industries (health, research and education, culture) are further disaggregated, resulting in 56 sectors in total. As a first step, the investment matrices were reclassified according to the 53 sectors in the Sraffian classification, which was in most cases a one-to-one correspondence.[9] Investment demand before 1993 was only available at an aggregate level in the aforementioned categories (1)–(5). For these years, the sectoral shares in the demand for the respective asset were calculated from the purchases of intermediate products. It is therefore assumed that sectors with higher demand for intermediate products related to a specific technology also invest more in capital goods of this technology. These estimations were backed up with investment data (industry by industry) from 1966 to 1992.

[7] The years 1970 until 1972 had to be excluded due to the lack of data reliability, because for these periods the results indicate a hardly viable system (i.e. with a profit rate close to zero or negative).

[8] This definition is widely accepted among empirical studies on ICT (see, e.g., Jorgenson et al. (2007)).

[9] The only industry that needed to be split up further was electricity, since in the original classification it is grouped together with gas and water supply. The assigned share was therefore derived from total deliveries of these two sectors to investment demand. However, the distribution of the respective output across sectors was assumed to be the same for the electricity and the gas and water-supply industry.

Employment Data

Regarding employment, total working hours of employed persons and self-employees were obtained from Statistics Denmark. For the discrimination of the labor force by education attained we used the Denmark labor input data provided by the EU KLEMS database (Edition 2008). This dataset comprises the shares in total working hours for three different qualification levels over a time span of 26 years (1980–2005). Since these data are only broken down for 15 sectors, each subsector was assumed to be characterized by the same labor composition. For the purpose of this paper, the only discrimination was made between low-skilled and higher (i.e. middle and high)-skilled workers; no differences in age and gender are considered. Low-skilled labor thereby refers to basic schooling, whereas middle and high-skilled labor comprises short, middle and long-cycle higher education as well as vocational education and training (for further details on the labor accounts see the EU KLEMS manual, pp. 24–31). For both qualification levels, the ratio between the respective wage share and the share in total working hours is calculated, in order to obtain the compensation level of the respective skills compared to the industry average. Additionally, for the period from 1983 until 2002 data on skill levels were complemented by labor force surveys conducted by the International Labor Organization, which report the type of occupation by economic activity.[10]

A Note on the Numéraire

The empirical analysis in this paper requires the specification of a numéraire. A number of different commodity bundles were tested. By means of sensitivity analysis the specification of the numéraire is chosen whose application fits best sectoral labor productivity growth as derived from the system of national accounts. Thus, the index finally selected is the share of each industry in the net product of the year 2000. This numéraire also makes sense intuitively due to its analogy to a consumer price index, and the year 2000 is chosen as the reference period, since the monetary input-output tables are set out in constant prices as of 2000:

$$d_n = \frac{x_n - \sum_{j=1}^{53} z_{nj}}{\sum_{n=1}^{53} y_n}$$

Figure 3.2 presents the growth of labor productivity (LPG) obtained from the national accounts,[11] together with the productivity measure derived from the Sraffian system (solid line). The LPG measure deviates in two years (1981 and

[10] For the period from 1983 to 1993, occupations by industry are classified according to ISCO68/ ISIC Rev. 2.1, for 2000–2002 according to ISCO88/ Rev. 3.1. The high aggregation (one-digit) level of occupation data did not allow a reclassification in any direction (either ISCO68 or ISCO88) as the logic of the scheme changed significantly in the revision process for ISCO88, pooling occupations according to skill levels rather than by economic activity (for further details see Ganzeboom (1996)).

[11] More precisely, for each period GDP at market prices is divided by total hours worked in the respective period.

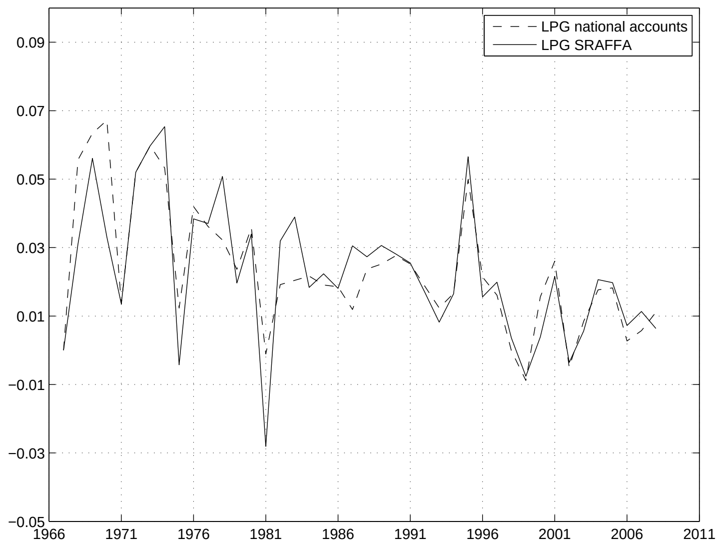

Figure 3.2: Labor productivity growth (LPG) from 1966 to 2007. Figures from the Sraffian system and the system of national accounts

1983) from the indicator based on national accounts, but otherwise represents a good fit to the conventional figures (with a correlation coefficient $\rho = 0.85$).

3.4 Results and Discussion

The results of the SDA are presented first on the aggregate level (subsection 3.4) and then on the meso level (subsection 3.4).

Aggregate Results

Figure 3.2 shows that labor productivity growth has been steadily decreasing in the past 40 years: 4.0% per annum in the 1960s compared to around 1% in the last decade. These historically low growth rates also lag behind other countries: Whereas Denmark ranked eighth among OECD countries in terms of labor productivity in 2000, it dropped back to position 12 by 2011 (McGowan and Jamet, 2012, 5). Table 3.1 contains the growth rate of aggregate labor productivity on an annual average in five-year intervals from 1966 to 2007 (first row). According to the focus of the paper, the 53 sectors are aggregated into ICT-producing, ICT-using and Non-ICT industries[12] (see appendix 3.B). Lines 2–9 present the decomposition of aggregate labor productivity growth into (1) technical change, (2) changes in labor composition, (3) substitution, and (4) final demand. The sign and magnitude of these factors depict the change over time in the amount of vertically integrated labor embodied in the specified commodity basket.

[12]The division into ICT-using sectors and Non-ICT sectors was done according to the share of ICT equipment in total investments in the year 2000 (with the threshold being 5%).

While technical change led to a reduction in total labor input and thus had a positive impact on LPG until the 1990s (except for the period 1975–1980), it became labor-using afterwards. Interestingly, technical progress in the ICT-producing industries stimulated labor productivity growth in the early 1990s, but this positive effect was compensated by the negative fabrication effects in the ICT-using industries. Conversely, the contribution of technical change in the ICT sector to LPG was negative between 1995 and 2000, while technical change in ICT-using industries had a positive impact (but was outpaced by the negative effects recorded in the remaining industries).

Employment also affected productivity growth in both directions:[13] Over the whole period of study, one can observe a decline in the employment of low-skilled labor, and an increase in hours of higher-skilled workers (therefore the negative sign). However, whereas in the first decade of study the economy operated in a manner that was labor saving, the early 1980s were characterized by a rise in total working hours: High-skilled persons, particularly scientists and engineers as well as technicians and clerical workers, were strongly demanded in the ICT-producing and ICT-using industries. These findings indicate a first phase of adjustment where industries started to experiment with the new technology. The second half of the 1980s features a positive effect of employment shifts on labor productivity. One could observe a strong decrease in unskilled labor, especially by workers in the agricultural sector, mining and transport, and still (though less pronounced) a rise in high-skilled labor. At an occupational level, the demand for sales workers increased throughout all sectors, reflecting the transition to a service economy. Between 1990 and 1995 as well as 2000 and 2005, the reduction in low-skilled labor outweighed the increase in higher-skilled workers. This period, reflecting the peak of the ICT era, experienced an ongoing surge for scientists and technicians, as well as managerial workers, but also a reduction in the employment of clerks, who mainly perform secretarial duties. As this is particularly observable in the ICT-using industries, the analysis shows that automation indeed replaced traditional jobs.

During the whole time span, labor productivity has been driven by an increase in gross output which, except for the early 1970s, outpaced the effect of employment shifts between different skill levels. The output effect can be further disentangled into a substitution and final demand effect. The substitution effect reflects the changing diversification of commodity inputs across sectors and has had a positive impact on labor productivity growth (except for the period 1970–1980). This effect was again most pronounced in ICT-using industries, where 'old' factors of production were substituted by new technology in the course of computerization. The most important source of LPG, however, was final demand. This result to some extent supports the hypothesis that changes in demand patterns drive the evolution of the economic structure (Pasinetti, 1993) as well as the direction of innovative activities (Antonelli, 2003); the latter is evidenced by the finding that the effect of investment demand for ICT products on labor

[13]Note that for the SDA different relative wages $\mathbf{u}$ were omitted as weights, since we are interested in the absolute change of working hours per skill level.

productivity change grew by factor seven over the entire period under study.

The remainder of table 3.1 presents the sectoral origins of growth. As also shown in figure 3.3, the contribution of Non-ICT industries to LPG is significant given their share in total value added of about 70% over this period. But it has been continuously declining, from 2.9% in the 1960s to 0.13% in the first decade of the 21st century. On the other hand, the contribution of ICT-using industries (which account for another one third of value added) was significant right from the beginning with a share in aggregate LPG of 24% or 1.99 percentage points between 1970 and 1975. This is due to the fact that at that time office machinery already played an important role in these sectors and the new ICT replaced the old technology step by step. In the following 20 years, the impact of ICT-using industries rose slightly (see figure 3.3), until the mid-1990s, where their contribution to labor productivity growth dropped to 15%. The period between 1995 and 2000 can be seen as the second phase of adjustment to the new technology, marked by significant advances in ICT, most importantly the internet, and a very strong demand for high-skilled labor in these industries. From 2000 onwards, it seems as if ICT has finally been rejuvenating growth: ICT-using industries account for 55% (0.55 percentage points) and, in the last period of study, even for 77% (0.66 percentage points) of aggregate labor productivity growth. This rise in magnitude can directly be traced back to the ICT-producing industries, despite their small share in value added (1966: 0.6%, 2007: 4.0%). From 1966 to 1970 these four industries (two in manufacturing, two in the service sector) contributed less than half a percentage point to aggregate labor productivity. Between 1970 and 2000 their share in LPG increased moderately from 2.5% to 4%. In the most recent years of study, ICT-producing industries accounted for 0.06 percentage points of LPG (or 8%).

These empirical findings point towards skill-biased technical change driven by computerization. However, the positive impact of ICT on aggregate labor productivity is only detectable in recent years, which reveals the long gestation period of this GPT as well as the profound adjustment process throughout the economic system.

Digging Deeper: The Impact of ICT on Sectoral Productivity

To uncover the role of ICT on the meso level, we will in the following examine both the sources and the evolution of ICT-induced productivity growth by answering two questions: (1) How large have been innovational complementarities, captured by the impact of technical change within the ICT sector on labor productivity growth in all other industries? (2) Which role can be attributed to ICT-related capital deepening? As Jorgenson et al. (2007) conclude, even though aggregate data are easier to handle and to present, they do not cover the heterogeneity between industries. Thus, the full range of data is exploited in showing the spillover effects of the GPT-producing sector for all other industries. For this analysis, the sectoral weights in the structural decomposition are dropped to show the impact of ICT for the different industries, regardless of their share in the net

	1966-1970	1970-1975	1975-1980	1980-1985	1985-1990	1990-1995	1995 2000	2000-2005	2005-2007
LPG (annual average)	4.01	3.32	2.32	2.71	3.01	2.35	0.86	1.02	0.85
Factors									
Technical change	0.45	0.11	(0.47)	0.06	0.21	(0.29)	(0.40)	(1.06)	(1.63)
Labor input	0.58	2.07	(0.92)	(0.25)	0.65	0.44	(1.86)	0.08	(1.64)
–*Low-skilled*	-	-	9.38	1.29	1.51	1.45	0.17	0.38	(25.14)
–*High-skilled*	-	-	(10.31)	(1.54)	(0.86)	(1.01)	(2.03)	(0.30)	23.50
Substitution	11.51	(11.65)	(0.92)	0.03	0.23	0.30	0.48	1.08	1.72
Final demand	(8.53)	12.78	4.65	2.87	1.92	1.90	2.64	0.92	2.40
–*ICT*	(0.14)	0.02	0.07	0.16	0.22	0.13	0.39	0.09	0.19
–*Non-ICT*	(8.40)	12.76	4.58	2.71	1.70	1.77	2.25	0.83	2.21
Industries									
ICT-producing	0.04	0.11	0.08	0.09	0.08	0.11	0.03	0.05	0.06
ICT-using	1.07	1.22	0.55	0.76	0.83	0.68	0.13	0.55	0.66
Non-ICT	2.89	1.99	1.70	1.88	2.10	1.59	0.67	0.40	0.13

Table 3.1: Growth in aggregate labor productivity in Denmark and corresponding growth factors. All figures are average annual percentages. The industry classification is defined in appendix 3.B. ICT includes mfr. of ICT equipment and computer and related activities. Source: Own calculations

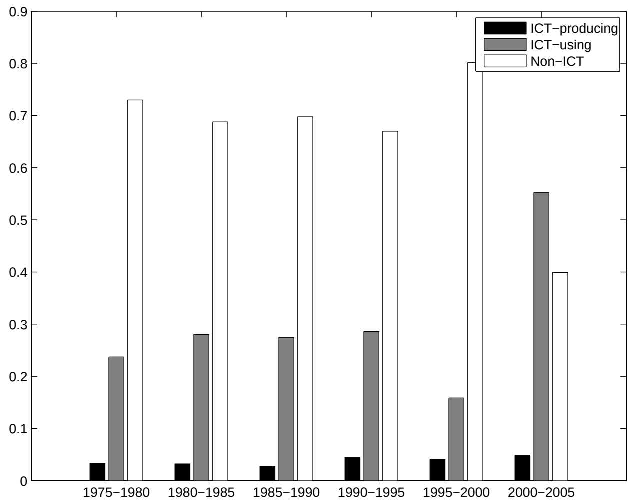

Figure 3.3: Sectoral contribution to annual labor productivity growth (LPG=1) in five-year interval from 1975 and 2005. Source: Own calculations

product.[14] In order to gain further insights into the relation between diffusion and productivity, the level of sectoral deployment of ICT will be shown as well. This diffusion path is calculated on the basis of an intersectoral transactions matrix covering both intermediate and capital demand produced domestically and abroad (see chapter 4). Industries are subsequently ranked (in descending order) according to the intensity of ICT in the respective production processes.

[14] Mathematically, this means that the numéraire is represented by a vector with all coefficients being equal to one.

Since the analysis involves a time span of 42 years and 53 different industries, and the full range of data across industries is to be examined, the results are visualized graphically. Moreover, as the effects within the source sector are usually the strongest, the respective ICT industry is removed from the graphs. Hence, just the intersectoral – and not the intrasectoral – contributions are pictured. The usage of ICT in each sector is represented by the color of the surface: The higher the share of ICT in production, the warmer the color. Industries that are displayed in red shades thus experience the highest ICT intensity.

Figure 3.4 shows the contribution of technical change *within* the ICT industries to sectoral labor productivity growth from 1966 onwards. An important criterion for identifying a GPT is its scope of improvement. In this context, we use technical change in the ICT-producing sector as measured from an input-output perspective as an indicator for advances in the technology itself. Figure 3.4 reveals that the positive effect of technical change in the ICT sector is highest in those sectors that adopted ICT at an early stage and use it most intensively relative to other industries. Thus, ICT had its strongest impact on labor productivity growth in the following manufacturing industries: mfr. of food, chemicals, as well as electronic, optical and medical instruments. The construction sector, other retail sale (covering electronic commerce) and air transport were also significantly affected. A particularly high impact can also be observed on post and telecommunications, auxiliary activities to financial intermediation (such as the administration of financial markets), and on sewage and waste disposal. For the time path, innovational complementarities manifest in labor productivity growth only from the 1990s onwards; the only exceptions are the electronic and optical/medical-equipment industries and financial intermediation, where the impact of ICT was visible throughout the period under study. Interestingly, advances in ICT initially led to a decrease in LPG in the manufacturing of machinery and other equipment.

Furthermore, the analysis of capital deepening regarding ICT shows important technical complementarities between the GPT-producing industries and the user sectors. In this regard, figure 3.5 exhibits a slightly different impact pattern of ICT: Capital deepening unfolds its (comparatively large) effects on labor productivity growth in two waves: The first wave started in the 1980s and triggered a modest rise in LPG in all industries, and a more pronounced one in the manufacturing and processing of basic metals, the electronic industry and the banking sector. The second wave started out at the beginning of the 1990s and had a more significant impact on the economy: The increasing demand for ICT capital raised labor productivity growth, particularly in retail sale (owing to the internet), R&D, consulting activities and public administration and membership organizations (which rely on association management software). In the case of post and telecommunications, investments in ICT already started in the mid-1980s, which caused labor productivity to drop significantly; this indicates the high adjustment costs involved in the early adoption of a GPT. The effects of ICT-capital deepening got visible in ICT-using as well as Non-ICT sectors: The textile and paper industries, for example, benefit from capital deepening in the industries upstream (see figure 3.5).

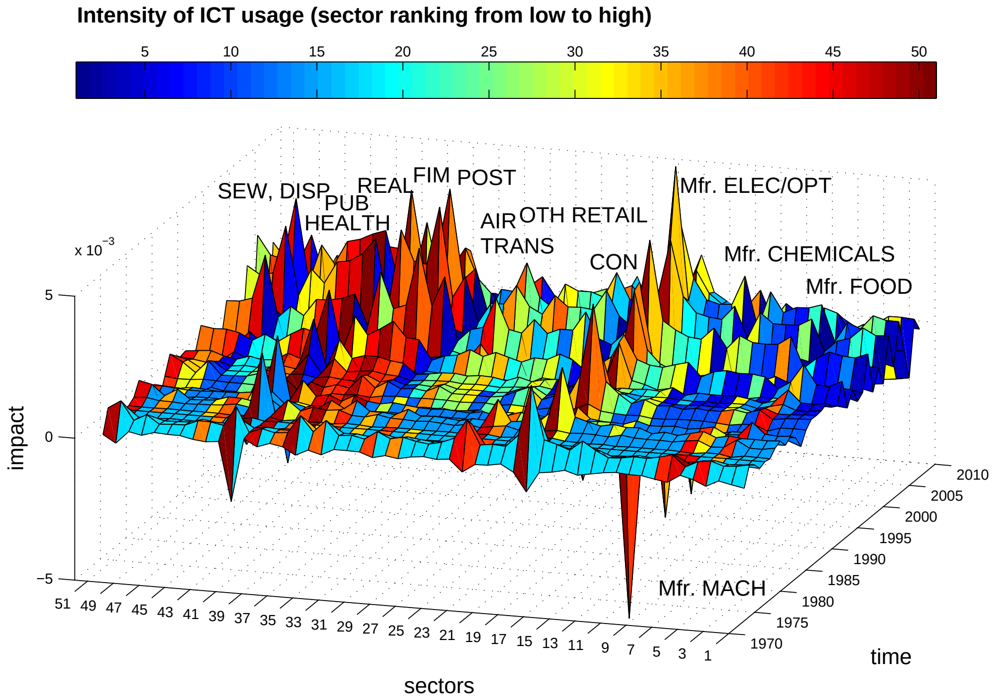

Figure 3.4: The contribution of technical change in the ICT sector to sectoral labor productivity growth.
Mfr.: Manufacturing of; FOOD: Food, beverages and tobacco; CHEMICALS: Chemicals and man-made fibres, etc., MACH: Machinery and equipment n.e.c.; ELEC/OPT: Electronic, optical and medical equipment; CON: Construction; OTH RETAIL: Other retail sale, repair work; AIR TRANS: Air Transport; POST: Post and telecommunications; FIM: Activities auxiliary to financial intermediation, REAL: Real estate activities; PUB: Public administration; HEALTH: Health care; SEW, DISP: Sewage and refuse disp. and similar activities

The intersectoral analysis of the role that ICT plays in changes to labor productivity also reveals industry clusters: Strongest impacts occur in high-tech manufacturing industries, such as the chemical industry or mfr. of electrical, medical and optical instruments as well as neighboring service sectors, e.g. financial intermediation and post and telecommunications. This supports the hypothesis that new technologies are first applied in similar industries (as reflected by akin methods of production), before they spread over more divergent sectors (Antonelli, 2003).

Diffusion of ICT and Skill-Induced Wage Dispersion

The emergence of a GPT can cause transitional wage inequalities if the new technology requires a higher level of skills for its efficient deployment. In fact, the analysis of the Danish labor market[15] reveals that ICT-producing and ICT-

[15] In this context, we revert to labor market data on the educational attainment of the workforce by industry from 1993 until 2006. Source: Statistics Denmark, available at

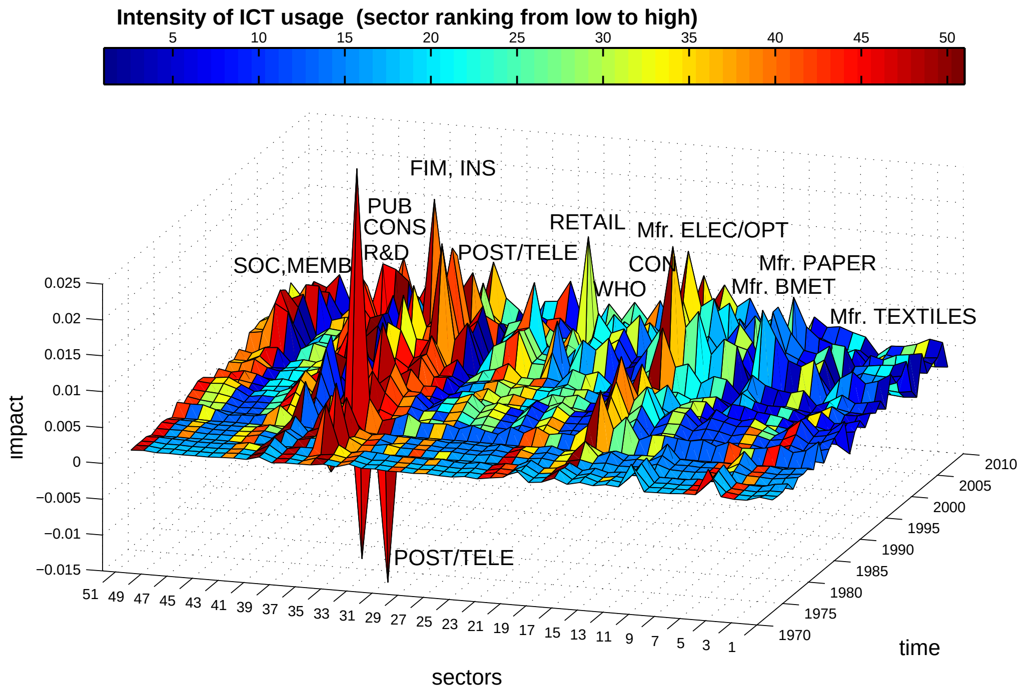

Figure 3.5: The contribution of ICT-capital deepening to sectoral labor productivity growth. Mfr.: Manufacturing of; TEXTILES: Textiles, wearing apparel, leather; PAPER: Paper production, printing and publishing; BMET: Other non-metallic mineral products; BMET: Basic metals; ELEC/OPT: Electrical, optical and medical equipment; CON: Construction; WHO: Wholesale and commisson trade, exc. of m. vehicles; RETAIL: (Other) retail sale, repair work; POST&TELE: Post and telecommunications; FIM: Financial intermediation; INS: Insurance and pension funding; R&D: Research and development; CONS: Consultancy etc.; PUB: Public administration; SOC: Social institutions; MEMB: Activities of membership organizations n.e.c.

using industries reported the strongest growth throughout the economy in the employment of persons with tertiary education. In 2001, immediately after the dot.com-crash, the number of workers dropped in all these industries irrespective of their skill level, but began growing again afterwards with regard to highly skilled labor, though at a slower pace than before 2000. In contrast, the number of low-skilled workers almost continuously decreased in ICT-producing and ICT-using industries; this trend was particularly observable in the telecommunication sector throughout the whole period under study, and within business activities and the ICT manufacturing sector since 2000.

Given the strong skill bias of ICT, one would indeed expect wages between lower-skilled and higher-skilled workers to spread at some extent. This wage dispersion, however, needs to be analyzed against the fact that Denmark disposes in general of a low wage gap.[16]

http://www.statbank.dk/HFU2.

[16]According to OECD (2013), the wage premium in 2005 amounted to 28% between high-skilled workers and medium-qualified workers (in comparison, the OECD average was 57%); and

For the following analysis, data on labor compensation from the EU KLEMS database are used to calculate the ratio between the respective wage share and the share in total working hours, in order to obtain the compensation level of the respective skills compared to the industry average.

As figure 3.6 reveals, between 1980 and 1990 the GINI coefficient as a measure of wage dispersion between lower-skilled and higher-skilled labor rose by two percentage points (or 16%) in the ICT-producing industries. After 1990, the GINI index shows a downward trend until 1997. This decrease was owed to a reduction in both enterprises and employees in the ICT-manufacturing sector. After 1997, the GINI coefficient increased again, driven by a significant growth in enterprises entering the ICT service industry (25% between 2000 and 2007, with the number of employees rising by 33%).[17] In the ICT-using sectors, the GINI evolves along a stable path between 1980 and the mid-1990s. Since 1997, wage dispersion again shows an upward trend, partially reflecting the increasing significance of business sectors in the economy. The hype of computerization created a bottleneck in the supply of qualified labor. Danish firms in fact saw the lack of e-skills, especially in-house, as a main obstacle for adopting the new technology (Statistics Denmark, 2006). Not surprisingly, wage dispersion in Non-ICT industries declined almost continuously over the whole period under study.

Figure 3.7 links the evolution of wages of low and high skilled labor to the diffusion of ICT. A technical coefficient above 0.01[18] for ICT manufacturing products and ICT services indicates that the respective sector has adopted this technology. The resulting diffusion path is plotted in figure 3.7, where the left ordinate presents the share of sectors that already use ICT, and the right ordinate gives the GINI coefficient as an indicator for the dispersion of wages of low and high-skilled labor. Since the ICT manufacturing sector (ICM) and computer-related service sector (ICS) follow a different time path, they are plotted separately. Contrasting the diffusion of ICT with the evolution of wage differentials, one can see that the wage dispersion peaked when the rate of adoption of ICT was about to take off in the mid-1990s. Furthermore, wage differentials between low and high-skilled labor have also increased significantly after 2000; this being a time when the diffusion process had already slowed down and ICT has begun to unfold its impact on labor productivity growth. This trend might be also associated with demographic changes in the labor market, reflecting the increasing participation of elder persons in the workforce, or indicates a new wave of skill-biased technological change.

18% between middle- and low-skilled labor (OECD, 2014, 142), with the OECD average being 22%.

[17] Data source for the number of enterprises by economic activity: SDBS Structural Business Statistics (ISIC Rev.3), available at OECD Stat: http://stats.oecd.org/Index.aspx?DataSetCode$=$ANBERD_REV# (see table A.1 in the annex).

[18] These calculations are based on the compound direct requirements matrix which includes intermediate products, imports and capital flows (see chapter 4).

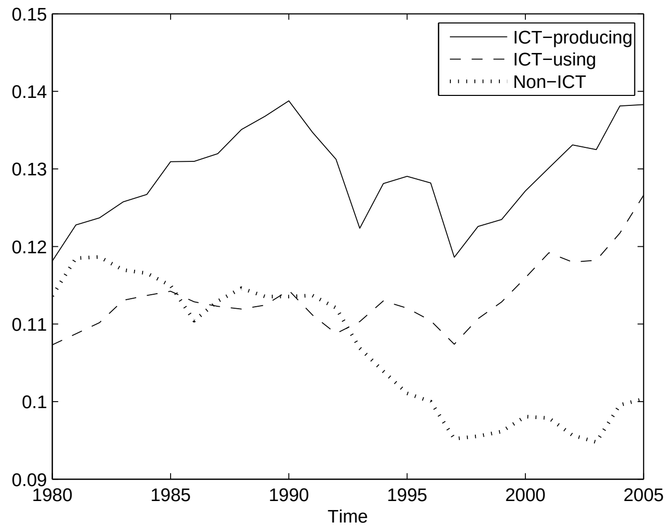

Figure 3.6: Dispersion of wages of low and high-skilled labor between 1980 and 2005

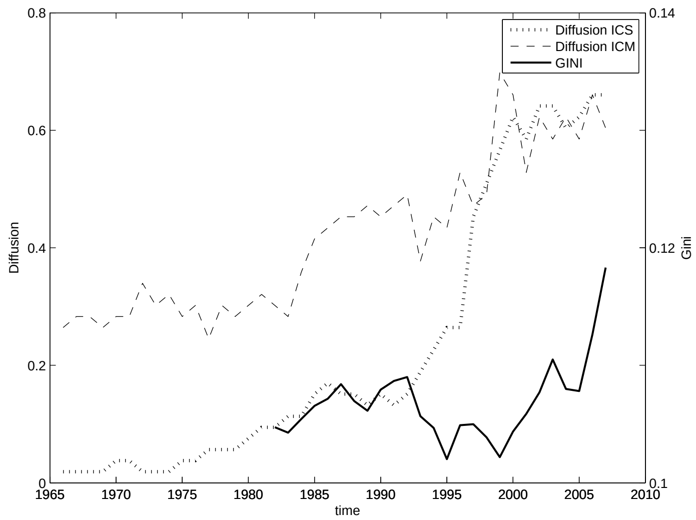

Figure 3.7: The diffusion of ICT manufacturing products (ICM) and ICT service products (ICS) across sectors (left ordinate) and the GINI for low and high-skilled labor (right ordinate)

3.5 Conclusion

The economic dynamics triggered by the arrival of a general purpose technology has been examined on both a theoretical and empirical level. This paper has presented an evolutionary multisectoral model which allows the analysis of general purpose technologies affecting the share of innovative firms in each application sector. An extension of this model can be found in Rainer and Strohmaier (2014), which deals with the potential slump in productivity growth after the arrival of the innovation, its retarded diffusion process, as well with as skill-induced wage dispersion, all characteristics that have been associated with GPTs (see chapter 6).

The model has subsequently been applied to the Danish economy to investigate the change in labor productivity and its sources, taking into account the vertical integration of sectors. Within this framework, the three major features of GPTs could be traced empirically, by breaking the analysis down to the intersectoral level: First, the scope for improvements in the technology was captured by technical change in the ICT sector. Showing the impact of the latter on sectoral labor productivity growth uncovered innovational complementarities, the second characteristic of GPTs. Last, the pervasiveness of ICT got particularly evident in the effects of capital deepening which have spread over the whole production system.

Limitations of the structural decomposition analysis include the choice of a fixed commodity basket for measuring the amount of labor embodied. Thus, results vary with the numeraire. However, it was shown that the use of the net product of 2000, which is also the base year for the price deflators, leads to a remarkably similar evolution of labor productivity, compared to conventional measures of LPG. Furthermore, while an SDA requires prices to be constant in order to reflect real changes, this also entails a substitution bias as preferences and prices change over time. This is particularly the case of ICT, which experienced falling prices throughout its lifetime. A possible solution would be to apply the analysis on input-output data at chained prices, which however would impose further requirements on the SDA. Last, but not least, our broad definition of ICT does still not cover all products related to this technology, as sectoral data was only available at the two-digit level. Nevertheless, the results show the rising impact of ICT and support theories on skill-induced technological change.

At the aggregate level, we have seen a falling trend of labor productivity particularly over the last decades. Regarding the impact on overall growth within the whole period, the ICT-producing and ICT-using industries show an increasing contribution. However, it took two decades for ICT to become a major source of productivity growth, which indicates the long time span necessary for a GPT to reach maturity and for the economic system to adapt to the new technology. Apparently, these adjustment processes also affected the labor market, as transitional wage dispersion in the ICT-producing and ICT-using industries could be observed during the rise of the IT era.

The intersectoral analysis demonstrates that the new information and communication technologies have also impacted those industries which do not produce at high ICT intensity. The empirical findings show that ICT played a crucial role for the Danish production system, particularly in the most recent years under study. By 2007, ICT pervaded virtually all sectors in the economy. Does this fact allow for the conclusion that ICT has already entered a phase of retention? Not quite. Given the position of Denmark as an innovation leader, one could observe that ICT acted as a lever of domestic innovation activities. This can be seen in its unfolding impact on the chemical industry and the machinery sector (that both subsume the bulk of biotechnology of which Denmark is a world leader). An analysis on a more disaggregated sector level may therefore give further insights into the significance of ICT for innovation and entrepreneurship in Denmark.

Our framework starts from a firm level, and investigates structural adjustment processes on the meso level that eventually cumulate into effects at the macro level. In our opinion, the sector level is an important object of study, particularly for the subject of technological change, as it represents the interface between the locus where innovation takes place and the locus where its scope eventually becomes evident. One of the primary features of our intersectoral approach is the fact that it allows for tracing both the source and direction of structural change and its impact on productivity growth. We therefore believe that an in-depth study of the vertical integration of industries also provides an important tool for innovation policy design.

Appendix

3.A Structural Decomposition Analysis

Given (3.11), the relative change in the maximum wage rate can be decomposed into four partial factors: (1) technical change (as indicated by a change in the direct input matrix A, $\Delta S \equiv S_t - S_{t-1}$), (2) change $\Delta \mathbf{l} \equiv \mathbf{l}_t - \mathbf{l}_{t-1}$ of total employment, (3) substitution effect (indicated by a change in A^T, $\Delta H \equiv H_t - H_{t-1}$) and (4) change $\Delta \mathbf{y} \equiv \mathbf{y}_t - \mathbf{y}_{t-1}$ of final demand. The result of each decomposition is an N-dimensional vector that shows the contribution of the respective determinant to sectoral labor productivity growth:

$$SS_{t-1} \equiv -\mathbf{d}^T \left[\Delta S \; \hat{\mathbf{l}}_{t-1} \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.12a}$$

$$ll_{t-1} \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}} \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.12b}$$

$$LL_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} [\text{diag} \; (\Delta H \; \mathbf{y}_{t-1})] \; \hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t \; \mathbf{e} \tag{3.12c}$$

$$YY_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} [\text{diag} \; (H_t \; \Delta\mathbf{y})] \hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t \mathbf{e} \tag{3.12d}$$

Depending on data availability, labor input is further decomposed into low-skilled (l^1) and higher-skilled (l^2) labor (hours per unit of output).

$$ll_{t-1}^1 \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}}^1 \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.13a}$$

$$ll_{t-1}^2 \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}}^2 \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.13b}$$

Equations (3.13a–3.13b) replace (3.12c) for the time span of 1980 to 2005. Furthermore, final demand is decomposed into ICT-related and Non-ICT investments:

$$YY_{t-1}^{ICT} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} [\text{diag} \; (H_t \; \Delta\mathbf{y}^{ICT})] \hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t \mathbf{e} \tag{3.14a}$$

$$YY_{t-1}^{NonICT} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} [\text{diag} \; (H_t \; \Delta\mathbf{y}^{Non-ICT})] \hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t \mathbf{e} \tag{3.14b}$$

Equations (3.14a) and (3.14b) sum up to (3.12d).

Equations (3.12a–3.12d) reveal an obvious index problem that affects precision and interpretation of the outcome whenever the number of partial factors exceeds two. So far all variables are weighted by $t-1$ values. However, in the case of four determinants we have 4! possible decompositions for each factor, resulting from the permutation of the variables with respect to time. Dietzenbacher and Los (1998) showed that the polar decomposition gets remarkably close to the average of all possible decompositions; thus it suffices to calculate the second polar decomposition, by starting with the values in period t instead of period

$t-1$ and taking the average of the two:

$$SS_t \equiv -\mathbf{d}^T \left[\Delta S \hat{\mathbf{l}}_t \; [\mathrm{diag}(H_t \mathbf{y}_t)]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.15a}$$
$$ll_t \equiv -\mathbf{d}^T \left[S_{t-1} \; \Delta\hat{\mathbf{l}} \; [\mathrm{diag}\;(H_t \; \mathbf{y}_t)]^{-1}\right] \; w_t \; \mathbf{e} \tag{3.15b}$$
$$LL_t \equiv \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} \; [\mathrm{diag}\;(\Delta H \; \mathbf{y}_t)] \; \hat{\mathbf{x}}_t^{-1}\right] \; w_t \; \mathbf{e} \tag{3.15c}$$
$$YY_t \equiv \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} [\mathrm{diag}\;(H_{t-1} \; \Delta\mathbf{y})] \; \hat{\mathbf{x}}_t^{-1}\right] \; w_t \; \mathbf{e} \tag{3.15d}$$

Hence, the initial decomposition of the labor productivity growth indicator[19] reads as follows:

$$\begin{aligned} g_t^l = \frac{1}{2}\mathbf{d}^T \; \big[&\{(LL_{t-1} + LL_t\} + \{YY_{t-1} + YY_t\} + \\ &\{SS_{t-1} + SS_t\} + \{ll_{t-1} + ll_t\} \big] \; w_t \; \mathbf{e} \end{aligned} \tag{3.16}$$

Intra- and Intersectoral Linkages

In order to show the impact of ICT on productivity changes across industries, the direct input matrices A and A^T are decomposed into their submatrices. Following Miller and Blair (2009, 603-605), changes in S and H are related to changes in the underlying direct input matrices:

Proposition 1. *Changes ΔA of the input matrix A translate into changes ΔH of the Leontief inverse and changes ΔS of the Sraffa inverse matrix according to*

$$\Delta S = S_{t-1} \; \Delta A \; S_t \quad \text{and} \tag{3.17a}$$
$$\Delta H = H_{t-1} \; \Delta A^T H_t. \tag{3.17b}$$

Proof. (3.17b) is the transpose of (3.17a). Thus one only has to show that

$$(\mathbb{I} - A_t)^{-1} - (\mathbb{I} - A_{t-1})^{-1} = (\mathbb{I} - A_{t-1})^{-1}(A_t - A_{t-1})(\mathbb{I} - A_t)^{-1}.$$

But this can be shown to be true by post-multiplication with $(\mathbb{I} - A_t)$ and pre-multiplication with $(\mathbb{I} - A_{t-1})$. □

Analyzing the impact of a specific sector on all other sectors requires a closer look at the economic structure. To assess how sectors are linked together, the direct input matrix A is split up in such a way that each row composes an own submatrix. By doing so, the isolated effect of one sector on the production technique can be traced back. Decomposing A into individual sectors means to create

[19]For equations (3.12c) and (3.12d) as well as for (3.15c) and (3.15d), note that $\hat{\mathbf{x}}_{t-1}^{-1}\Delta\hat{\mathbf{x}}\hat{\mathbf{x}}_t^{-1} = \hat{\mathbf{x}}_t^{-1}\Delta\hat{\mathbf{x}}\hat{\mathbf{x}}_{t-1}^{-1} = -\Delta(\hat{\mathbf{x}}^{-1}) \equiv \hat{\mathbf{x}}_{t-1}^{-1} - \hat{\mathbf{x}}_t^{-1}$.

submatrices such that $\Delta A = \sum_{i=1}^{N} \Delta A^{(i)}$ with

$$\Delta A^{(i)} \equiv \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ \Delta a_{i1} & \dots & \Delta a_{ij} & \dots & \Delta a_{in} \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix}.$$

By recalling Proposition 1 and introducing $\Delta A^{(i)}$ into equations (3.12a) and (3.15a), the effect of changes in the production process of a specific sector due to, for instance, technical change on labor productivity growth in all other sectors can be analyzed:

$$SS_t \equiv -\mathbf{d}^T \left[S_t \; \Delta A \; S_{t-1} \; \hat{\mathbf{l}}_t \; \operatorname{diag}(H_t \mathbf{y}_t)^{-1} \right] w_t \; \mathbf{e}$$

Applying the same procedure to equations (3.12c) and (3.15c) allows tracking the effect of changes in demand for a specific factor, i.e. the effect of substituting one input for another:

$$LL_t = \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} \; [\operatorname{diag}\; (H_t \; \Delta A^T \; H_{t-1} \; \mathbf{y}_t)] \; \hat{\mathbf{x}}_t^{-1} \right] \; w_t \; \mathbf{e}$$

Finally, the role of fixed capital provided by the ICT sector is scrutinized. It is obvious that a big part of the output of the ICT industry represents assets that remain longer than a year in the production process. These assets are therefore not captured within the direct input matrix, but are recorded in the investment demand of an input-output table, so that for a comprehensive analysis changes in ICT capital have to be taken into account. For doing so, we incorporate investment flows into the previous analysis by disentangling the final demand vector $\mathbf{y}$ into different categories; furthermore, the column of investment demand is replaced by the respective investment matrix Y_{inv}, which shows (similar to the industrial transaction matrix) the intra- and intersectoral deliveries of capital assets:

$$YY_{t-1} = \mathbf{d}^T \; [S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} \; [\operatorname{diag}\; (H_t \; \Delta(Y_{\text{inv}}\mathbf{e} + \mathbf{y}_{\text{rest}}))] \; \hat{\mathbf{x}}_{t-1}^{-1}] \; w_t \mathbf{e}$$

3.B Industry Classification

Table 3.B.1: Aggregation of Danish industries. The numbers in the second column indicate the assignment of the respective sector to NACE Rev. 1.1, the third column to ICT-producing, ICT-using and Non-ICT industries.

	Industry	NACE	ICT classification
1	Agriculture	01	Non-ICT
2	Horticulture, orchards etc.	01	Non-ICT
3	Agricultural services; landscape gardeners etc.	01	Non-ICT

Continued on next page

Table 3.B.1 – continued from previous page

	Industry	NACE	ICT classification
4	Forestry	02	Non-ICT
5	Fishing	05	Non-ICT
6	Extr. of crude petroleum, natural gas etc.	11	Non-ICT
7	Extr. of gravel, clay, stone and salt etc.	14	Non-ICT
8	Mfr. of food, beverages and tobacco	15	Non-ICT
9	Mfr. of textiles, wearing apparel, leather	17-19	Non-ICT
10	Mfr. of wood and wood products	20	Non-ICT
11	Mfr. of paper prod.; printing and publish.	21,22	Non-ICT
12	Mfr. of refined petroleum products etc.	23	Non-ICT
13	Mfr. of chemicals and man-made fibres etc.	24	Non-ICT
14	Mfr. of rubber and plastic products	25	Non-ICT
15	Mfr. of other non-metallic mineral products	26	Non-ICT
16	Mfr. of basic metals and fabricated metal products	27,28	Non-ICT
17	Mfr. of machinery and equipment n.e.c.	29	ICT-using
18	Mfr. of ICT equipment	30,32	ICT
19	Mfr. of electrical, optical and medical equipment	31,33	ICT-using
20	Mfr. of transport equipment	34,35	ICT-using
21	Mfr. of furniture; manufacturing n.e.c.	36,37	Non-ICT
22	Electricity supply	40.1	Non-ICT
23	Gas and water supply	40.2,40.3	Non-ICT
24	Construction	45	Non-ICT
25	Sale and repair of motor vehicles etc.	50	ICT-using
26	Ws. and commis. trade, exc. of m. vehicles	51	ICT-using
27	Retail trade of food etc.	52.2	ICT-using
28	Department stores	52.2	ICT-using
29	Re. sale of phar. goods, cosmetic art. etc.	52.3	ICT-using
30	Re. sale of clothing, footwear etc.	52.41	ICT-using
31	Other retail sale, repair work	52.44	ICT-using
32	Hotels and restaurants	55	Non-ICT
33	Land transport; transport via pipelines	60	Non-ICT
34	Water transport	61	Non-ICT
35	Air transport	62	Non-ICT
36	Support. trans. activities; travel agencies	63	Non-ICT
37	Post and telecommunications	64	ICT-using
38	Financial intermediation	65	ICT-using
39	Insurance and pension funding	66	ICT-using
40	Activities auxiliary to finan. intermediat.	67	ICT-using
41	Real estate activities	70	ICT-using
42	Renting of machinery and equipment etc.	71	ICT-using
43	Computer and related activities	72	ICT
44	Research and development	73	ICT-using
45	Consultancy etc. and cleaning activities	74	ICT-using
46	Public administration etc.	75	Non-ICT
47	Education	80	Non-ICT
48	Health care services	85	Non-ICT
49	Social institutions	85	Non-ICT
50	Sewage and refuse disp. and similar act.	90	Non-ICT
51	Activities of membership organ. n.e.c.	91	ICT-using
52	Recreational, cultural, sporting activities	92	Non-ICT
53	Other service activities	93	ICT-using

Chapter 4

Neither Mushrooms nor Yeast: Measuring Pervasive Technological Change

The growth potential of an industry is tied to other sectors upstream (via its demand for intermediate and capital goods) and downstream (via its supply of products). This is all the more the case for industries that provide general purpose technologies (GPTs) which spur economic growth via their pervasive use. The present paper proposes an extended linkages indicator for uncovering key sectors, that explicitly considers the notion of pervasiveness. The derived measures allow studying both the robustness of an industry and the density of its trade network. Given the change in states over time, the trajectories of sectors along these two dimensions can be analyzed. The framework is subsequently applied to the general purpose technology currently at work, information and communication technology (ICT). The empirical findings show that if pervasive use is taken into account, the ICT sector has evolved to the core of the economic system, and that the need of complementary products for the efficient use of a GPT translates into multiple, though interrelated, diffusion paths.

Keywords | general purpose technologies, input-output, linkages, diffusion, ICT

4.1 Introduction

Measuring economic connectedness and its implications for policy design has been a long and extensive debate in the input-output literature. A fierce controversy took place between Hirschman (1958) and Nurkse (1953) as to whether resources should be spread throughout all industries equally or used to promote only the most promising in terms of growth. Nurkse argued in favor of balanced growth, while Hirschman advocated the unbalanced growth perspective. From his point of view, industries do not expand at the same rate, since they are at different stages of development. A strategy that supports the sector with the highest growth potential and the most intense linkages to others would therefore be preferable. Four decades later, in his presidential address to the American Economic Association, Harberger (1998) paraphrased the same argument by drawing an analogy to mushrooms and yeast: yeast-like industries grow at the same rate, whereas the mushrooms among industries are characterized by a rapid expansion and real cost reductions for the sectors linked to them.

In terms of methodology, Rasmussen (1956) was the first to propose the idea of forward and backward linkages for measuring the potential of an industry. Hirschman (1958) used this concept for identifying key sectors in an economy, postulating that particular industries with above-average linkages actually drive economic development and structural change. He therefore promoted the linkage concept as an important tool for policy design, especially for developing countries, since the impulse given to key sectors is eventually channeled through the whole economy. This impulse can be set either by industries with relatively strong backward linkages, i.e. with a high demand for products upstream, or those sectors which represent important suppliers of intermediate products downstream (forward linkages). As Lenzen (2003, 2) points out, in the wake of the intersectoral trading network, "the sectors growing most rapidly are not the key sectors themselves, but may be the sectors that are most closely linked to them". Rasmussen's and Hirschman's approach caused quite a struggle among scholars in this field (for an overview see Lenzen (2003) and Miller and Blair (2009)). Early alternative contributions to linkage analysis were made by Chenery and Watanabe (1958), Hazari (1970), Yotopoulos and Nugent (1973), and Jones (1976). Later on, Clements (1990) and Sonis et al. (1995) added new perspectives. Critics to the significance of linkage analysis as a planning tool led these measures to be applied in a descriptive manner, rather than as an empirical instrument, which corresponds to Rasmussen's initial idea.

Most recently, the linkage concept experienced a revival in the studies of R&D and innovations (see, e.g., Papconstantinou et al. (1998) and Hauknes and Knell (2009)). In this respect, Verspagen (2004) uses conventional linkage analysis to investigate the impact of ICT as a basic innovation in the Schumpeterian sense for the U.S. economy in the postwar period. Structural change is studied on the basis of input-output data as well as patent data from 1958 until 1998.[1] It is shown that despite strong intrasectoral forward linkages, the ICT sector did not interact to a great extent with the other sectors in the economy in the beginning of the IT era. But even in the later decades under study, the impact of ICT as measured by the traditional linkages method was not quite as strong as expected. Verspagen thus concludes, in an analogy to Solow's famous statement from 1995, that "we can see computers everywhere, except in the input-output tables" (p.1120).

Large similarities to linkage analysis can be found in social network literature: Bothner et al. (2010) derive a model in which members who dispose of diversified relations to others that have themselves a wide range of linkages occupy a *robust* position in the network. This concept makes use of the Herfindahl-Hirschman index of concentration and is subsequently applied to different socioeconomic networks.

The present paper proposes an explicit operationalization of the notion of

[1] The calculations are based on current prices since according to Verspagen, (a) price decreases are part of the diffusion process and should be included in the analysis and (b), because of the fact that constant prices would mean to have a recent base year, where the diffusion rate is the highest, so that the results of the last (and most important) years would not change. For a detailed comparison of linkage indicators in current and constant prices see annex B.

pervasiveness in the context of input-output analysis and in doing so derives an extended linkage indicator for measuring the impact of radical innovations. We follow Freeman and Perez (1988) whereby it is rather the diffusion process – and not (the act or product of) inventing as such – through which a technological breakthrough unfolds its effects on the economic system. In doing so, we revert to the concept of general purpose technologies (GPTs) which emphasizes the large field of application of a technology and its diffusion process. This paper will argue that conventional linkage analysis is not concise enough to comprise the case of general purpose technologies due to their defining characteristics which qualify the sectors producing them as *neither* mushrooms *nor* yeast. We therefore propose an extended linkage indicator that captures the widespread use of inputs in production as a descriptive tool for studying pervasive technological change. For the empirical application, Denmark is chosen due to its position as a net importer of ICT products and the extent of the available data.

Results are subsequently linked to the taxonomy of sectoral patterns of innovations by Castellacci (2008), whereby industries are grouped according to their technological capabilities and their position in the production chain into four sectoral blocks. Each class thus characterizes a specific innovation pattern of its corresponding sectors. The taxonomy represents a generalization of Pavitt's sectoral patterns of technical change (Pavitt, 1984), for both, manufacturing and service sectors, and has been mainly supported by data derived from community innovation surveys. Testing our diffusion-oriented approach against this taxonomy, we can therefore examine to what extent structural dynamics differ among industry groups with distinctive innovation profiles.

The paper proceeds as follows: Section 4.2 gives a brief overview of the traditional linkage measures in input-output analysis and explains why they fall short of uncovering pervasive technological change. Referring to social network theory, the extended linkage indicator will be introduced thereafter. Section 4.3 describes the data handling, while the empirical findings are discussed in section 4.4. Section 4.5 gives concluding remarks.

4.2 Methodology

When it comes to pervasive innovations, conventional linkage analysis fails on two grounds: Firstly, as an empirical tool for policy design, it cannot cope with the particular expansion path of a GPT-producing industry, characterized by a retarded takeoff followed by a strong upturn. This means that on the one hand, it is not able to show the potential of a GPT in its infancy, given its long gestation period. The application of this policy instrument would thus ultimately lead to withholding essential investments for the development of the crude technology in favor of other sectors that are more promising at that time. On the other hand, the promotion of a GPT-producing industry at a late maturity stage of the technology, where it is indeed classified as a key sector according to the linkage measure, might prolong its life cycle beyond its efficient utilization and hamper the upcoming of a new general purpose technology. Secondly, even if used only in a descriptive manner, linkage analysis does not explicitly account for the pervasive character of a GPT. The latter critique has been the key motivation for this paper. In the following section, traditional linkages will be discussed briefly, before introducing the notion of pervasiveness. Regarding notation, we draw on Lenzen (2003) in the following.

Rasmussen proposed the conventional Leontief quantity model to derive measures of forward and backward linkages:

$$\mathbf{x} = A\,\mathbf{x} + \mathbf{y} = (\mathbb{I} - A)^{-1}\,\mathbf{y} = L\,\mathbf{y} \tag{4.1}$$

where a vector of exogenous final demand $\mathbf{y}$ is linked to total output of the economy, $\mathbf{x}$. A denotes the matrix of input or technical coefficients necessary to produce one unit of output in the respective sectors, with

$$A = \{a_{ij}\}_{n\times n} = \left\{\frac{z_{ij}}{x_j}\right\}$$

Each element l_{ij} in L gives the direct and indirect requirements of industry i, $i = 1, \ldots, n$ to produce one unit of output for final demand from industry $j = 1, \ldots, n$.

The direct backward linkages of sector j, $U^d_{\bullet j}$, i.e. its dependence on inputs provided by sectors upstream, can then be simply calculated by the sum of the elements in the jth column of the direct input coefficient matrix:

$$U^d_{\bullet j} = \sum_i a_{ij} \tag{4.2}$$

Taking into account the indirect linkages in an economy as well, column sums of the Leontief matrix were proposed as a total backward linkage measure $U^t_{\bullet j}$:

$$U^t_{\bullet j} = \sum_i l_{ij} \tag{4.3}$$

In its normalized form, Rasmussen (1956) calls this measure the index of 'power of dispersion':

$$\overline{U}^t_{\bullet j} = \frac{n\sum_i l_{ij}}{\sum_{ij} l_{ij}} \tag{4.4}$$

where n denotes the number of industries in the economy. Thus, the strength of linkages of the average sector j is normalized to unity, and an industry j with backward linkages of $\overline{U}^t_{\bullet j} > 1$ has an above-average demand on intermediate products from other sectors due to a unit increase in final demand of sector j.

With regard to forward linkages, the Ghosh model has been widely used as a starting point. Ghosh (1958) relates primary inputs $\mathbf{v}$ with total output through the following equation:

$$\mathbf{x} = \mathbf{v} + B\,\mathbf{x} = \mathbf{v}\,(\mathbb{I} - B)^{-1} = \mathbf{v}\,G \tag{4.5}$$

B thereby denotes the matrix of output or allocation coefficients b_{ij} that measure the input from sector i in sector j as a fraction of the seller's output x_i:

$$B = \{b_{ij}\}_{n \times n} = \left\{ \frac{z_{ij}}{x_i} \right\}$$

$G = (\mathbb{I} - B)^{-1}$ is the Ghosh inverse that measures how much output of industry j is necessary to utilize a unit of primary input in industry i. Various authors (see, e.g., Lenzen (2003) and Miller and Blair (2009) for a summary of this discussion) questioned the feasibility of taking Ghosh coefficients as quantity coefficients, but rather suggested their reinterpretation as a price model (Dietzenbacher, 1997; Oosterhaven, 1996). In this sense, "primary input 'prices' change exogenously, are entirely passed on to price-taking purchasers and change only output 'values', while quantities are fixed" (Lenzen, 2003, 5). Therefore, the Ghosh inverse can only be employed *ex post*, in a descriptive manner, and not as a policy instrument.

Analogous to above, direct and total forward linkages based on the Ghosh model can thus be stated as follows:

$$\overline{V}^{d}_{i\bullet} = \frac{n \sum_j b_{ij}}{\sum_{ij} b_{ij}} \tag{4.6}$$

$$\overline{V}^{t}_{i\bullet} = \frac{n \sum_j g_{ij}}{\sum_{ij} g_{ij}} \tag{4.7}$$

The measures proposed in equations (4.4) and (4.7) just consider the strength of interindustrial (backward and forward) linkages of a specific sector, but not its significance in the economy as such. It might be the case that an industry exhibits strong ties to others, but a comparatively low level of economic activities. The size of a sector should thus also be taken into account, either by weighting the conventional linkage indexes with final demand (from the perspective of income use) or by some sort of output measure (and thus from the income generation side). The first was suggested by Rasmussen and has been widely applied since then, whereas the latter (as proposed by Rao and Harmston (1979)) faced some critics (for example, Lenzen (2003) shows that for the case of Australia, forward measures and output are positively correlated). However, according to Rao and Harmston (1979), weighting with shares of final demand would shift the power from the production to the consumption side, which is more volatile over time.

For the purpose of this paper, we suggest to use the sector shares in value added as weights, since we are interested in the impact of a GPT on the production system and less so on its effects for final consumption. Conversely, for backward linkages, sector shares in final demand will be used. Regressions on linkage measures show an equal, non-significant (positive) correlation with any of the proposed weights.

Pervasiveness As this paper argues, the conventional linkage indicators fall short of measuring pervasive technological change, the more so as the term pervasiveness lacks a clear-cut definition according to Field (2011, 214):

> If pervasiveness simply means that 'a lot of technology' is used, then most of the technologies [subsumed under the notion of GPT] appear to qualify. But if broad applicability means that the technology is used across many sectors, the situation becomes murkier. It's hard to see, for example, how a sailing ship with three masts measures up, unless we mean simply that vessels using this design carried many types of raw materials and manufactured goods. If we adopt such a broad interpretation, however, [...], we will quickly get to a point where it is difficult to distinguish between single-use and general-purpose technology, given the nature of input-output matrices. On the other hand, if we adopt the narrower approach, insisting on direct use of the technology in the sector or industry, the measure of pervasiveness is to a certain extent hostage to industrial organization, particularly the degree of vertical integration.

Thus, measuring pervasiveness by the indicators derived in equations (4.4) and (4.7), which take into account both direct and indirect linkages of an industry, would blur the distinctive characteristics of single-use and general-purpose technology. The calculation of direct linkages alone, however, would blank out the production chain, and yet would not give any information on how widely a product is used across sectors. This is important in so far as a sector that provides a technology to many other sectors imposes different dynamics on the system as an industry that only supplies to a few others. A potential explanation can be found in the theory of social networks. According to Bothner et al. (2010), pervasive social relations underpin the robustness of the person's status in the network, whereas higher concentration uncovers the fragility of some members because their nodes in the network depend on a few others and not on a broad base; hence, robustness is defined as "diversification across the diversified" (Bothner et al., 2010, 945). On the methodological level, Bothner et al. therefore apply the Herfindahl concentration index to assess the robustness of a node within a social network.

Picking up this argument, a generality measure based on the Herfindahl-Hirschman index as proposed by Trajtenberg et al. (1997) will be in the following included[2] as a measure of dispersion in the derived indexes.[3] Similar generality

[2] Alternatively, Hazari (1970) suggested analyzing row and column variation coefficients as a second indicator *besides* the basic linkage measures.

[3] It can be easily shown that the Herfindahl-Hirschman index $H_{i\bullet}$ is strictly related to the variation coefficient cv_i. Let h_{ij} be the elements of the Herfindahl matrix H for sectors $i, j =$

indicators have been widely applied in the field of industrial organization as well as in the empirical patent literature linked to GPTs (see, for example, Hall and Trajtenberg (2004) or Nomaler and Verspagen (2008)).

Let $h_{ij}^{(u/v)}$ be the elements of the Herfindahl-Hirschman matrix $H^{(u/v)}$ for sectors $i, j = 1, \ldots, n$, with

$$h_{ij}^{(u)} = \frac{z_{ij}^2}{\left(\sum_i z_{ij}\right)^2}$$

in case of backward linkages (measuring the concentration of demand for intermediate products), and

$$h_{ij}^{(v)} = \frac{z_{ij}^2}{\left(\sum_j z_{ij}\right)^2}$$

in case of forward linkages (thus measuring the concentration of supply of intermediate goods).

The dispersion index $\rho \in \langle 0, 1]$ is then defined as

$$\rho_{\bullet j} = 1 - \sum_i h_{ij}^{(u)} \tag{4.8}$$

in the case of backward linkages, and

$$\rho_{i\bullet} = 1 - \sum_j h_{ij}^{(v)}. \tag{4.9}$$

$1, \ldots, n$, with

$$h_{ij} = \frac{\sum_j x_{ij}^2}{\left(\sum_j x_{ij}\right)^2}.$$

Then the mean of the numerator is $\overline{x_i^2} = 1/n \sum_j x_{ij}^2$, and the mean $\overline{x_i}$ of elements in row i of the original matrix X is equal to $\overline{x_i} = 1/n \sum_j x_{ij}$. Hence, $H_{i\bullet}$ can also be reformulated as

$$H_{i\bullet} = \frac{n \cdot \overline{x_i^2}}{(n \cdot \overline{x_i})^2} = \frac{\overline{x_i^2}}{n \cdot \overline{x_i}^2}.$$

Using the variance of row $\mathbf{x_i}$, $\sigma_i = \overline{x_i^2} - \overline{x_i}^2$, $H_{i\bullet}$ can be also stated as follows:

$$H_{i\bullet} = \frac{\overline{x_i^2}}{n \cdot \overline{x_i}^2} = \frac{\overline{x_i^2} - \overline{x_i}^2 + \overline{x_i}^2}{n \cdot \overline{x_i}^2} = \frac{\sigma_i + \overline{x_i}^2}{n \cdot \overline{x_i}^2} = \frac{1}{n}\left(\frac{\sigma_i}{\overline{x_i}^2} + 1\right) = \frac{1}{n}\left(cv_i^2 + 1\right).$$

for forward linkages. The higher the value of ρ, the more diversified are the relations of the respective sector to all other industries, i.e. the more robust is its position in the economic network.[4]

The conventional total linkage indicator derived in equations (4.4) and (4.7) is pre-multiplied by this generality index, weighting the total linkages to the producer network by the strength of direct relations (as expressed in the direct requirements matrix Z).

Hence, the index of supply ψ_i^S and use pervasiveness ψ_j^U for sectors $i, j = 1, \ldots, n$ can be formulated as follows:

$$\psi_i^S = n \left(\frac{\rho_{i\bullet}}{\sum_i \rho_{i\bullet}} \cdot \frac{\sum_j g_{ij}}{\sum_{ij} g_{ij}} \cdot \frac{v_i}{\sum_j v_j} \right)^{\frac{1}{3}} \tag{4.10}$$

$$\psi_j^U = n \left(\frac{\rho_{\bullet j}}{\sum_j \rho_{\bullet j}} \cdot \frac{\sum_i l_{ij}}{\sum_{ij} l_{ij}} \cdot \frac{y_j}{\sum_i y_i} \right)^{\frac{1}{3}} \tag{4.11}$$

These linkage measures thus consist of three subindices: the distribution of the direct sales and purchases of one sector to/from other industries, which indicates the degree of pervasive supply/demand; the conventional total (forward/backward linkage) measure for the identification of key sectors; and the normalized sectoral GDP/final demand which accounts for the scale of economic activity. In contrast to most other weighted linkages in input-output economics, the weights are outside the sum (and not attached to the coefficients), in order to assess the impact of each factor on its own.[5] The multiplicative relation prevents any factor from fully compensating the other, as may be the case if the partial indexes are just added up. Moreover, the normalization procedure allows the usual interpretation: $\psi^{S_i/U_i} > 1$ indicates a pervasive key sector while industries with $\psi^{S_i/U_i} < 1$ may qualify for a key sector in one aspect, but not with regard to all.

4.3 Data

Denmark as a Case Study

Denmark is chosen due to its position as a net importer of ICT products and the extent of the available data. Most of the empirical studies on GPTs (such as Hall and Trajtenberg (2004) or Moser and Nicholas (2004)) focus on the U.S., whose ICT sector exhibits strong export activities. Since we are primarily interested in the effects of ICT as an 'enabling' technology, Denmark as a global leader in other technologies fits the purpose of our analysis better. Regarding the latter, Statistics

[4]Note that ρ equals zero if a specific sector is tied to only one other sector. Thus, industries of this kind are excluded from the analysis. This is not a severe drawback, as, on the one hand, pervasiveness by definition requires a broad range of linkages, and, on the other hand, none of the direct requirement matrices under use have captured this case.

[5]For another example of linkages with weights outside the sum see Rao and Harmston (1979).

	Industries $1, \ldots, n$				Final Demand $\mathbf{y}$				
	Sector 1	Sector 2	...	Sector n	Private Consumption fc_{pr}	Public Consumption fc_{gv}	GFCF ce_{pr} / ce_{gv}	Changes in Stocks st	Ex-ports ex
Sector 1 Sector 2 ⋮ Sector n	Domestic Transaction Matrix Z^D				Y^D				
Sector 1 Sector 2 ⋮ Sector n	Import Matrix M				Y^M				
Imports nec.									
Taxes									
Value Added	$\mathbf{v}$								
Output	$\mathbf{x}$								

Schematic presentation of an input-output table (industry by industry)

Denmark also provides very good data that includes annual input-output tables (industry by industry) at constant prices of the year 2000 and covering domestic and import inter-industry flows (assuming for each product the same market shares as domestic supply); as well as capital flow tables spanning from 1993 to 2007 (see Strohmaier and Rainer (2013) and chapter 3 for a detailed description of the data handling).[6] For the missing years (1966–1992), we extrapolated the investment tables by calculating an average capital coefficient matrix that was subsequently multiplied with the gross fixed-capital consumption vector in the final demand. In order to smooth irregular investment activities, different time spans (over 3, 5, and 10 years) were used to derive a mean coefficient matrix. Finally, a sensitivity analysis showed that the results (i.e. the ranking of the industries) are robust against the different extrapolations.

Organization of Input-Output Data

In order to make a comprehensive investigation of the ICT sector, it is necessary to cover all channels through which ICT-related products could enter the production system (presented by the transaction matrix) and we therefore incorporate imports as well as capital flows. The first makes sense, as the purpose of this chapter is not to uncover key sectors that strengthen domestic economic activity, but to show the relevance of this technology for production; the latter is essential, as most products of ICT, such as computers and office machinery, are of fixed capital type and are thus not included in the intermediate demand. Regarding the calculation of the direct Leontief and Ghosh requirement matrix, we therefore follow Lenzen (2001) and Verspagen (2004) by partially closing the input-output

[6] All flows are expressed in basic prices, apart from imports that are valued in C.I.F and contain custom duties, in order to reflect the price level at which the respective commodity competes with the domestic product.

system:

$$A^* = A^D + K^D + A^M + K^M \tag{4.12}$$

with all flows referring to domestic output $\mathbf{x}$, so that for any intersectoral flow of transactions $T = \{t_{ij}\}_{n \times n}$, the direct input matrix A is calculated as[7]

$$A^{\bullet U} = T\ \hat{\mathbf{x}}^{-1} \tag{4.13}$$

for backward linkages, and

$$A^{\bullet S} = \hat{\mathbf{x}}^{-1}\ T \tag{4.14}$$

in the case of forward linkages.

A^D and A^M denote the domestic and imported intermediate demand. K^D is the domestic capital flow matrix, K^M is the matrix of capital flows produced by foreign industries.[8] In order to keep row sums equal to column sums, imports and investments were deducted from exports and gross fixed capital formation, respectively, while row-wise, value added was adjusted by capital flows. Thus, Verspagen (2004) indicates, these coefficients cannot be interpreted as technical coefficients any longer, since investments represent future consumption of fixed capital rather than current one.

In the context of this paper, we resort to a *generic* definition of ICT products and do not restrict it to a specific technology (which distinguishes our analysis from Bresnahan and Trajtenberg (1995) who dealt with semiconductors, and Lipsey et al. (2005) who discussed the computer and internet separately). However, most of the other empirical studies take a broad view on ICT. The classification of the ICT-producing sector based on ISIC Revision 3.1 thus contains the manufacturing sectors: (30) office machinery and computers, (32) radio and communications equipment etc.; as well as the service sectors: (72) computer activities, and software consultancy and supply. Since input-output data were just available on a two-digit level, we had to narrow down the ICT sector to its core industries, excluding four-digit industries that also produce ICT products.[9] Also, in contrast to Verspagen (2004), ICT-related services will be analyzed separately from other business services.

[7] A hat on a vector denotes the diagonal matrix built from this vector.

[8] Note that the capital flow matrix only comprises the deliveries of five sectors ((1) buildings other than residential, (2) machinery, (3) transport, (4) software, and (5) construction), excluding residential buildings, net aquisition of valuables and original works, all of which have been added to final consumption.

[9] Apart from the industries stated above, the OECD definition of the ICT sector contains the following industries: (3130) mfr. of insulated wire and cable; (3312) mfr. of instruments and appliances for measuring, checking, testing, navigating and other purposes, exc. industrial process control equipment; (3313) mfr. of industrial control equipment; (5151) wholesale of computers, computer peripheral equipment and software; (5152) wholesale of electronic and telecommunications parts and equipment; (6420) telecommunications; (7123) renting of office machinery and equipment (including computers).

4.4 Results and Discussion

Whilst the analysis was also undertaken over 130 sectors, the results shown here are based on calculations at a more aggregate level of 53 sectors and 32 sectors for the sake of better representation. The usual critical remarks on biasing results by aggregation apply here as well. Based on the indicators derived in equations (4.10) and (4.11), we will first discuss the extent of pervasiveness of the Danish industries from 1966 until 2007. Afterwards we will present the case of general purpose technologies, using the example of the new information and communication technology.

Our empirical findings will be compared to Castellacci's sectoral patterns of innovations, in order to examine if innovative sectors also exhibit a specific diffusion pattern of their products. Castellacci (2008) distinguishes four classes of sectors, each of which have two subcategories and characterize a distinct innovation profile. The taxonomy can be found in table 4.A.1. Referring to the notion of technological paradigms (Freeman and Louca, 2001), advanced knowledge providing sectors (such as machinery and equipment, and IT and knowledge-intensive business services), science-based manufacturing industries (e.g. ICT manufacturing, chemicals) and network infrastructure services (telecommunications and financial services) can be closely linked to the current general purpose technology, ICT.

In contrast, scale-intensive manufacturing sectors (such as rubber, plastic products and motor vehicles), supplier-dominated industries (mainly producing personal goods and services) and physical infrastructure services (i.e. wholesale and transport) are associated with the Fordist paradigm that characterized production in the post-war period.

Pervasive Key Sectors

Table 4.1 lists those industries that recorded above-average linkages throughout the period between 1966 and 2000. The detailed industry ranking is presented in table 4.A.1 in the appendix. Regarding downstream pervasiveness, the traditional sectors of manufacturing have played a key role in the four decades under study. Not surprisingly, construction also qualifies as an important supplier industry. Concerning the service sector, those industries that show the strongest ties to others downstream are mainly assigned to infrastructure and distributive services, and include, e.g., public administration, wholesale and transport as well as real estate. On the other hand, the food and textile manufacturing industries have continuously been important with respect to pervasiveness in the utilization of intermediate inputs (upstream). According to Castellacci's taxonomy, the technological trajectories of these sectors can be categorized as supplier-dominated; i.e. the bulk of technical progress in the sectors has been created by the industries upstream. To the extent that intersectoral linkages also represent the exchange of technological information embodied in products, our empirical findings underpin this taxonomy. Furthermore, education, health and social work have shown significant linkages upstream. Table 4.1 also depicts real estate activities and public administration as key sectors both in terms of use and supply pervasiveness.

Supply Pervasiveness		**Use Pervasiveness**	
ISIC	Activity	ISIC	Activity
21	Mfr. of paper prod.; printing and publish.	15-16	Mfr. of food, beverages and tobacco
27	Mfr. and processing of basic metals	17-19	Mfr. of textiles, wearing apparel and leather
29	Mfr. of machinery and equipment n.e.c.	60	Land transport
45	Construction	70	Real estate activities
51	Wholesale	75	Public administration & defense
70	Real estate activities	80	Education
74	Other business activities	85.1	Health care
75	Public administration & defense	85.3	Social work activities

Table 4.1: Pervasive key sectors in Denmark between 1966 and 2000

Figure 4.1 plots the ranking positions (in ascending order) of the 53 industries with regard to these two indicators for 2007. As one can see, the indices are positively correlated due to the sectoral weights that were chosen. However, there are a few outliers: The food and textile industries show significant linkages to their supplier industries, while they rank low in downstream pervasiveness. The opposite case holds for construction and other business activities.

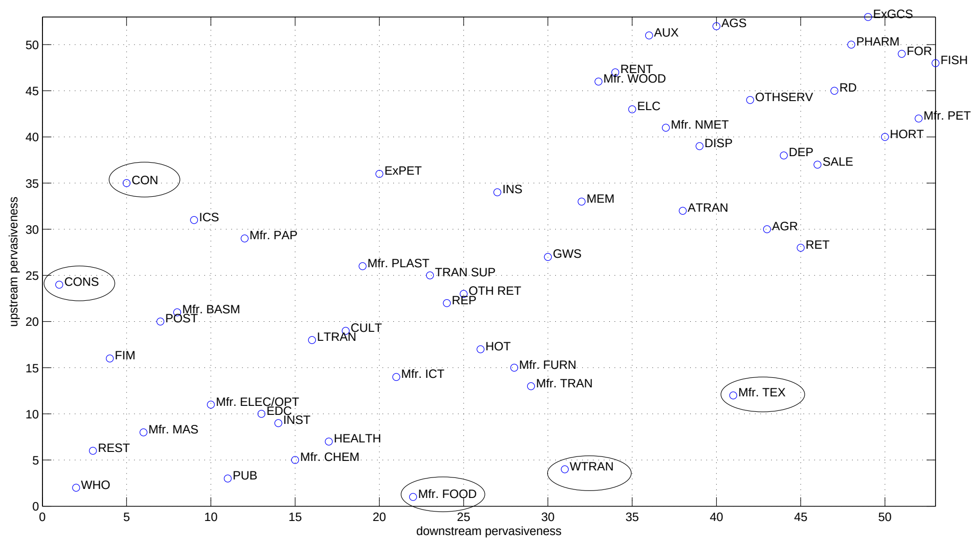

Figure 4.1: Downstream versus upstream pervasiveness according to the industry ranking (in ascending order). The industry classification is listed in table 4.A.1.

Turning to sectoral dynamics, figures 4.2 and 4.3 show the change in ranking positions between 1966 and 2007. Each industry is thereby defined by its Herfindahl generality index and the total (forward/backward) linkages, which together constitute the angle, as well as its ranking position, which translates into the radius of the polar plot. For organizational purposes, the industries were aggregated to 32 industries. The core of the polar grid contains the ten most important sectors according to our indicator. The further an industry moves to the periphery, the lower it ranks. The origin represents the average degree of pervasiveness and intersectoral impact in terms of linkages. Thus, the upper right area contains those sectors that are connected directly and indirectly to a broad range of sectors. The lower right area is characterized by high diversification, but low impact. The further one moves clockwise, the less pervasive the industries become. The upper left area comprises those industries that have a high total impact upstream (downstream), but concentrate their demand (supply) only over a few other sectors.

Fig. 4.2 shows that most of the key industries in terms of downstream pervasiveness – located in the core – relate to supporting infrastucture services, in particular transport (TRANS), wholesale trade (WHO), financial services (FIN/RE), and most recently, post and telecommunications (POST). Out of the ten most important industries, machinery and equipment (MACH), post and telecommunications (POST) and other business activities (OBA) provide their products to a broad range of sectors. The latter two are closely linked to the ICT-producing sector and reflect the ongoing outsourcing processes of business services from manufacturing firms. In contrast, personal consumer goods and services such as those provided by the food and textile industry (FO/TEXT), or sale and repair of motor vehicles (S/R VEH) can be found in the left half of the figure.

With regard to upstream pervasiveness, figure 4.3 shows a less balanced distribution of the industries along the polar grid. More specifically, the bulk of sectors with a diversified demand for intermediate products have a low impact upstream (and are therefore located in the bottom right area of the plot). The only industries in the core that are both pervasive and characterized by strong total linkages upstream are those that provide science-based manufacturing goods, i.e. the ICT sector as well as machinery and equipment (MACH).

Dynamics Furthermore, the polar representation allows studying the dynamics in the industry networks. For doing so, we split the period of 42 years into 10-year intervals, and calculate the Euclidean distance between the position of each industry at time t and $t+10$. Adding up these distances is used as a proxy of how dynamic the respective sector has been over the whole period under study. Table 4.2 reports the ten most dynamic sectors in terms of supply and use pervasiveness. Regarding supply pervasiveness, half of the industries represent advanced knowledge providers (ICS, R&D, OBA) or science-based manufacturing sectors (ICS, CHEM), while only two sectors (VEH, HOT) can be linked to consumer-oriented industries. The remaining sectors are not classified under Castellacci's taxonomy. The petroleum (PET) and chemical (CHEM) industry have become more con-

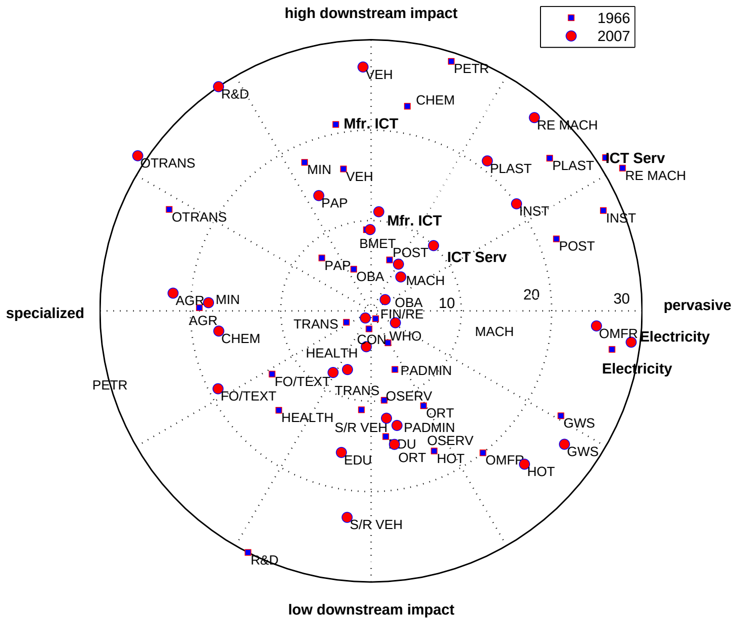

Figure 4.2: Comparison of the industry structure according to supply pervasiveness

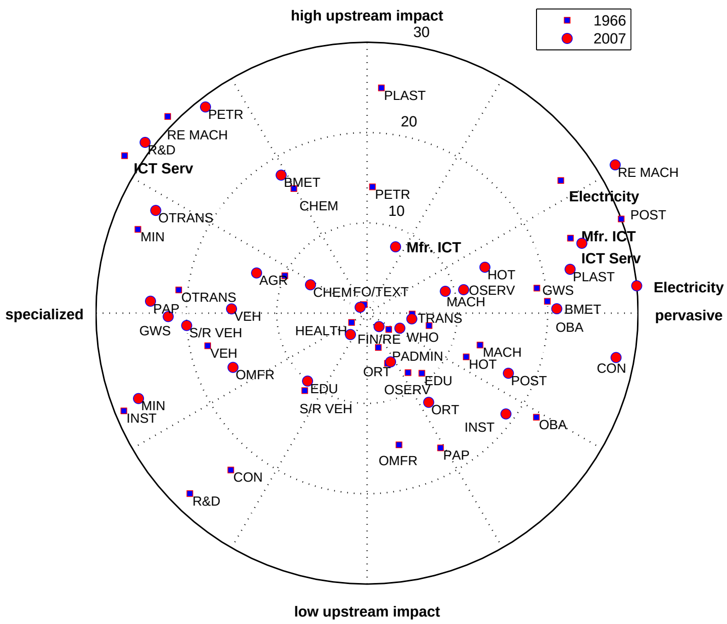

Figure 4.3: Comparison of the industry structure according to use pervasiveness

centrated in terms of supply between 1966 and 2007, while R&D also shows a lot of dynamics by densifying its trade network to the industries downstream (see figure 4.4). This is not reflected in its ranking position though, as the sector's share in total value added is relatively low. Turning to use pervasiveness, the industries linked to the ICT-producing sector, i.e. ICT manufacturing and services (ICM, ICS), machinery and equipment (MACH), electrical apparatus & medical and optical instruments (INST) as well as post and telecommunications (POST) exhibit the strongest dynamics. Interestingly, all of them are strongly associated with the IT paradigm and have diversified their demand upstream. This is especially the case for ICT services and medical and optical products which moved from far left to the right half of the plot (see figure 4.3). The findings underscore the 'restlessness' of these sectors due to the emergence of ICT, and the profound changes in intersectoral linkages up and down the production chain.

Rank	Code	Supply (downstream)	Code	Use (upstream)
1	OMFR	Other manufacturing	POST	Post and telecommunications
2	PET	Extr. of petroleum etc.	INST	Mfr. of electrical, & optical equipment
3	ICM	ICT manufacturing	ICS	ICT services
4	VEH	Mfr. of mothor vehicles	CON	Construction
5	CHEM	Mfr. of chemicals etc.	RE/MAS	Renting of machinery and equipment
6	R&D	Research & development	ICM	ICT manufacturing
7	RE/MAS	Renting of machinery and equipment	HEALTH	Health activities
8	ICS	ICT services	MIN	Mining and quarrying
9	HOT	Hotels and restaurants	TRANS	Transport services
10	OBA	Other business activities	FO/TEXT	Food and textile industry

Table 4.2: Ranking of industry dynamics according to supply and use pervasiveness

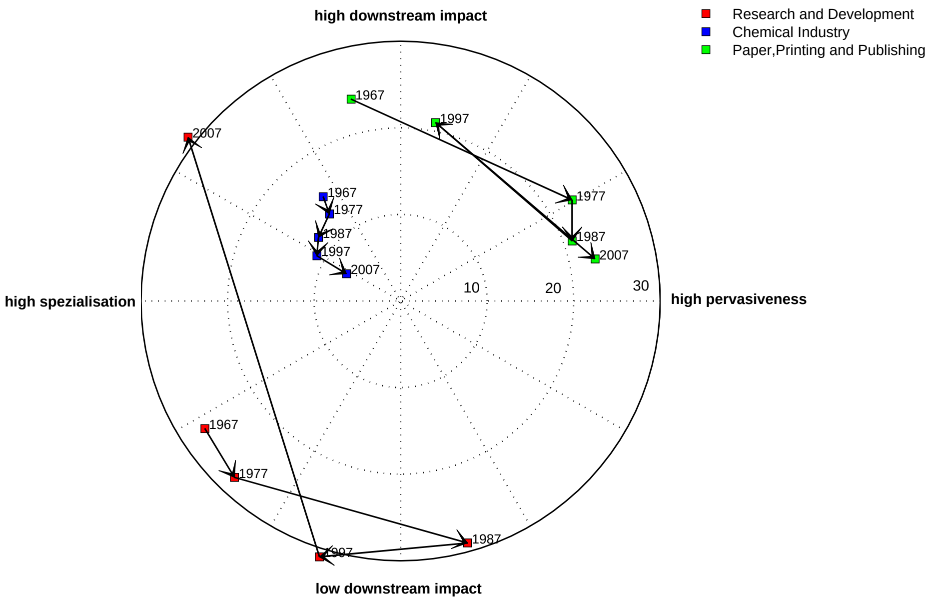

Figure 4.4: Industry dynamics in terms of supply pervasiveness

The Case of ICT

Table 4.3 lists the change in ranking positions over time (based on a 53-sector classification) for the ICT core sectors as well as for those industries closely related to them. As can be seen, all sectors have gained in both downstream and upstream pervasiveness, but to a different extent: In terms of downstream pervasiveness, the ICT manufacturing and ICT service industries show the biggest improvements (by 28 and 40 positions, respectively). Considering upstream pervasiveness, the ICT manufacturing sector as well as post and telecommunications climbed up significantly in the ranking (by 39 and 26 positions, respectively).

			1966		1980		1990		2000		2005	
Code	ISIC	Activity	down	up	down	up	down	up	down	up	down	up
ICT	30,32	Mfr. of ICT	47	46	41	38	35	26	22	13	19	7
INST	31,33	Mfr. of electrical and optical equipment	15	36	16	26	16	21	13	10	11	12
POST	64	Post and/ telecommunications	24	45	17	45	13	39	9	25	8	19
RE/ MAS	71	Renting of machinery and equipment etc.	53	50	52	50	53	46	38	48	34	47
ICS	72	Computer and related activities	49	53	39	53	31	49	15	34	9	31

Table 4.3: Ranking of the ICT-producing sector and related industries. The numbers in the second column indicate the assignment of the respective sector to the ISIC Rev. 3.1 two-digit classification, columns 4-13 show the ranking of each industry according to its pervasiveness downstream (down) and upstream (up).

Figure 4.5 depicts the trajectories of downstream pervasiveness for current general purpose technologies, ICT and electricity. The polar plot shows that these industries indeed provide their products to a wide range of sectors, since they are located in the right half of the figure. However, different dynamics are at work: Whereas the electricity sector exhibits a very low degree of dynamics (the scatter is very dense), the ICT industries have clearly been moving to the core. Furthermore, in the ICT manufacturing industry in particular, one can see that the trade network of this sector was rather concentrated in the first decade, thus it did not qualify as a GPT right from the beginning. Only after it had become more widespread, as reflected by a movement of ICT manufacturing to the right along the horizontal axis in figure 4.5, it started approaching the core in the mid-1980s.

By means of the extended linkage indicators, it is possible to identify the key sectors in the economy, and the structural dynamics (in terms of both industry rankings and distances between annual positions) over time. However, these tools do not allow for analyzing the evolution of *intersectoral* linkages, and thus tracing the diffusion path of a technology supplied by a specific industry. A GPT is characterized by its pervasive employment in the production process of other industries. In order to see this, one would need to keep the information on the disaggregated level and to examine the change in the respective input coefficients. The compound transactions matrix, which includes not only domestic and im-

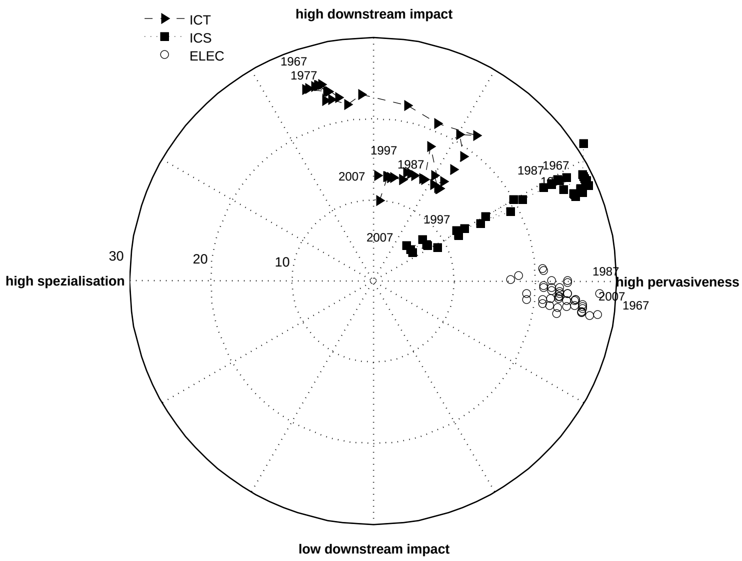

Figure 4.5: Change in ranking over time for ICT manufacturing and service sector, as well as for electricity

ported flows of intermediate products, but also of fixed capital, is used in the following to derive the diffusion pattern of ICT. Furthermore, we will distinguish between ICT manufacturing and ICT service sectors, due to the rapid growth and the increasing significance of the latter. An input share above 0.01 for ICT manufacturing and service products was arbitrarily chosen as an indicator that the respective sector has adopted this technology in its production.

Figure 4.6 translates the deployment pattern of ICT into the cumulative share of adopters, as a measure of extensive use of this technology. ICT manufacturing products have been steadily employed in over 10 per cent of the sectors since the 1960s, but experienced a takeoff in the mid-1980s with the emergence of the new information and communication technology.[10] Another leap is observable before the dot.com crash in 2000.[11] For ICT-related services, particularly software, the diffusion rate accelerates between 1970 and 1985 and then again between 1992 and 2000. Fitting the scatter plot, the diffusion path approaches the typical sigmoid curve for both ICT industries.[12] It is interesting to note that the best curve fit for ICT services is achieved by splitting the whole period in two subintervals. This

[10]Note that data are based on constant prices of the year 2000, thus figures for the early period under analysis contain an upward bias in the use of ICT due to the significant price deterioration this technology saw prior to the reference year.

[11]The relatively low adoption rate for ICT manufacturing products of about 60 per cent in 2007 can be explained by our narrow definition which excludes important industries such as the semiconductor industry and the measuring/control equipment industry.

[12]The norm of the residuals is equal to 0.013 and 0.026 for ICT services and 0.067 for ICT manufacturing. The latter value can be mostly explained by the outlier in 2000 that reflects unusually high investments in ICT manufactured capital in that year.

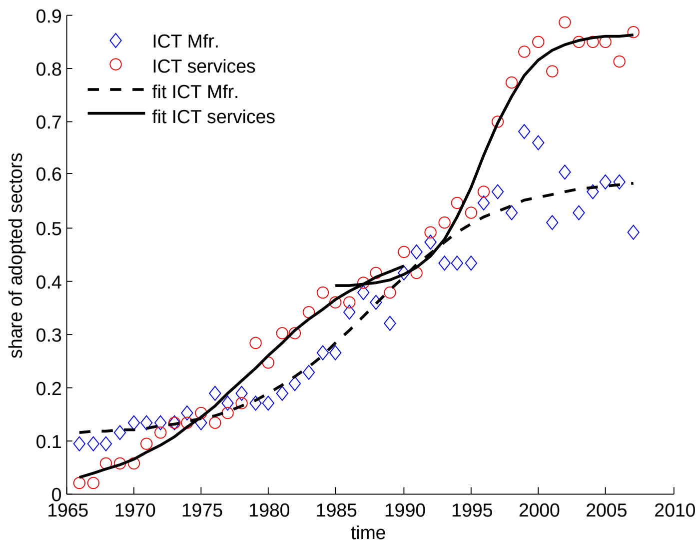

Figure 4.6: Diffusion path of ICT

reveals the significance of complementary products for the diffusion of a general purpose technology. Firms operating in a GPT-producing industry face a high level of uncertainty for their R&D expenditures. Investing in the development of a new technology only pays off if other companies also start developing complementary components and a broad range of sectors is willing to adopt the new technology. This ultimately causes a *retarded* takeoff of the industry depending on the intrasectoral rate of innovation and the intersectoral adoption rate. Figure 4.6 shows that the diffusion of ICT-manufacturing in the beginning of the 1980s was indeed boosted by developments in the ICT service industry. The accelerated adoption process for manufacturing products in turn sped up the diffusion of ICT services after 1992. This supports the argument that the pervasive use of a general purpose technology requires a facilitating environment that allows different sectors to switch to the new technology.

Figure 4.7 depicts the intensity of use of ICT manufacturing products and ICT services in the Danish economy from 1966 until 2007. The contour plot shows that ICT goods and ICT services initially spread over the neighboring industries, such as mfr. of machinery and equipment n.e.c. (MAS), mfr. of other electrical, medical and optical equipment (INST), as well as real estate activities (RES) and renting of machinery and equipment (incl. office computers) n.e.c. (RE/MAS). In the mid 1970s, post and telecommunications (POST) and the financial markets (FIM) started to utilize ICT. Almost a decade later, one can see the beginning of online sale (ORE) and online auctioning (CONS), and the entry of ICT in research & development (RD). Afterwards, the technology spread over most sectors in manufacturing and services, with the primary industries as the last sectors to adopt it.

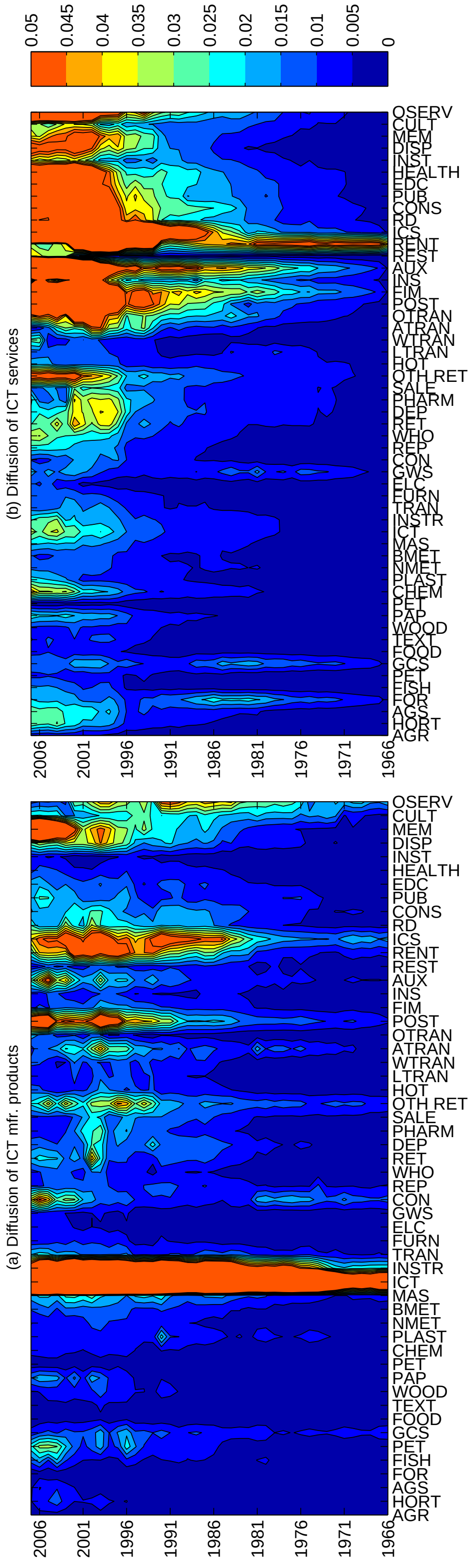

Figure 4.7: Intensity of use of ICT manufacturing products (a) and ICT services (b) across sectors

4.5 Conclusion

This paper has attempted to show that when it comes to general purpose technologies, the conventional tools for identifying key sectors in the economy are not sufficient, as they do not embrace the specific characteristics of pervasive technological change. We argue, in line with social network theory, that a diversified producer (user) network across industries reflects the robustness of a specific industry in the economic system. The ability to reduce costs in its application sectors may be the most important feature of an innovation; and then it would make a difference whether the technological breakthrough is of single or general purpose. The latter leads *ad hoc* to efficiency gains in a broad range of sectors that progressively channel through to the other industries tied to them. In this aspect, general purpose technologies form a robust base in the economy. The traditional indicator is therefore extended by a dispersion index, in order to explicitly capture the direct linkages of one sector to the other. However, if the size of economic activity is not sufficiently large, a pervasive sector has no impact on the production system and thus should not qualify as a GPT. Hence, the proposed index also features a proxy for the economic performance. By means of this indicator, it is also possible to trace industrial dynamics over time.

The application of these measures for Denmark uncovers that ICT is indeed a general purpose technology at work, and thus complements conflicting findings for the U.S. economy which are based on conventional linkage analysis (see Verspagen (2004)). The results show that ICT manufacturing and service industries have been continuously evolving towards the core of the economic system. The analysis also reveals that the distinction between ICT manufacturing and services is important, as they show a different, though clearly interrelated, diffusion path. Our figures certainly underestimate the impact of ICT, because our definition does not comprise all ICT-producing sectors. This is because data is only available on two-digit level, which does not allow to differentiate between subindustries, for example, in the electric machinery and apparatus industry. We could therefore only capture those industries that entirely produce ICT goods or services. In this context, a classification according to ISIC Rev. 4.1 would have been preferable, since this industry aggregation discloses ICT activities more concisely.

The present analysis has also been related to sectoral patterns of technical change. The taxonomy proposed by Castellacci (2008) was used to examine how far sectors with similar innovation profiles also exhibit a coherent utilization and diffusion pattern of their products. En gros, our empirical findings support the classification, since all sectors related to the Fordist paradigm (supplier-dominated goods and services, physical infrastructure services, and scale-intensive manufacturing) have moved towards the periphery of the economic network and got more concentrated in their supply (see figure 4.B.1 in the appendix). On the other hand, the industry groups associated with ICT (advanced knowledge providers, science-based mass production goods and network infrastructure services) are located in the right half of the plot and show a high degree of pervasiveness.

In this regard, our diffusion-oriented approach is able to detect shifts in technological regimes by their impact on the intersectoral network. Together with innovation indicators at the firm level, it can help to identify the locus and range of radical technical change and the maturity stage of the related technology. Our analysis also highlights the distinct notion of a technological paradigm and a general purpose technology: While ICT indeed represents a GPT, the Fordist paradigm of production does not meet the criterion of pervasiveness during the period under study.

Furthermore, the paper at hand stresses the close link between vertical integration and the diffusion of a new technology. As we have demonstrated empirically, the functional classification of sectors found in most of the endogenous growth literature, and specifically in the theory of GPTs, which differentiates between an R&D sector, an intermediate good as well as consumer good sector, is not able to span the great variety not only in innovation activity, but also in the degree of economic integration among sectors. Our study thus also underscores the necessity of multisectoral approaches in growth literature that take into account the circular flow of production and the cross-dependencies between heterogeneous industries.

Appendix

4.A Industry Ranking

Table 4.A.1: Ranking of Danish industries. The second and third column indicate the assignment of the respective sector to the ISIC Revision 3.1 two-digit classification, the fourth column refers to the taxonomy by Castellacci (2008), columns 5-11 contain the ranking of each industry according to its pervasiveness downstream (down) and upstream (up) in ascending order.

				1966		1980		1990		2000	
Code	ISIC	TAX	Activity	down	up	down	up	down	up	down	up
AGR	1		Agriculture	40	20	44	19	41	17	33	29
HORT	1		Horticulture, orchards etc.	50	26	48	34	47	36	49	37
AGS	1		Agricultural services	36	51	40	51	40	51	43	52
FOR	2		Forestry	44	43	45	46	49	48	51	49
FISH	5		Fishing	45	28	49	37	51	35	52	47
PET	11		Extr. of crude petroleum, natural gas etc.	28	44	35	44	20	47	18	35
GCS	14		Extr. of gravel, clay, stone and salt etc.	34	48	38	48	43	52	48	53
FOOD	15-16	PGS1	Mfr. of food, beverages and tobacco	14	1	14	1	15	1	19	1
TEX	17-19	PGS1	Mfr. of textiles, wearing apparel, leather	31	8	34	12	38	10	39	12
WOOD	20	PGS1	Mfr. of wood and wood products	25	41	30	40	36	40	32	40
PAP	21-22	PGS1	Mfr. of paper prod.; printing and publish.	8	25	8	28	9	25	11	24
PET	23		Mfr. of refined petroleum products etc.	42	3	52	3	52	30	53	44
CHEM	24	MPG1	Mfr. of chemicals and man-made fibres etc.	23	21	18	11	14	9	16	7
PLAST	25	MPG2	Mfr. of rubber and plastic products	32	40	21	32	18	28	20	26
NMET	26	MPG2	Mfr. of other non-metallic mineral products	22	31	25	30	37	43	35	41
BMET	27,28	MPG2	Mfr. and processing of basic metals	7	27	6	20	7	22	5	21
MAS	29	AKP2	Mfr. of machinery and equipment n.e.c.	6	15	3	10	5	8	6	8
ICT	30,32	MPG1	Mfr. of ICT	47	46	41	38	35	26	22	13
INST	31,33	MPG1 AKP2	Mfr. of electrical machinery and apparatus & Medical, precision and optical instruments	15	36	16	26	16	21	13	10
TRAN	34,35	SIS2	Mfr. of transport equipment	11	19	15	18	24	11	31	14
FURN	36,37	PGS1	Mfr. of furniture; manufacturing n.e.c.	21	18	23	14	27	13	27	15
ELC	40		Electricity	39	34	31	27	28	45	30	45
GWS	40,41		Gas and water supply	30	22	32	24	25	33	26	27
CON	45		Construction	1	30	1	23	4	34	4	36
REP	50	PGS2	Sale and repair of motor vehicles etc.	10	13	10	13	19	16	25	20
WHO	51	SIS2	Ws. and commis. trade, exc. of m. vehicles	3	4	5	4	3	3	2	3
RET	52	PGS2	Retail trade of food etc.	26	11	29	17	32	20	40	22
DEP	52	PGS2	Department stores	41	39	42	42	42	42	46	39
RE/PH	52	PGS2	Re. sale of phar. goods, cosmetic art. etc.	51	49	50	49	50	50	50	50
RE/CF	52	PGS2	Re. sale of clothing, footwear etc.	48	38	47	41	46	41	47	42
ORE	52	PGS2	Other retail sale, repair work	17	12	22	22	30	24	28	23
HOT	55	PGS2	Hotels and restaurants	18	10	20	16	21	14	24	17
LTRAN	60	SIS2	Land transport; transport via pipelines	4	16	9	9	10	12	10	18
WTRAN	61	SIS2	Water transport	52	17	52	15	48	15	34	11
ATRAN	62	SIS2	Air transport	38	32	28	29	34	31	42	28
OTRAN	63	SIS2	Support. trans. activities; travel agencies	29	24	24	25	22	23	21	32
POST	64	SIS1/2	Post and telecommunications	24	45	17	45	13	39	9	25
FIM	65	SIS1	Financial intermediation	13	29	12	31	8	18	8	16
INS	66	SIS1	Insurance and pension funding	33	33	36	39	33	32	36	31
AUX	67	SIS1	Activities auxiliary to finan. intermediat.	43	52	46	52	44	53	44	51
RES	70		Real estate activities	2	6	2	5	1	4	3	6
RE/MAS	71		Renting of machinery and equipment etc.	53	50	52	50	53	46	38	48
ICS	72	AKP1	Computer and related activities	49	53	39	53	31	49	15	34
RD	73	AKP1	Research and development	46	42	43	43	45	44	45	46
CONS	74		Consultancy etc. and cleaning activities	5	37	4	36	2	27	1	30
PUB	75		Public administration etc.	9	2	7	2	6	2	7	2
EDU	80		Education	12	5	11	6	11	5	12	5
HEALTH	85		Health activities	20	7	19	7	17	7	17	9
SW	85		Social work	19	9	13	8	12	6	14	4
DISP	90		Sewage and refuse disp. and similar act.	35	47	33	47	29	37	37	38
MEMB	91		Activities of membership organ. n.e.c.	37	35	26	33	26	29	29	33
CULT	92		Recreational, cultural, sporting activities	27	23	27	21	23	19	23	19
OSERV	93-99		Other service activities	16	14	37	35	39	38	41	43

Abbr.: AKP: advanced knowledge providers ((1) knowledge-intensive business services, (2) specialized suppliers manufacturing); MPG: mass production goods ((1) science-based manufacturing, (2) scale-intensive manufacturing); SIS: supporting infrastructure services ((1) network infrastructure, (2) physical infrastructure); PGS: personal goods and services ((1) supplier-dominated goods, (2) supplier-dominated services).

4.B Results for Castellacci's Taxonomy of Sectoral Patterns of Innovations

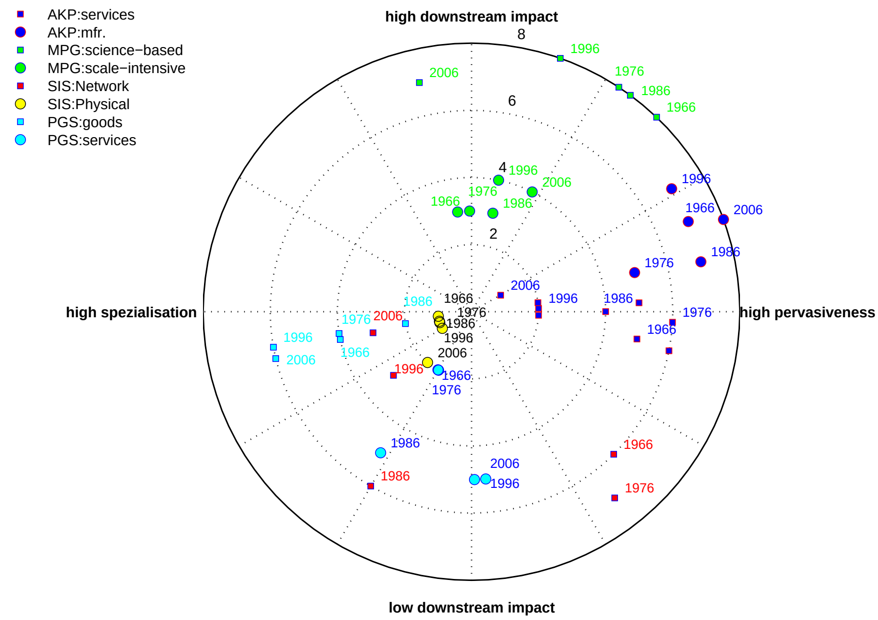

Figure 4.B.1: Dynamics in the industry structure according to Castellacci's taxonomy of sectoral patterns of innovations (Castellacci, 2008). AKP: advanced knowledge providers; MPG: mass production goods; SIS: supporting infrastructure services; PGS: personal goods and services

Chapter 5

The Evolution of Economic Structure under Pervasive Technological Change: A Social Network Approach

A breakthrough in a general purpose technology (GPT) distinguishes from other types of innovations in both its significance in the economic system and by its diffusion process over the industrial network. In order to trace GPTs at the sectoral level, we propose a novel method for analyzing structural change, based on a dynamic social network approach, and in doing so derive a technical tree that represents the economic structure under the notion of pervasiveness. We apply this framework to the GPT currently at work, information and communication technologies (ICT), showing the evolution of ICT-producing sectors and their impact on the economic structure in Denmark between 1967 and 2009. Our findings reveal that the proposed framework is able to detect general purpose technologies by the locus of their production, and that ICT services, but not the ICT manufacturing sector, have become one of the core industries of the Danish economy.

Keywords | general purpose technologies, social network theory, input-output, evolutionary economics, organizational structure

5.1 Introduction

The economic system is an indeterminate, heterogeneous, irreversible system which is in constant disequilibrium and contains evolutionary characteristics (Janssen, 1998). This holds *a fortiori* true when a new general purpose technology (GPT) enters the system, which affects all sectors due to its variety in use and fosters innovative activities in the whole economy as an essential part of the adaption process.

In the mid-1990s pervasive technologies became a widely-debated issue in economics, not least because of the emergence of the new ICT whose impact became very evident in daily life and was yet not visible in the productivity accounts. Dynamic theories were evolving around the notion of GPTs which was introduced into the economic literature by Bresnahan and Trajtenberg (1995), emphasizing the impact of major technological change on the economic structure and on long-term economic growth. The general content of this discussion was nevertheless not new, but can be linked to other concepts explaining long waves in economic history, most prominently to the pioneering work of Schumpeter (1997). Since then, a variety of theories have been centered around drastic technological change (see, for example, the theory of technoeconomic paradigms (Dosi, 1982; Perez, 1983), the notion of macroinventions (Mokyr, 1990), or enabling technologies (Lipsey and Bekar, 1995), spreading the seeds of evolutionary economics. Acknowledging the similarities on the content level, Verspagen (2004) calls the literature on GPTs the American counterpart of Schumpeterian economics.[1] Nevertheless, the concept of general purpose technologies is by no means a re-inventing of the wheel (or squaring the circle by embedding it into a dynamic equilibrium model), but has its own right to exist; not least because of its emphasis on the generality of purpose of a technological breakthrough, i.e. its inherent potential to be used throughout the economic system. All other characteristics assigned to a GPT can subsequently be derived from the notion of pervasiveness: (1) the novelty in design that ensures the technology to be demanded in all other sectors, but simultaneously prevents it from being employed upon arrival; (2) the specific life cycle of the technology in which its impact on the system unfolds itself only at a later stage, after the diffusion process has faded out; (3) the coordination problems on the mesoeconomic level among the GPT-producing industry and its application sectors which – due to the pervasiveness of the technology – translates into cumulative effects on the macroeconomic level. When it comes to detecting these changes in the economic structure, indicators based on direct and indirect inter-industrial linkages as reported in input-output tables have become a popular tool for identifying key sectors (see, e.g., Rasmussen (1956), Hirschman (1958), Jones (1976), Sonis et al. (1995), Lenzen (2003)). An impulse given to any of those industries would not only affect sectors directly tied to them, but would eventually channel through the whole intersectoral network.

However, these conventional tools do not sufficiently explain general purpose technologies, as they do not consider the specifics of this type of technological change.

The methodology proposed henceforth will evolve around the notion of pervasiveness as the crucial feature that distinguishes a GPT from other radical innovations and interpretes it in the light of a general theory of economic evolution. Despite composing the heart of the theory of GPTs, the term lacks a clear-cut definition. According to Field (2011), whichever way you look at it in input-output tables – either considering only direct linkages of the GPT-producing sector to other industries or also taking into account the multiplier effects – is unsatisfactory; the former would underrate the impact of a general purpose technology, the latter would subsume basically each kind of technology under the notion of a GPT.

An explanation of why 'general purpose' is a significant criterion of a technology is offered by the theory of social networks. Analogously to Bothner et al. (2010), we argue that an industry occupies a rather robust position in the eco-

[1] See Lipsey et al. (2005) for an excellent review of GPT theories and related concepts.

nomic system the more diversified the network is which it belongs to, as the impact of an innovation is crucially dependent on the range of sectors adopting it and their ties to other industries. To the extent that robustness means "diversification across the diversified" (Bothner et al., 2010, 945), GPT-producing sectors form the robust base in the economy.

In support of our hypothesis, we apply the concept of organizational structure in the analysis of the inter-industrial network, in order to derive a tree data structure, called technical tree, and explore the dynamics of the evolving technical tree over time. With regard to GPTs, we hypothesize twofold: (i) Upon arrival of a new GPT, the GPT-producing industry is located somewhere at the bottom of the technical tree; (ii) over time, advances in the GPT lead to new opportunities in application, so that the GPT-producing industry evolves close to the core of the community and disposes of an increasing number of descendants. The framework is subsequently applied to the Danish economy over a time span of 43 years. Annual input-output tables and investment matrices together with data on the capital consumption of 130 industries from 1967 to 2009 describe the structure of inter-industry relationships.

The paper proceeds as follows: Section 5.2 introduces the method, section 5.3 describes the data handling, while the empirical findings are discussed in section 5.4. Section 5.5 gives concluding remarks and proposes some direction for future research.

5.2 Methodology

A major technological breakthrough leads to the (trans)formation of (new) industries producing it, but unfolds its impact on the whole economic system primarily via the diffusion process. The latter requires intersectoral coordination whose success/failure determines the life time of the technology and of the sector producing it, as well as the evolution of the economic system on the whole.

Unlike most of the other work in the field of general purpose technologies, our analysis does not focus on the technology as such, but on the industry that provides the technology to other sectors for its potential application. We therefore follow Dopfer and Potts (2008) by putting emphasis on the meso unit as the "analytical nexus of economic evolution of structural change" (59).

The proposed framework draws on two distinctive approaches in the field of social network theory (namely on Bothner et al. (2010) and Qiu and Lin (2011)) and contains three steps: (1) A modified centrality measure ranks the industries according to their importance, i.e. the degree of robustness in the network. (2) A random walk on the graph transforms the inter-industrial network into a tree data structure. (3) A tree learning algorithm allows for deriving the evolving community tree. In the following, each step will be explained separately.

Industry Ranking according to Robustness

Bothner et al. (2010) argue that higher concentration in social networks uncovers the fragility of some members, because their nodes in the network depend on a few others and not on a broad base. Hence, pervasive social relations underpin the robustness of a member's status in the network, and therefore need to be taken into account. On the methodological level, the authors combine the Hirschman-Herfindahl concentration index with Bonacich's recursive method for measuring centrality in networks (Bonacich, 1987). As is also shown, this concept can be applied to industries as well, where the relational matrix represents the interconnectedness of sectors up and down the production process. In the context of this paper, we will use the indicator for measuring only the linkages of a sector downstream, i.e. its importance as supplier to other sectors. The relational matrix based on transaction flows between industries thus transforms into:

$$H = \{h_{ij}\}_{n\times n}$$

$$h_{ij} = \left\{\frac{z_{ij}}{\sum_j^{n-1} z_{ij}}\right\}^2$$

with elements h_{ii} being zero (i.e. intrasectoral linkages are not taken into account). z_{ij} are the deliveries of industry i to all other industries $j = 1, \ldots, n$, hence h_{ij} are the squared sectoral shares of industry i's output.

$H_{i\bullet}$ ranges between 0 and 1. The *lower* its value, the *wider* is the range of other industries a sector is connected with. The dispersion coefficients h_{ij} are subsequently introduced into Bonacich's recursive equation to account for coupling (Bonacich, 1987, 1173), in order to derive a measure of fragility:

$$f_i(\alpha,\beta) = \sum_j (\alpha + \beta f_j) h_{ij} \tag{5.1}$$

or in matrix notation, given that β is less in value than the reciprocal of the largest eigenvalue λ associated with the dispersion matrix[2]:

$$\mathbf{f}(\alpha,\beta) = \alpha\,(\mathbb{I} - \beta H)^{-1}\,H\;\mathbf{e} \tag{5.2}$$

with $\mathbf{e}$ being a column vector whose n entries equal one and α denoting a scaling parameter. β represents the degree to which a member's status depends on the status of those to which she is linked to. If β is zero, the fragility measure

[2] If $\beta < \lambda^{-1}$, equation (5.1), in matrix notation, becomes

$$\mathbf{f}(\alpha,\beta) = \alpha \sum_{k=0}^{\infty} \beta^k H^{k+1}\mathbf{e} = \alpha\left(H + \beta H^2 + \beta^2 H^3 + \ldots\right)\;\mathbf{e},$$

which in the limit corresponds to equation (5.2). $\sum_{k=1}^{\inf} \beta^{k-1} H^k = \sum_{k=0}^{\infty} \beta^k H^{k+1}$ is the total number of ties attached to a node in the network.

reduces to the Herfindahl index, and thus only accounts the strength and range of direct linkages to other sectors. The higher in magnitude, the more the status of the alters is considered, and $f_i(\alpha,\beta)$ becomes a function of direct and indirect linkages in the network.

With regard to inter-industrial relations, H as defined above only considers the distribution of a sector's sales to the rest of the industries, and not to final demand, and neither the size of economic activity. However, it is important to take the latter into account, because the mere fact that one industry's supply to the economic network is rather diversified does not qualify it for a key sector. In order to incorporate the scale of economic activity, the fragility index of sector i is weighted by its logarithmic share in total output $\sum_j x_j$:

$$\chi_i = ln\left[\frac{x_i}{\sum_j x_j}\right](-1)$$

Note that all shares are below 1, thus χ_i turns negative by taking the log. Multiplying the logarithmic shares by (-1) results in assigning higher values to smaller shares. This is essential, since equation (5.2) represents the level of fragility of an industry, and a small contribution to the annual output relative to other industries should even amplify the comparative weakness. Thus, equation (5.2) is extended to

$$\mathbf{f}^*(\alpha,\beta) = \alpha\,\mathrm{diag}(\chi)\,(\mathbb{I}-\beta H)^{-1}\,H\;\mathbf{e} \tag{5.3}$$

$\mathrm{diag}(\chi)$ denotes a diagonal matrix whose elements represent the individual weights of the industries regarding the annual output.

Since robustness is defined as the complement to fragility, we derive the following equation for ranking industries according to their robustness:

$$\mathbf{r}(\alpha,\beta) = \mathbf{e} - \mathbf{f}^*(\alpha,\beta) \tag{5.4}$$

The last term on the right hand side represents the vector of weighted fragility scores $\mathbf{f}^*$. The shifting parameter α is used to normalize $\mathbf{f}^*$ such that the sum of the squared lengths of the individual fragility indices equals the size of the network (see Bonacich (1987, 1173) and Bothner et al. (2010, 952)). A fragility index of 1 thus means that the respective industry has an average degree of fragility, irrespective of the number of members in the network. Using the unit vector $\mathbf{e}$ as the minuend, a robustness score of $r_i > 0$ indicates that industry i has a robust position in the network, while $r_i < 0$ reveals the respective industry to be rather fragile.[3] β allows determining the extent of vertical integration one wishes to analyze. Analogous to Bonacich (1987), β reflects a radius within which the

[3] As the industries are subsequently ranked according to their robustness score, the minuend can be chosen arbitrarily, because the ordinal structure does not change with the shifting parameter.

robustness of a node can be measured, gradually shifting from the local structure ($\beta = 0$ and the direct network) to the global structure ($0 < \beta < \lambda^{-1}$, which considers direct and indirect linkages via coupling). The robustness score $\mathbf{r}$ will be in the following used to derive the technical tree.

Deriving the Technical Tree

The seminal paper of Bresnahan and Trajtenberg (1995) shows that in a decentralized economy, the generality of purposes together with increasing returns to scale in the GPT producing sector generates coordination problems among up- and downstream sectors. As a conclusion, not only the inner organization of the inventing industries must be examined more closely, but also sectoral interrelations have to be investigated more carefully, since "the locus of technical change" matters (Bresnahan and Trajtenberg, 1995, 85). Even though the theoretical framework is completely different, Dopfer and Potts (2008, 50) argue in a similar way regarding the meso level, as it is primarily the carrier population – not the single carrier of a technical rule – that evolves. Questions of the industrial organization on the micro level thereby find their analogue in the problem of coordination on the macro level: While the first is triggered by inventive activities of microeconomic agents, the latter occurs in consequence of a meso change. Applying a model of organizational structure on the meso level may therefore give fruitful insights into changes on the macro level.

However, so far our tool is one-dimensional, as it only gives the position of each industry in a ranking, but does not reveal inter-industrial connections; we want to show the latter while preserving the original ranking. This inevitably leads to a tree structure where the most robust industries are located close to the root of the tree (see figure 5.1).[4] In order to transform the sectoral network into this kind of data structure, inter-industrial relations are reinterpreted as a weighted and directed graph, where each node represents an industry which shares an edge with another node in the network if there are transaction flows between the two respective industries. The magnitude of the transaction flows gives the weight of the edge, the destination of the flows its direction (for a detailed analysis of the network topology of input-output tables, see McNerney et al. (2013)). Performing a t-step random walk on this graph would then provide a measure of the volume of paths between two nodes (Szummer and Jaakkola, 2002); the higher the number, the stronger the relation between the two members. The outcome is covered by a transition probability matrix where each entry is the sum of all paths of length t between the respective pair of nodes.

In their analysis of the organizational structure of networks, Qiu and Lin (2011) use a forward random walk on an undirected graph to derive a community tree. We follow a slightly different approach, as the graph underlying the economic

[4] The idea of representing the economic structure as a tree was actually inspired by Bresnahan and Trajtenberg (1995, 102) who discuss coordination problems between up- and downstream production stages as moving down the 'technological tree'.

structure is directed. For this sake, we revert to finite Markov processes,[5] which share the same mathematical framework with random walks on directed graphs (albeit the first was developed in probability theory, the latter in network theory). Markov processes can also be used to reflect non-stochastic relations: Kemeny and Snell (1976) showed that the Leontief input-output model can be interpreted as an absorbing Markov chain (AMC). In an AMC each state (as the equivalent to a node in graph theory) can reach an absorbing state that, once entered, cannot be left anymore. In the scope of an input-output model, final consumption represents the absorbing state of the system, as goods that end up here will not enter the production system anymore.[6]

In the following, the technical coefficients a_{ij} of the n production processes will thus be used to derive the one-step transition probability matrix Q for transient states:

$$Q = \{q_{ij}\}_{n\times n} \text{ where } q_{ij} = a_{ij} = \frac{z_{ij}}{x_j} \tag{5.5}$$

In input-output terms, a_{ij} denotes the quantity of good i on average necessary to produce one unit of good j. Treating the technical process as a Markov process, q_{ij} gives the probability that a process starting in state i ends in state j after one step.[7] Since any finite regular Markov process will eventually end up in an absorbing state, each q_{ij}^n approaches zero as n tends to infinity. Therefore, the so-called fundamental matrix N of an AMC can be calculated as the infinite sum of the n-step transition probability matrix for transient states (see Kemeny and Snell (1976, 46)):

$$N = (\mathbb{I} - Q)^{-1} = \mathbb{I} + Q + Q^2 + \ldots = \sum_{n=0}^{\infty} Q^n \tag{5.6}$$

Readers familiar with input-output analysis will immediately notice the equivalence to the Leontief inverse $(\mathbb{I} - A)^{-1}$, which gives the direct and indirect inputs required for producing one unit of final demand y_i, $i = 1, ..., n$:

$$\mathbf{x} = (\mathbb{I} - A)^{-1}\,\mathbf{y} \tag{5.7}$$

[5]A Markov process is a random process in which the probability distribution for the future prediction depends only on the most recent state, not on any other states in the past.

[6]A similar approach has recently been developed by Duchin and Levine (2010) who combined an input-output model with an AMC for uncovering resource-specific networks in the field of ecological economics. Our study differs in so far as we incorporate capital consumption flows in the inter-industrial transactions matrix, which are subsequently deducted from final demand. In this regard, the consumption vector comes closer to the notion of an absorbing state as if investments, which also belong to final demand, are fully taken into account.

[7]Absorbing Markov chains are of particular interest for studying the behavior of transient states. The ergodic set of an AMC does not change during n steps, since the probability of staying in an absorbing state is by definition 1.

In terms of Markov processes, entries in N denote the mean number of times a specific process is in various transient states before reaching its absorbing state. On the basis of this matrix, we derive an algorithm which estimates for each industry its most likely parent:

Deriving the technical tree (TT):

$TT = \mathbf{0}_{k\times 1}$	1. Build a technical tree (TT) with all k industries attached to the root node denoted by 0.
for $i, j = 1 : k$	
if $i == j$	
$n_{ij} = 0;$	2. Remove intrasectoral linkages from the fundamental matrix N.
end	
end	
for $j = 1 : k$	
$\mathbf{ix}_j \leftarrow$ sort $N_{\bullet j}$	3. Sort supplying industries in descending order of $N_{\bullet j}$, where ix_{ij} denotes the industry assigned to ranking position i among the set of suppliers for industry j.
for $l = 1 : \gamma$	4. Define the range $\gamma \in [1, k-1]$ of industries in which the algorithm is looking for a parent node for industry j.
if $r(ix_{lj}) > r(j)$	5. If the robustness score of industry j is smaller than the robustness score of its l-th most important supplier industry, this industry represents the parent node of sector j.
$TT_j = ix_{lj};$	
end	
if $TT_j > 0$ break	6. As soon as a parent node is found among the γ top supplying industries, break loop #4 and start the search for the parent node of industry $j+1$.
end	
end	
end	

The algorithm searches for each sector j the γ most important supplier industries (in descending order), and picks the first sector that ranks higher in robustness as parent of the industry under analysis. Note that the robustness score determines the construction of the tree; thus if the ranking position of a potential parent candidate is lower, then the corresponding industry by definition cannot act as the immediate 'leader'. In case that none of the γ most important supplier industries ranks higher than sector j, the parent node of j is the root of the tree. The resulting technical tree is derived as a column vector TT, where element TT_i denotes the parent of industry $i, i = 1, ..., n$ (see figure 5.1 for a graphical representation). Industries that are directly connected to the root node represent core industries (C) iff. they span a community, i.e. act as a parent (P) of other industries. If not, this indicates that the robustness score does wrong in assigning them a high rank. This paradox happens whenever the industry to be investigated predominantly produces final consumption goods. Since the relational matrix used to derive the robustness index only takes into account the production network, an industry's contribution to final demand is ignored in the calculation. The algorithm improves the existing approach by filtering out those 'false' core industries as leaves (denoted as L in figure 5.1), i.e. nodes without descendants.

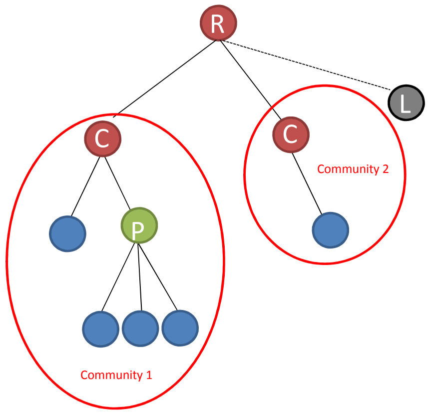

Figure 5.1: Schematic presentation of a technical tree (R denotes the root node, C a core node, P a parent node, L a leaf)

The core industries generate the basic grid over which the economic network is spanned. The tree data structure allows differentiating between these key industries at the root of the technical tree and other sectors that act as parent industries further down the tree. This distinction is important in so far as changes in the set of core industries trigger off processes of deep coordination on the macro level (Dopfer and Potts, 2008) and thus reveal radical structural change.

Three things need to be pointed out: First, the dependencies in the tree data structure are still not unidirectional, running from the root to the leaves; although a community depends on its parent industry, each member in the community strengthens in turn the position of its parent node, since the tree is based on the robustness score, which makes parent and child node mutually dependent. Second, parameter γ reflects the strength of the hierarchical structure; the lower γ, the flatter the hierarchy, as it becomes more likely for an industry not to find a parent and remain at the root. On the other hand, if γ equals the size of the network, the whole economic system is entirely spanned up by the top-ranked industry. Third, N represents the technical coefficients denoting the share of each good directly and indirectly used for the production of sectoral output. This is a better indicator for inter-industrial relations than the absolute value of the direct transactions. In the following, the derived technical tree will serve as a reference tree in the process of building the evolutionary technical tree.

Deriving the Evolving Technical Tree

The previous algorithm allows us to build a static tree, representing the economic structure at one point in time. If one is interested in the evolution of economic structure over a specific time span, the framework presented so far can be applied for a static comparative analysis by investigating for each period the corresponding technical tree. Each tree then describes the macro trajectory at a specific point in time. However, if the network size varies over time, or if the data underlying the analysis are rather volatile, a method which ensures a smoother path of the macro trajectory would be preferable.

The first argument is of less importance, since for now we deal with a fixed number of industries over time, given by the sector classification of the input-output tables. Yet the second argument is to be considered because the transactions that spin the edges of the interindustrial network may vary considerably from one period to the next. This volatility would lead to a technical tree that is rather unstable over time, as industries jump from one year to the next onto very different positions in the tree. For this reason, we implement a tree learning algorithm that constructs node by node hypothetical trees based on a weighted average ranking of two consecutive years. At each step of the construction process, each of these subtrees is being compared to the static technical trees of the previous and current year, respectively. The candidate that is most similar to the existing static trees (as measured by a tree edit distance function) is passed on to the next stage, where a new node is attached to the existing graph. In this manner, the tree evolves until all sectors have been considered. The algorithm was developed by Qiu and Lin (2011) who used it in the context of a varying network size over time:

Deriving the evolving technical tree (ET):

In case of a varying network size (#1–#3):

$S_{ET} = S_{t-1} \cup S_t$ 1. Collect those industries that belong to the economic network at time $t-1$ and t.

for $i \in S_{ET}$: 2. Calculate the robustness score r of the industries in ET as a
$r(i) = (1-\alpha)r_{t-1}(i) + \alpha r_t(i)$ weighted average score ($\alpha = [0, 1]$)
end

$S_{ET} = \{i \in S_{ET} \mid r(i) > \varepsilon\}$ 3. Only consider those industries whose robustness score exceeds a specific threshold parameter ε.

$ET = \{0\}$ 4. Build a technical tree which only consists of a root node.

5. Create a collection of candidate evolving trees EC by putting industry $i \in S_{ET}$ in descending order of r under each industry in the evolving tree ET.

$d_n = \sqrt[2]{D(EC_n, TT_{t-1})^2 + D(EC_n, TT_t)^2}$, 6. Calculate the distance errors between the candidate evolving tree EC_n and the previous TT_{t-1} and current technical tree TT_t, by use of the tree edit distance algorithm $D()$.

$EC_k \leftarrow \arg\min_{EC_n}(d)$ 7. Choose the candidate with the minimum value in d.

if $d(EC_k) > d(ET)$ 8. The selected tree constitutes the evolving tree for the next
  $ET \leftarrow EC_k$ iteration, where the next industry will be attached as a leaf.
end

The tree edit distance $D(T_1, T_2)$ computes the minimum costs of converting tree T_1 into T_2, by deleting, inserting and relabeling nodes. As it is used only as a technical tool to add more flexibility to the model, we abstain from presenting the algorithm here and refer the interested reader to Bille (2005) for a survey on the general tree edit distance problem, and to Zhang and Shasha (1989) for a rigorous discussion of the Zhang-Shasha algorithm on ordered trees which was used in the scope of this analysis.

5.3 Data

Denmark as a Case Study

The empirical analysis will focus on the evolution of the new information and communication technology in Denmark, as the current GPT at work. Several remarks should be pointed out:

(1) Denmark has been chosen due to its position as a net importer of ICT products. This allows us to trace the effects of ICT on the system of production without considering its impact on economic development via export activities.

(2) In national accounts, sectors are classified by the output they produce. Concerning the definition of the ICT sector, we adopt a rather broad view, including not only the manufacturing industry, but also services related to ICT. The following industrial and service classes comprise the notion of ICT in the scope of the present analysis: manufacture of computers and communication equipment etc.; manufacture of wires and cables; telecommunications; information technology service activities; information service activities. While this list certainly covers the major part of ICT producing industries, it is not exhaustive: The wholesale sector of ICT products, for example, was not included in our study, because, on the one hand, the data were only available at a fairly aggregate industry level that did not allow distinguishing different industries in the wholesale sector; and on the other hand, this sector needs to be treated carefully in input-output analysis, as the data depict the accumulated trade margins on all inputs of one sector. Wholesale therefore does not represent a producing (and consuming) industry, but a sector where commodities are passed through to end up in the production process of other industries (Miller and Blair, 2009). Therefore, the wholesale sector will be excluded from the analysis.[8]

(3) Since the paper aims at studying the impact of a general purpose technology over the whole meso trajectory, a comprehensive investigation requires data of inter-industry relations at a fairly detailed level and over a reasonably long

[8]The same case applies to the transportation sector, which reflects the transportation margins on factors of production, but to a lesser extent, since the data for this industry also record real transport services for intermediate consumption.

time span. In this regard, Statistics Denmark also provides a very good data base that entails annual input-output tables (grouping of 127 industries in NACE 2.1. sector classification) for the period between 1966 and 2009, depicting domestic and import flows in basic current prices and prices of the previous year, as well as investment tables spanning from 1993 to 2007[9] and capital consumption data[10] over the whole time span.

(4) The incorporation of capital flows is essential in the analysis of technological change. In the case of ICT, most products, such as computers and office machinery, are of fixed capital type and are thus not included in the intermediate demand presented within an input-output table. In order to estimate intersectoral capital flows, we revert to investment tables which show the transactions from supplying sectors of fixed capital to all other industries. Since we only wanted to consider activities of reinvestment, data were smoothed across time, so that single investment peaks were eliminated. The tables were used then to derive for every industry annual coefficients which give the share of each sector in the capital formation (per fixed-capital category) of the respective industry. However, these coefficients cannot be interpreted as technical coefficients any longer (Verspagen, 2004), because investments represent future consumption of fixed capital rather than current one. Therefore the coefficient matrix was subsequently multiplied by capital consumption,[11], assuming the same time structure for capital consumption as of capital formation.[12]

(5) A time series analysis requires the unit of measurement – in our case the relative prices of the commodity produced in each industry – to be kept constant over time. Price relativities, however, do change and reflect the economic situation less and less, the further away the period under study is from the base year, i.e. the year whose prices indexes are derived from. This holds inevitably true for computers, for which relative prices have fallen considerably since the 1970s. In order to reduce this so-called substitution bias, national statistics offices have progressively started to use chained indexes in the deflation process. Deriving a chained index over a time series simply means to constantly change the base period; i.e. for each period, data are valued in current prices and prices of the previous year, which allows calculating an annual fixed weighted (usually Laspeyres or Paasche) index. Subsequently, one year is arbitrarily chosen as a reference period, and all other years are linked to that period by chaining (i.e. multiplying) the respective indices for consecutive years together (see Eurostat

[9]For the missing years (1966–1992 and 2007–2009), we extrapolated the investment tables by calculating an average capital coefficient matrix.

[10]Capital formation and consumption data comprise the following fixed-capital items: (1) buildings, (2) machinery and equipment, (3) transport, (4) structures, and (5) fixed capital n.e.c. (software, livestock, mineral exploration, and original works).

[11]Consumption of fixed capital are based on estimates of gross capital stock from Statistics Denmark. The data is reported in the 127-sector classification for each category of fixed capital and for the whole time span under study. The methodology for deriving these estimates can be found in Jensen (1997).

[12]This assumption can be easily modified by including time lags between capital formation and actual consumption.

(2001) for a detailed explanation of the methodology). Since our study is about the evolution of ICT between 1967 and 2009, we constructed a set of constant price data for all transaction flows (domestic and imported intermediate demand and capital formation, as well as final consumption, output, and value added), by calculating the Laspeyres volume index between consecutive years for each period under investigation (43 years in total). The year 2005 was chosen as a reference period, because data on capital consumption had been compiled by Statistics Denmark in chained prices of that year. Subsequently, each time series of indices was separately re-referenced to 2005 (=100), and then weighted again with the volumes of 2005. The drawback of chained prices is the loss of additivity; this is especially the case for input-output tables which are balanced by definition. Thus, intermediate consumption and value added do not sum up to total output anymore in years other than 2005. To overcome this issue, we follow Yamakawa and Peters (2011) by using the sum of chained transactions as the new output.

Organization of Input-Output Data

In order to make a comprehensive investigation of the ICT sector, it is necessary to cover all channels through which ICT-related products could enter the production system and we therefore incorporate imports consumed domestically (M^D) as well as domestic and imported capital flows (Z_K):

$$Z = Z^D + M^D + Z_K^D + Z_K^M \tag{5.8}$$

This transaction matrix Z will be used to derive the relational matrix, H, for calculating the robustness score of each industry, as well as the transition probability matrix, Q, and the fundamental matrix of the AMC, N.

The analysis was conducted on the level of 127, 66 and 36 sectors (corresponding to the standard national industry grouping). Unlike other social networks with individual entities, the treatment of industries as nodes leads *ipso facto* to different results depending on the level of aggregation (McNerney et al., 2013). We chose to present the results of a system composed of 69 sectors, mainly for two reasons: The more detailed (127-sector) classification may have a bigger bias due to the fact that the investment flows are recorded based on an outdated sector classification; whilst on the 66-sector level almost every industry in the new grouping corresponds to one sector in the old grouping, an analysis on the most detailed aggregation level would imply the need to break down the individual industries even further.On the other hand, grouping the 127 industries into 36 sectors leads to large innersectoral transaction flows, reflecting the high aggregation level. Since the flows within a sector are not considered, a lot of information would get lost by analyzing an economic network of this size.

5.4 Results and Discussion

In the following, our framework is applied to the Danish economy on an annual basis from 1967 until 2009.[13] Special emphasis will be thereby put on the ICT sector as the supplying meso unit of this technology. During the phase of adoption of ICT, the meso unit spans a growing population of industries; they in turn act as the backbone of their parent industry, empowering the latter to evolve to the core of a whole community. Since these 'descendants' represent meso units themselves, a community represents a cluster where members coevolve. The investigation of the meso unit over time gives the meso trajectory, the evolution of the community structure the core trajectory.

Studying the Meso Trajectory: The Case of ICT

Studying input-output tables over more than four decades according to a constant industry classification means that the node in the network remains the same, even though the industry assigned to it may have undergone huge organizational and technological changes. The ICT sector, for example, represents the same network member throughout the period under study, even though the industries composing this sector in 1967 have little – if anything – in common with the ICT producers of today. Thus, in the scope of input-output data, a new GPT does not form a new or further sector, but *trans*-forms an existing sector. Figure 5.1 shows how the population of each ICT-producing sector has been evolving since the 1960s.

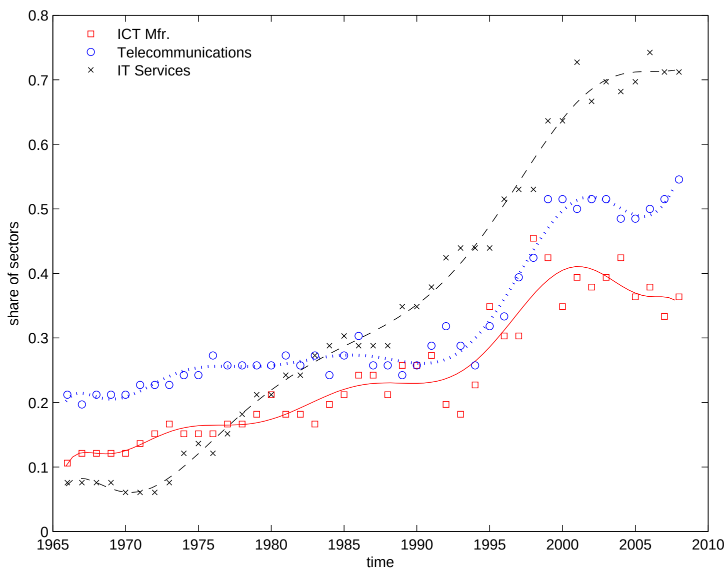

Figure 5.1: Share of sectors with above-average demand on ICT per ICT-producing sector

[13]Regarding the programming tasks, MatLab was used as the main software for preparing and processing data, while the tree learning algorithm was run in Java. And finally, the network graphs were drawn with Cytoscape, an open-source program for network visualization.

The share of application sectors only contains those industries that employ ICT rather extensively (as measured by an above-average demand for the respective ICT commodity in the production process).[14] Back then, the ICT manufacturing sector, which produced traditional office equipment, as well as telecommunication services already formed an integral part of the economic system by being utilized in 20 and 10 percent of all sectors, respectively. While these shares did not change much between 1967 and 1980, the diffusion rate of IT services was growing rapidly from the 1970s onwards, when highly innovative companies such as Microsoft and Apple were founded, and the first microcomputers went to the market. By mid-1980s the IT service sector already exceeded the other two ICT industries and has become the most important IT sector in Denmark since then. Between 1990 and 1995, all ICT activities showed an equally significant upward trend in their adoption rate, reflecting the big advances in this GPT. After the IT bubble burst in 2000, the IT manufacturing sector has shown a slight decrease, partially due to outsourcing of domestic IT activities; this has mostly affected ICT manufacturing, as the lower level of skills demanded by this sector (compared to IT related services) facilitated the offshoring of production; whereas the telecommunication sector reveals increasing shares after 2005. This sector has also become the most rapidly growing IT industry in terms of export shares of IT products, R&D investments and sectoral turnover. After 2000, the IT consultancy sector showed a relatively stable population of more than 70% of all sectors.[15]

Applying our network approach with parameter values $\beta = 1$, $\gamma = 6$, table 5.1 shows the rank, parent node and number of descendants for each ICT industry between 1969 and 2009.[16]

Figures 5.2 and 5.3 present the key figures graphically. The x- and y-axes denote the parent, i.e. the industry that the respective IT sector depends on upstream, as well as the number of children, i.e. the most depending industries downstream in the production process. The color of the circles indicates the ranking position with regard to the robustness score, while the radius reflects the size of the subtree. The development over time (depicted on the z-axis) thus shows when and to what extent ICT started to unfold their impact on the economic system, and which sector enabled this change.

Fig. 5.2 reveals that telecommunications was one of the most robust industries between 1967 and 1971 (as reflected by a rank between 1 and 3), entailing a highly diversified purchaser network. However, this sector was not able to span a com-

[14] Strohmaier (2013) entails a more detailed discussion of the diffusion path of the ICT sector, differentiating between intensive and extensive utilization; the first refers to the degree of utilization in each application sector, the latter to the adoption rate across sectors.

[15] Note that not all IT related activities could be taken into account due to the industry classification; this especially explains the low level of adoption of ICT manufacturing products, as important subindustries such as manufacture of instruments for measuring and navigation and manufacture of optical instruments could not be taken into account.

[16] In order to allow comparing the results with our findings in chapter 4, we present the baseline approach without executing the third algorithm. Since we use capital consumption flows and smoothed investments, data volatility is low, so that results do not change significantly.

	1969	1974	1979	1984	1989	1994	1999	2004	2009
ICT manufacturing									
Rank	54	53	50	38	30	25	16	19	26
parent node	15	15	15	16	19	19	19	19	19
no. descendants	0	0	0	0	0	0	0	0	0
Telecommunication									
Rank	6	7	7	8	10	9	10	7	4
parent node	0	30	30	30	30	30	39	39	39
no. descendants	0	0	0	0	0	1	0	5	5
IT services									
Rank	28	20	11	9	11	7	3	2	3
parent node	46	45	46	46	46	46	0	0	46
no. descendants	0	0	0	1	0	1	4	12	12

Table 5.1: Evolution of the ICT sector 1969–2009. Rank denotes the ranking position of the respective industry, numbers in parent node refer to the sector ID (see table 5.A.1).

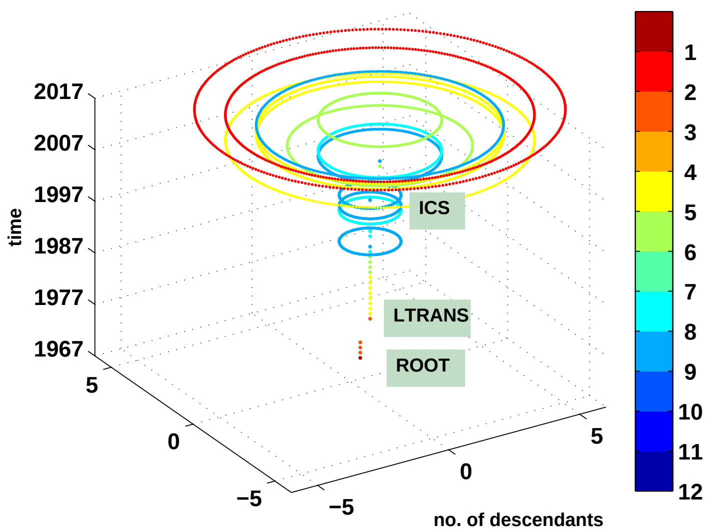

Figure 5.2: Evolution of telecommunications

munity downstream, which means that it did not belong to the 6 most important suppliers for any sector in the economy. At that time, telecommunication services were also oriented towards final consumption, and to a lesser extent towards intermediate demand. From the early 1970s until 1990, the telecommunications sector was rooted in land transport, indicating that many of the services provided in this period were related to postal activities.[17] By 1987, the telecommunications sector also became an important supplier for the producer network, especially for postal

[17] In fact, the old classification based on Nace Rev. 1.1 grouped post and telecommunications together, which shows the similarity in the services provided at that time. Both activities were subsumed under transportation. With the rise of the internet and mobile phones, NACE Rev. 2.1 gave credit to the new wireless telecommunication services and assigned them to the information and communication sector.

activities and business services. From 1997 onwards, when the era of the internet and mobile communication began, telecommunications became part of the IT service cluster. With the change in the community, the scope of telecommunications as a supplier of intermediate products has been growing, spanning postal activities, employment activities, the private R&D sector and market research.

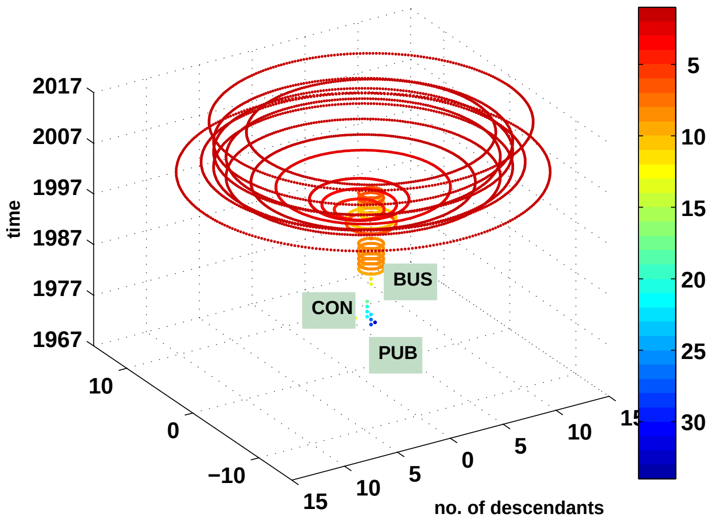

Figure 5.3: Evolution of IT services

In comparison to figure 5.2, one can see at first glance from figure 5.3 that IT services have undergone a more radical change, both in terms of their ranking position and their ability to span depending industries. Interestingly, IT services originated in the public administration sector, which supports the notion of an entrepreneurial state (Mazzucato, 2013) that takes the risk of allocating subsidies to a new technology which has the potential to become groundbreaking in the future, but bears a high level of uncertainty in the presence. In the early 1970s, the IT service sector made large investments in buildings, which made real estate the parent industry during that time. After 1977, the IT service sector joined the business services cluster and promoted the growth of this community. Eventually, in 1997, IT services became a core industry, reflecting its dominant role in the economic system. Its development since then will be discussed below, together with the other core industries in the Danish economy.

A quite different picture can be drawn from the ICT manufacturing sector. Its ranking position was almost continuously improving between 1967 and 1999 (from position 54 to 26), but it never became a parent, and much less a core industry. This may be connected to the fact that not all industries which manufacture ICT products could be taken into account due to the high level of aggregation in the industry classification, but also reflects the relative rise of IT services; if a company outsources activities such as software programming and data processing, the need for computer hardware inhouse decreases, which *ceteris paribus* leads to declining demand of ICT capital on the sectoral level.

Evolution of the Community Structure: The Core Trajectory

For ease of reading, the network graphs in a time interval of 14 years between 1967 and 2009 are presented in the appendix of this paper. Detailed data of the evolving tree for every 20 years are shown in table 5.A.1.

Figure 5.A.1 in the appendix presents the Danish economy in 1967 as a technical tree. The nodes directly attached to the root node display those industries that have no parent industry as immediate leader. However, not all of them are able to generate a community. As already mentioned, whenever an industry is ranked high according to the robustness criterion, but has nevertheless low significance as a supplier of immediate products to other sectors, it represents a leaf of the technical tree. This is the case, for example, of the sector 'accommodation and food service activities' (HOT), which is hanging on the root and yet does not have any industries depending on it downstream. The opposite is true for the construction sector (CON): by spawning virtually the whole economic system in 1967, it represents a core in the economic structure. The present section is devoted to the systematic analysis of these core industries and their related communities.

All in all, the set of core industries has been rather stable over time: From the network of 67 sectors, the algorithm picks 19 industries located at the root of the tree in at least one period of time in the course of 43 years. Out of these sectors, 10 different industries turn out to be cores in at least one industry network; the remaining sectors always act as leaves of the tree. On average, 6 sectors open up the economic system in a specific point of time. Regarding the sector assignment, two belong to manufacturing, five to the broad class of service sectors as well as construction and transportation sector.

Taking the economic network from 1967 as a starting point, figure 5.4 depicts the root path of the different industries that so far have acted as cores in a five-year interval until 2009. The y-axis displays the parent industries, while each line denotes the path of the respective core industry. Thus, whenever a respective sector represents its own parent industry, it serves as a core. Those sectors that have persistently been attached to the root (e.g. public administration) are omitted. The diagram entails two typical candidates for a GPT: ICT services (38, 39) and electricity (24). The latter has occupied a constant position in the technical tree, except for 2002. Telecommunications (38) and IT services (39), on the other hand, have largely been part of different communities (land transport and business services). In 1997, IT services became a core industry spanning their own cluster of industries, to which the telecommunications sector has belonged to since then. Business services (46) represent the most fluctuating core industry, while construction (27) and manufacturing of machinery (19) show inverted development, where one acts as parent industry of the other depending on the period under study. So whenever there is a persistent switch in these core industries at the root of the tree, this signifies radical technical change on the macro level. In the case of Denmark, we could detect this kind of change in the beginning of the 1980s with regard to the construction sector which was replaced by the machinery sector, and about the same time with regard to the business sector. 10 years later, the IT core subsumed the business service sector as well as the transportation sector.

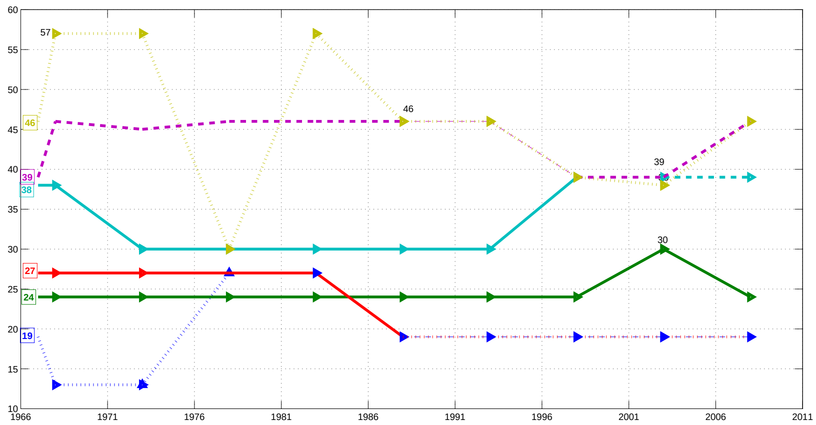

Figure 5.4: Path of core industries. The labels denote the following industries: (19) mfr. of machinery and equipment; (22) mfr. of furniture and other mfr; (24) electricity, gas and steam; (30) land transport; (35) accommodation and food services; (38) telecommunication services; (39) IT services; (57) public administration

In the following, we adapt some properties of dynamic social networks from Qiu and Lin (2011) to our purpose: (1) a community or cluster (c_i) within a technical tree is defined by its core industry (i.e. a specific meso unit) and the set of industries attached to it. (2) Core trajectory (t_c): While a meso trajectory depicts the origination and diffusion of a single meso unit, the core trajectory tracks the evolution of a whole industry cluster. The longest life line (max), i.e. the interval in which an industry continuously spanned a community, is an indicator of the persistence of the core over time. (3) Promoters (P): industries that are stable or recurrent members (no less than five times) in a community lifetime; they detect the community pattern. Additionally, we introduce (4) the range of a core trajectory (R_c), which counts the different industries that have entered and exited the community within the period under study; dividing this metric by the number of promoters (N_p) serves as a measure of 'restlessness' or volatility within the cluster. And finally, (5) stability (ϕ), measured as the weighted ratio between the number of promoters and the average community size (N_c), indicates the level of institutionalization of the cluster.

Applying these metrics, all core industries (in ascending rank order) are listed in table 5.2 which summarizes the development of the communities they generate.

The two top ranked sectors, public administration and accommodation and

ID	Core Activity	RK	$t_c(max)$	t_p^{max}	promoters	N_p	R_p	N_c	σ_c	ϕ
57	Public administration	1	23 (9)	2	–	0	4	1.5	–	–
35	Accommodation, food service	2	12 (11)	11	39,46,55,29,45,48, 56,47	8	36	11.4	0.3	0.6
46	Business services	3	9 (4)	8	39,55,47,48,50,29, 45,52,56,34,42,38, 41,51,65	15	32	13.2	0.9	1.0
30	Land transport	4	28 (23)	15	38, 65, 59, 54	4	49	7.4	0.5	0.3
24	Electricity, gas and steam	5	27 (19)	26	53	1	7	1.4	0.8	0.5
55	Other business serv.	7	5 (3)	2	–	–	20	14.0	–	0.0
39	IT and information services	11	9 (8)	9	34,38,41,46,47,53, 56,37,42,50,51,40, 52,58,43,48,55,64, 65	19	25	17.6	1.0	1.1
19	Manufacture of machinery	19	20 (17)	20	1,3,4,5,6,7, 10,11,12,13,14,15, 16,17,18,20,21,23, 25,27,28,31,49,61, 62,63,32,44,60,8, 9,33,66,54,36	35	53	39.9	1.0	0.9
27	Construction	20	21 (21)	21	2,25,37,41,44,49, 51,60,61,62,63,3, 7,15,16,17,19,20, 21,23,58,43,1,5,12	25	58	38.2	1.0	0.7
22	Other mfr.	24	5 (3)	5	64	1	1	1.0	0.2	0.2

Table 5.2: Core structure of the Danish economy 1967–2009.
The following abbreviations are used: RK (rank); t_c (length of the core trajectory), max (longest life line); t_p^{max} (maximum period of a promoter industry in the community c); N_p (no. of different promoters); R_c (range of distinct industries in c); N_c (average size of community); σ_c (weight: t_p^{max}/t_c); ϕ (stability)

food services, appear in every year between 1968 and 2009. Within these 42 years, they represent a core industry 23 and 12 times, respectively. Whereas public administration does not show any community pattern (as none of the depending industries appear more than two times in the community), the cluster generated by the accommodation and food service sector is entirely service-related (the sector IDs are given in table 5.A.1 of the appendix). The community itself is rather volatile, as only 8 out of 36 industries that have entered the community remain in there for more than five periods (while the maximum length of time of a member in the community is 11). As the average cluster consists of 11 industries, this results in a low stability index (ϕ) for the food and accommodation sector.

Next in the ranking is the business service sector which shows a far shorter history as a core of the economic network; it appeared in only nine years, and four years in successive periods. Its promoters, 15 in total, all belong to the service sector. About every second industry that has ever entered the community has stayed for longer than five years. This, together with the average community size of 14, gives the second highest stability score. The only transportation sector represented in the core is land transport; it is located at the root of the tree in 28 periods (23 years successively). Four industries have promoted the cluster. The sector shows the highest spectrum of different industries relative to its community size, thus the community itself is less persistent over time. Finally, the electricity sector, occupying the fifth rank, has one of the longest trajectories (27 times, but only 19 years in a row). As a general purpose technology, electricity was expected to span a large community; this is not at all the case, since it hardly ever belongs to the set of industries that provide one of the most important inputs to one sector. This might be due to technical change which has decreased the energy intensity in production processes. Given the high range of different industries relative to the low community size, the electricity cluster is rather unstable.

The three sectors with the lowest rank of all core industries are essentially those that span up the bulk of the industry network. As already mentioned, IT services have only recently entered the core of the economic system. More than 75% of industries entering this cluster have lasted for more than five years. Like business services, the number of recurrent sectors is even higher than the average community size of 18 industries, which makes this cluster the most stable one in the economy. The community not only comprises the bulk of financial and business sectors, but also telecommunications and the R&D sector.

Manufacturing of machinery shows similar characteristics, even though it reveals a way longer trajectory. Whereas the core service industries also generate a service-oriented community, members of the machinery network are predominantly other manufacturing sectors, as well as agriculture and mining. The machinery sector essentially replaced construction which has continuously acted as a core for 21 years. Almost every second industry in the community became a persistent member, as is evident by a high stability measure.

For the sake of completeness, table 5.2 also lists other business services and mfr. of furniture and other manufacturing as core industries; nevertheless they will not be discussed in detail, as they have a shorter trajectory and no commmunity pattern.

5.5 Conclusion

This paper has proposed a framework that uncovers changes in the economic structure under pervasive technological change. Given that one can determine the locus of production in the economy, it is possible to track a general purpose technology provided by a specific sector through space and time, by studying transaction flows between members in a dynamic industry network.

The starting point was the idea to derive an industry ranking based on industrial relations without losing the intersectoral information. The methodological approach was driven by recombining knowledge from different fields of research. On the one hand, the analysis of organizational structure in social groups is to some extent similar to the problem of how sectors coordinate on the meso level. On the other hand, it is also important to assess the role of an industry by the position it occupies in the network. Since pervasiveness is an essential feature of a general purpose technology, we drew on a social network approach which measures an industry by its degree of robustness. The outcome was a hierarchical structure (or technical tree), in which sectors are still mutually dependent on each other.

It is important to note that both approaches complement each other; applying the notion of robustness on industries without considering the size of economic activity nor the ability to generate communities would lead to biased results, as for example is shown in the case of the accommodation sector. By deriving the technical tree, those consumer-oriented industries are detected as leaves. On the other hand, traditional tools for studying key sectors based on input-output tables fail to detect pervasive technologies, which led to the motivation of the paper at hand.

The application of the proposed network approach to the Danish economy is able to detect the current GPTs on the meso level. Moreover, it confirms the hypotheses suggested at the beginning in the case of the ICT service sector, but not for ICT manufacturing; the latter has indeed become more robust, but never made it to the core or created a subnetwork. In contrast, both ICT service industries have approached the root of the technical tree over time, but while IT services already act as a core industry, telecommunications does not span their own cluster, as they show a strong dependency on products from the IT service sector. However, *within* the IT community, telecommunications disposes of a growing number of adjacent industries downstream, which not only strengthens its own position in the network, but also the one of its parent industry. Moreover, these results match other figures on ICT usage which show Denmark as a highly advanced information society.

Regarding the community structure, the technical tree gives a simple representation of an otherwise complex network of transaction flows. Considering the evolution of the core industries and their related industries, the analysis demonstrated that the machinery sector replaced construction at the root, while IT services prevailed over business services. Telecommunications, on the other hand, became detached from the transportation sector only at a stage where ICT had already spread over the production system. Thus, our analysis of the core allows one to draw conclusions on the ongoing structural change in the economy.

Furthermore, the analytical investigation of core industries arrives at similar findings as the historical study by Lipsey et al. (2005). The authors list six technology classes that have generated GPTs: (1) materials, (2) power, (3) information and communication technologies, (4) tools, (5) transportation, (6) organization. All of the sectors that we identified as cores can indeed be broadly associated with these areas, which underpins the suitability of the robustness filter for detecting major technological change.

This framework has been fitted within an evolutionary theory of economic change which puts the meso unit at center stage (see Dopfer and Potts (2008)). It would be worthwhile exploring the full range of empirical applicability of the concepts proposed, such as the scale and velocity of the core trajectory, as well as the coevolution of cores, outlining a potential direction of future research.

For the approach to give reliable results, all channels by which a commodity can enter the production system, such as imports and capital flows, need to be taken into account. The assessment of the ICT intensity across sectors based solely on the intermediate matrix would lead to a strong underestimation of the true impact of ICT; to put simple, a USB drive would be counted whereas a laptop would not. Thus, whenever it is about technological change analyzed within an input-output framework, the incorporation of capital flows seems to be essential.

Furthermore, the focus in this study lies on the pervasive character of a GPT and not on its potential to trigger phases of strong innovative activity. However, it would be easy to extend the framework to further factors of production, such as investments in R&D or the employment of heterogeneous labor, by letting the algorithm search for the most innovative industries among the supplier network (see annex C). This would give further insights into Denmark's top position among innovation leaders in Europe, also with regard to ICT, as the last decade was marked by a highly proactive IT policy to foster the domestic ICT sector.

Appendix

5.A Tree Dynamics

Table 5.A.1: Evolution of the technical tree. The first column gives the sector ID, the second and third column indicate the economic activity and corresponding abbreviation, respectively, the columns 4-12 record the ranking of each industry according to the robustness score in descending order (pos), the parent industry (par), as well as the number of descendants (desc). The value 0 in 'par' denotes the root node, parameter α in the tree learning algorithm was set to 0.5.

			1969			1989			2009		
ID	Activity	Label	pos	par	desc	pos	par	desc	pos	par	desc
			pos	par	desc	pos	par	desc	pos	par	desc
1	Agriculture and horticulture	AGR	63	5	0	65	5	0	65	5	0
2	Forestry	FOR	56	27	0	60	27	0	63	19	0
3	Fishing	FISH	65	19	0	66	10	0	66	19	0
4	Mining and quarrying	MIN	62	10	0	62	27	1	60	27	0
5	Manufacture of food, tobacco	MFOOD	52	30	0	50	19	2	55	19	1
6	Textiles and leather products	MTEXT	10	27	2	27	27	0	14	19	0
7	Manufacture of wood etc.	MWOOD	55	27	0	54	16	0	61	16	0
8	Manufacture of paper etc.	MPAP	24	6	1	35	27	2	41	19	1
9	Printing etc.	MPRINT	48	8	0	41	8	0	49	8	1
10	Oil refinery etc.	OIL	34	30	4	56	27	1	40	27	2
11	Manufacture of chemicals	MCHEM	36	30	2	39	19	0	27	19	1
12	Pharmaceuticals	MPHARM	64	11	0	52	11	0	53	11	0
13	Manufacture of rubber etc.	MRUB	14	27	0	21	19	1	22	19	0
14	Manuf.of glass, concrete etc.	MGLASS	61	10	0	64	4	0	64	19	0
15	Manufacture of basic metals	MBMET	39	19	6	43	19	0	48	16	0
16	Manufact. of fabricated metal	MFMET	38	19	0	32	19	1	34	19	2
17	Manufacture of ICT	ICT	54	15	0	30	19	0	26	19	0
18	Electronic/electrical equipment	MELTR	35	19	0	24	19	0	25	19	0
19	Manufacture of machinery	MMACH	29	13	2	17	0	11	12	0	23
20	Manuf. of motor vehicles etc.	MVEH	40	15	0	48	15	0	44	19	0
21	Mf. of ships, transport equip.	MTRAN	50	15	0	51	15	1	59	19	0
22	Manuf.of furniture, other manuf	MOTH	41	15	0	5	0	0	10	0	1
23	Repair, inst. of machinery etc.	RMACH	53	15	0	53	15	0	54	19	0
24	Electricity, gas and steam	ELC	4	0	1	6	0	2	9	0	0
25	Water collect. purification etc.	WAT	27	27	0	38	27	0	46	27	0
26	Sewerage,waste collection etc.	WASTE	9	27	0	14	46	0	17	19	0
27	Construction	CON	7	0	26	18	19	22	30	19	6
28	Sale, repair of motor vehicles	SRVEH	32	19	0	37	13	0	32	19	0
29	Retail sale	RET	23	45	0	36	45	0	24	45	0
30	Land transport, pipelines	LTRANS	11	27	7	4	0	4	13	19	0
31	Water transport	WTRANS	47	10	0	57	10	0	39	19	0
32	Air transport	ATRANS	37	10	0	49	33	0	52	19	0
33	Support activities for transp.	STRANS	43	30	0	33	30	1	35	19	0
34	Postal and courier activities	POST	3	0	0	8	46	0	11	38	0
35	Accommodation, food service	HOT	2	0	0	2	0	1	6	0	0
36	Publishing activities	PUBL	17	30	1	34	30	0	42	39	0
37	Radio, TV, movie, video, sound	RADIO	30	27	0	25	39	0	37	39	0
38	Telecommunications	TELE	6	0	0	10	30	0	4	39	5
39	IT and information services	ICS	28	46	0	11	46	0	3	46	12
40	Financial service activities	FIS	26	45	0	28	27	0	23	39	2
41	Insurance and pension funding	INS	60	27	0	23	27	0	21	39	0
42	Other financial activities	OFIS	45	45	0	61	46	0	58	39	0
43	Buying, selling of real estate	REAL	59	27	0	63	27	0	56	39	0
44	Renting of resident. buildings	RENTRB	22	27	0	29	27	0	19	19	0
45	Owner-occupied dwellings	OWNB	13	27	6	19	27	2	16	19	2
46	Legal, account., cons.activit.	BUS	5	57	0	3	0	6	2	0	1
47	Architecture and engineering	ARCH	57	45	0	58	46	0	47	39	0
48	Research and developm.(market)	RD	66	45	0	47	45	0	57	38	0
49	Research and dev. (non-market)	RD (nm)	42	27	0	46	27	0	50	45	0
50	Advertising, market research	ADV	25	36	0	16	46	0	20	38	0
51	Oth.techn.serv., veterinary act	OTSERV	58	27	0	55	27	0	33	38	0
52	Rental and leasing activities	RLACT	33	27	0	42	46	0	18	19	0
53	Employment activities	EMPL	18	24	0	13	24	0	28	38	0
54	Travel agent activities	TRAV	15	30	0	15	0	0	29	19	0
55	Cleaning, other business serv.	OBUS	16	27	0	9	46	0	5	38	0
56	Rescue service ect. (market)	RESC	51	21	0	59	39	0	62	39	0
57	Public administration etc.	PUB	1	0	2	1	0	1	1	0	0
58	Adult-, other education(market)	OEDU	21	27	0	31	27	0	15	39	0
59	Education (non-market)	EDU	19	30	0	22	27	0	36	39	0
60	Human health activities	HEALTH	31	27	0	40	27	0	31	27	0
61	Residential care	RCARE	44	27	0	44	27	0	38	27	0

Continued on next page

Table 5.A.1 – continued from previous page

			1969			1989			2009		
ID	Activity	Label	pos	par	sub	pos	par	sub	pos	par	sub
62	Arts, entertainm., other culture	CULT	46	27	0	45	27	0	51	27	0
63	Sports, amusement, recration	RECR	20	27	0	26	27	0	45	27	0
64	Activities of membership org.	MEMB	12	27	0	7	46	0	8	39	0
65	Repair of personal goods	RPERS	8	0	0	12	0	0	7	39	0
66	Other personal services	OPSERV	49	11	0	20	27	0	43	19	0

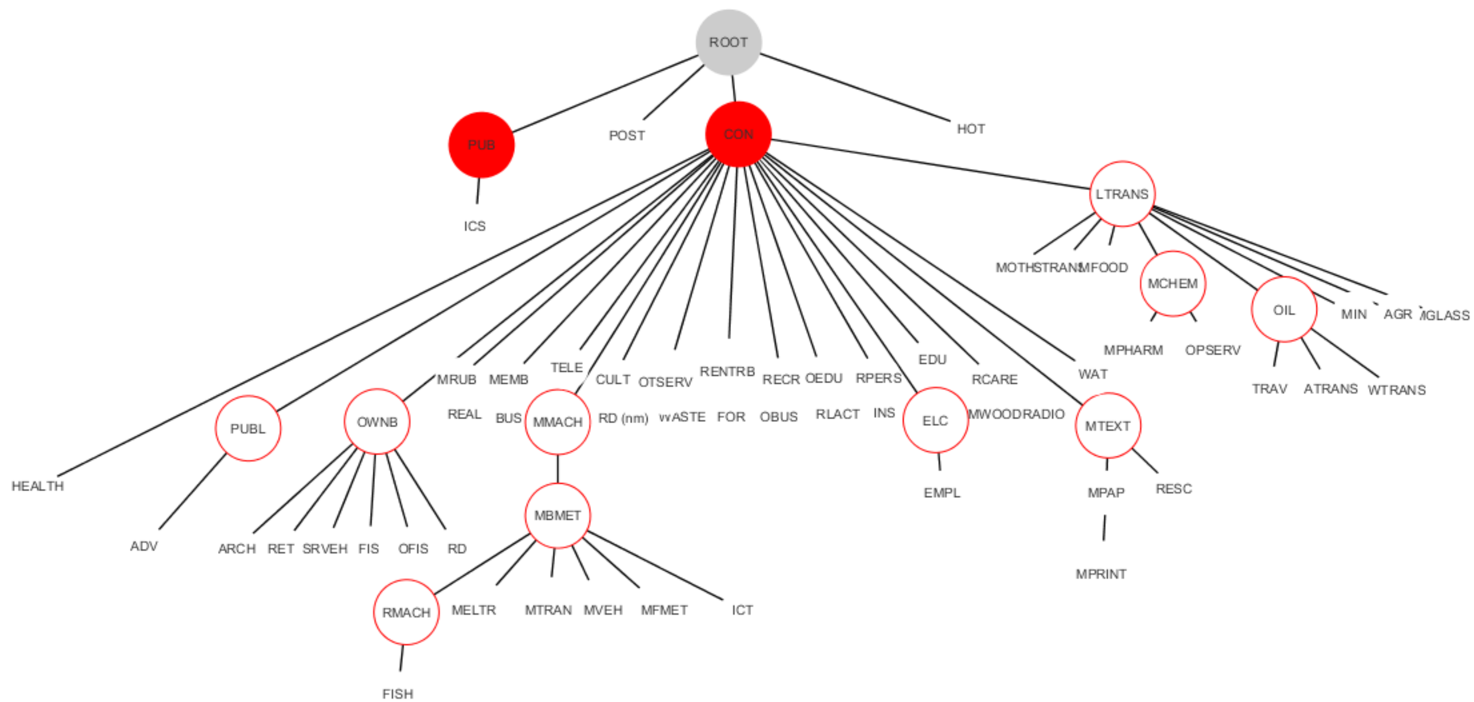

Figure 5.A.1: Technical tree in 1967

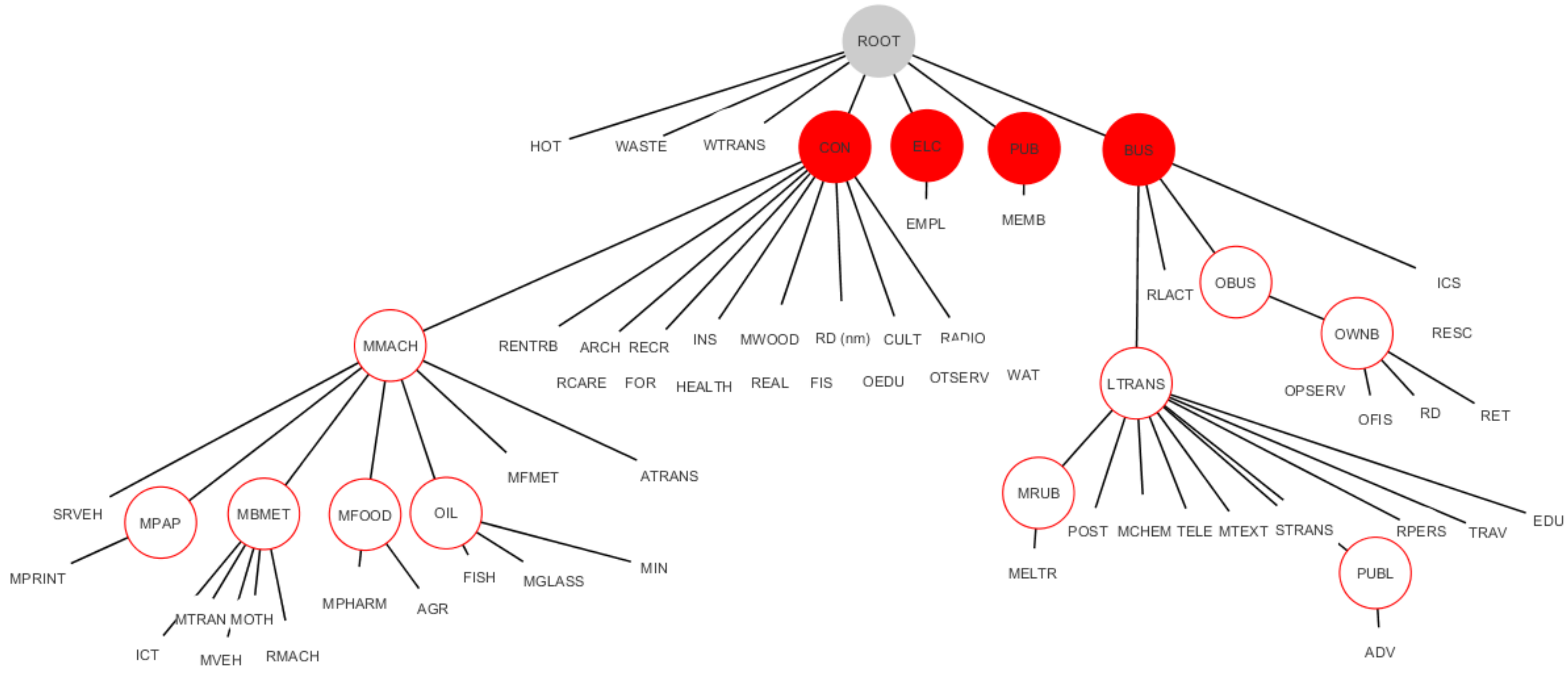

Figure 5.A.2: Technical tree in 1981

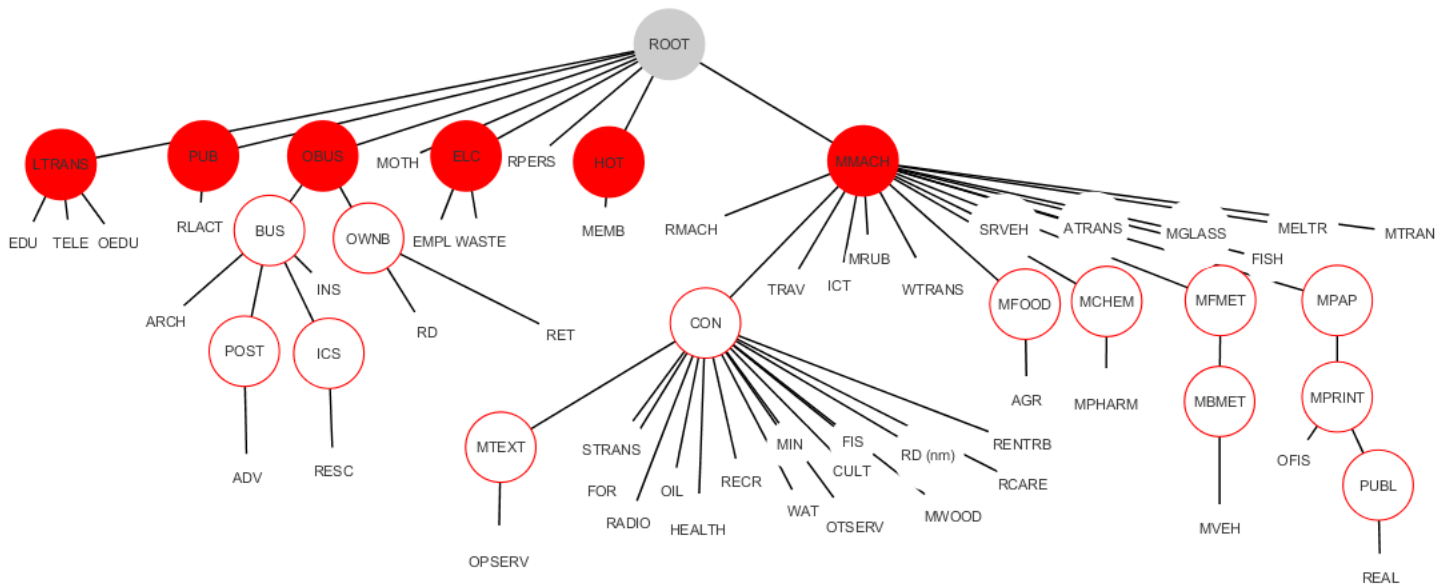

Figure 5.A.3: Technical tree in 1995

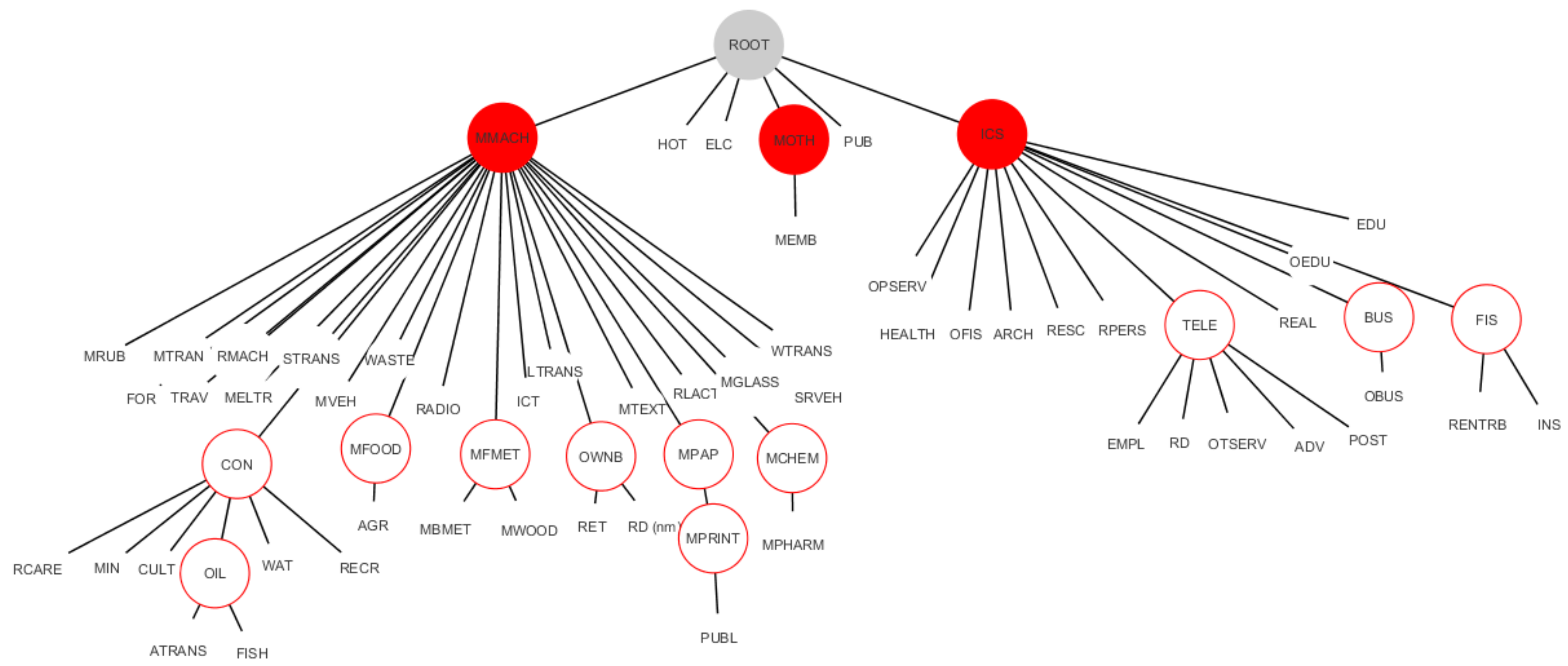

Figure 5.A.4: Technical tree in 2009

Part II

Modeling Pervasive Technological Change

Chapter 6

Modeling the Diffusion of General Purpose Technologies in an Evolutionary Multi-Sector Framework

General Purpose Technologies (GPTs) are characterized by their pervasive use in the economy. The introduction of a new GPT (product innovation), as well as increasing productivity within a GPT sector (as a consequence of process innovations) affect the economy in several ways. First, a new GPT offers the opportunity to produce goods by means of cheaper processes; secondly, technical change within the GPT sector induces productivity gains in related sectors. Also social consequences such as changing wage share, technical unemployment and transitional wage inequality can be observed. Finally, the emergence of a GPT often coincides with output decline, preceding economic growth. This paper introduces a multi-sector diffusion model to study these effects by combining classical economics and replicator dynamics. Empirical evidence is given by the ICT sector in Denmark and its impact on the economic structure from 1966 to 2007.

Keywords | general purpose technologies, classical economics, replicator dynamics, technical change

6.1 Introduction

General Purpose Technologies (GPTs) are basic innovations that change the production structure of the economy via their pervasive use. The steam engine and electricity as well as the information and communication technology (ICT) in the past decades are examples of GPTs. Their emergence (as product innovations) paved the way for process innovations and hence for productivity gains. Intersectoral spillover effects by the introduction of a new GPT and by technical change within a GPT-producing sector implied aggregate economic as well as distributive (and hence social) consequences: A downturn of aggregate output, transitory wage inequality, technical unemployment and changing skills are examples of effects associated with the emergence of a new GPT.

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Several formal economic models were set up to facilitate the understanding of economic and social consequences of a new GPT and of technical change in the GPT sector (Aghion and Howitt, 1998a; Carlaw and Lipsey, 2006; Helpman and Trajtenberg, 1998a,b; Petsas, 2003). These models are based on assumptions concerning the individual behavior of economic agents, including the rational expectations hypothesis and endogenously modeled technical change due to R&D activities. So far, the link between technological change (i.e. product innovations) and technical change (process innovations) has been dealt with insufficiently in this literature; the paper therefore presents a complementary approach based on a classical multi-sector framework which is merged with the formalism of replicator dynamics, in order to model the dynamics of technical change by means of *diffusion* of innovations.

The first – static – part of the model is based on the approach of Sraffa (1960), in the notation of Kurz and Salvadori (1995). The dynamic part, represented by replicator dynamics, is an offshoot of evolutionary game theory as introduced by Weibull (1997) and utilized by evolutionary economics in the tradition of Nelson and Winter (1982). The following features are incorporated: (1) Different sectors of the economy are related to each other by some unit production input-output matrix. Technical change in one sector can therefore induce productivity changes as well as technical change in other sectors. Product innovations are implemented by increasing the dimension of the technology matrix of the model. (2) Different skill levels with differing remuneration are factored in to model wage inequality. Productivity gains lead to a rising wage rate, and also the investigation of the development of the wage share is conducted to enable discussions concerning distributional issues. (3) The different technologies within each sector are of Leontief type, assuming instantaneous constant returns to scale. (4) A population view of the economy is introduced. Each sector comprises a population of firms which host the respective processes. A population is therefore defined by the sector respectively by the homogeneous good produced in this sector:

> The obvious candidate for the status of an evolutionary population is an ensemble of business units that differ individually in terms of their behavioral traits, technology, organization, strategic purpose, but are members of an evolutionary population by virtue of being subjected to common, market selective processes operating on that population. (Metcalfe, 2008, 31)

If more than one process exist, this population is divided into several *species*, each one characterized by the technical coefficients of the specific process attributed to it. Depending on its profitability for given prices and wage rate, processes exhibit different growth potentials. The resulting growth patterns of technologies imply changes of the cost structure, which in turn lead to altering prices and wages. These again influence the extra profits generated by some technology, hence affecting the growth potential of some species.

Concerning the empirical analysis that accompanies this model, the focus lies on the meso unit and the changes it triggers off for the economic system, “as it is the population, not the carrier, that evolves" (Dopfer and Potts, 2008, 50). The dynamics of the model are placed in juxtaposition to the development of the ICT sector in Denmark and its influence on related sectors. Spanning the period from 1966 to 2007, the analysis covers the time before and after the emergence of important innovations in the field of information and communication technology, such as microcomputers in the 70ies or the Internet in the late 90ies of the last century. The new ICT indeed features the characteristics commonly attributed to GPTs (see, e.g., Jovanovic and Rousseau (2005a)): (1) It has affected virtually all sectors of the economy, (2) persistent improvements in the technology have led to economy-wide productivity gains, and (3) it has spurred inventive activities, especially in the development of complementary goods that ensure its widespread use. Other key technologies – such as electricity or the steam engine – share the same characteristics, but to a different extent: In comparison to the preceding GPT, electricity,[2] the information technology has been diffusing at a much slower pace and triggered a stronger productivity slowdown upon its arrival (Jovanovic and Rousseau, 2005a). Like ICT, electricity also had deep impacts on the labor market: Not only were workers replaced by the new technology, electricity also lowered the basic skill level required for formerly skilled jobs (Lipsey et al., 2005). Thus, whereas electricity led to a falling demand for human capital, ICT caused the opposite due to the high knowledge level required for its utilization. Yet it was the former technology that enabled the development of the latter.

Denmark is chosen due to its position as a net importer of ICT products and due to the extent of the available data. The first is important in so far as this allows to analyze the effects of ICT predominantly on the production side without needing to consider its impact on economic development via export activities. As regards the latter, Statistics Denmark provides a comprehensive database that entails annual input-output tables in constant prices and employment data from 1966 to 2007, as well as capital flow tables spanning from 1993 to 2007 (see Strohmaier and Rainer (2013), for a detailed description of the data handling). The following industrial and service classes comprise the notion of ICT: (1) mfr. of office machinery and computers, (2) mfr. of radio and communications equipment etc., (3) computer activities, software consultancy and supply.[3] To study the distributive consequences of a GPT on an empirical level, labor input data from Denmark provided by the EU KLEMS database (Edition 2008) is used. This dataset comprises the shares in total hours worked together with the shares in total labor compensation for three different qualification levels, covering a time span of 26 years (1980–2005).

This paper proceeds as follows: In section 6.2 the multisectoral model of economic diffusion is introduced. The spread of GPTs as some product innovation

[2]The era of electricity was triggered by the invention of the dynamo in 1867 and spanned from the end of the twentieth century until 1930. This time was characterized by big transformations in the economic system, as new products and industries arose and the industry organization changed from small-scale production to assembly lines.

[3]Telecommunications could not be included, because the classification scheme does not list it as a separate activity.

and the subsequent influence of process innovations within the GPT sector are studied in section 6.3. A demonstration of wage inequality, changing wage share and output downturn is included. In addition to the model, empirical evidence is provided for the case of the ICT sector in Denmark from 1966 to 2007. Finally, section 6.4 concludes.

6.2 Multi-Sector Diffusion Model

A static multi-sector model is described in subsection 6.2. It is augmented by dynamic elements in subsection 6.2, to simulate the transition path in the presence of diverse processes per sector.

Mutual Dependence of Sectors

Let N be the number of different sectors in a closed economy. Within each sector m, an amount x_m of a homogeneous good is produced. This commodity can either be used as input factor of production or for final consumption y_m. $a_{nm} \geq 0$ denotes the quantity of good m, which is *on average* necessary to produce one unit of good n. Let $g_n = \dot{x}_n / x_n$ denote the growth rate of sector n. Final consumption y_n as the net residual of gross production is then given by

$$y_n = x_n - \sum_{m=1}^{N} a_{nm} x_m - \sum_{m=1}^{N} g_m a_{nm} x_m \tag{6.1}$$

The second term in (6.1) is the amount of good n used for productive purposes, whereas the third term is the correcting factor due to sectoral growth. Defining the $N \times N$ matrix A by the technical coefficients a_{nm}, the N equations stated in (6.1) are given in matrix notation by

$$\mathbf{y}^T = \mathbf{x}^T \left[\mathbb{I} - (\mathbb{I} + \hat{\mathbf{g}}) A \right] \tag{6.2}$$

$\mathbb{I}$ is the identity matrix, $\mathbf{y}, \mathbf{x}$ and $\mathbf{g}$ are the column vectors of final demand, of gross output and of the sectoral growth rates, respectively.[4] Equation (6.2) is the *market clearing condition*, which is assumed to hold (changing inventories are neglected).

Let l_{nk} denote the quantity of skill k necessary to produce one unit of good n. The $N \times K$ matrix L of labor input coefficients l_{nk} together with A characterizes the presently used technology. Skill k is remunerated by some wage rate w_k, which are the coefficients of vector $\mathbf{w}$ of wage rates. Relative wage premia w_k/w_j are taken to be exogenously given and constant over time for all k and j. Hence, it is possible to introduce some vector $\mathbf{u}$ characterizing relative wages by $\mathbf{w} = w\mathbf{u}$, defining the wage rate w.

[4] Superscript T denotes transposition and a hat on a vector means the diagonal matrix built from this vector.

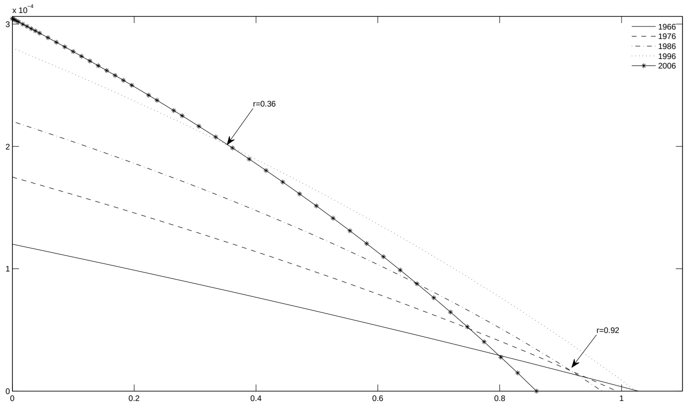


Figure 6.1: Wage-profit curve for Denmark from 1966 to 2006

Labor is *ex post* remunerated by the prevailing wage rate. Let r denote the *normal rate of profit* which prevails in case of free competition, then average unit production costs c_n of good n are given by

$$c_n = (1+r)\mathbf{p}^T\mathbf{a}_n + w\mathbf{u}^T\mathbf{l}_n \tag{6.3}$$

with $\mathbf{a}_n$ and $\mathbf{l}_n$ denoting the n-th row of A and L, respectively. Prices p_n are taken to equal average unit production costs, hence (6.3) implies the price equation

$$(1+r)A\mathbf{p} + wL\mathbf{u} = \mathbf{p} \tag{6.4}$$

with price vector $\mathbf{p}$. Prices are normalized with respect to some commodity bundle $\mathbf{d}$ (the *numéraire*) by $\mathbf{d}^T\mathbf{p} = 1$. Then from (6.4) the wage rate w can be derived to

$$w = \frac{1}{\mathbf{d}^T \left[\mathbb{I} - (1+r)A\right]^{-1} L\mathbf{u}} \tag{6.5}$$

The evolution of this $w-r$ relationship provides information about the kind of technical change that takes place. The intersections with the axes determine the maximum wage rate (for $r = 0$), and the maximum rate of profit (for $w = 0$), respectively. Pure capital-saving technical change corresponds to an anti-clockwise rotation around its intersection with the y-axis. Pure labor-saving technical change leads to a clockwise rotation of the $w-r$ curve around its intersection with the abscissa, where the rate of profit is plotted. Neutral technical change induces a parallel shift of the $w-r$ curve outwards, indicating an increase both in labor productivity and in the output-capital ratio. Figure 6.1 shows the development of the wage-profit curve for Denmark from 1966 to 2006. Until 1986 the curve rotates clockwise around a more or less stable rate of gross profit[5] in the range of

[5] Most studies that deal with $w-r$ curves refer to the profit rate net of depreciation; however,

0.92. Since the aggregate gross profit rate in Denmark has been far lower over this time span – at around 10.5%[6] – one can conclude that in the 20 years between 1966 and 1986 technological change was labor saving. For 1996 the $w - r$ relationship shows unambiguous technical change, because both intersection points moved outwards. Since then, the maximum rate of profit has continuously been decreasing and the curves of 1996 and 2006 intersect at a rate of profit equal to 0.36. Nonetheless, since the actual gross profit rate in Denmark was about 10% on average, technical change turns out to be indeed labor-saving and capital-using.

Modeling Technological Diffusion

The technical coefficients, collected in A and L, are defined as average inputs necessary for unit production. This average either is determined by one single process, or it is the result of a collection of different processes which are operated in this sector. Let the population of sector n be divided into I_n different species, the latter being characterized by some specific process i_n which produces good n. $\mathbf{a}_n^{i_n}$ and $\mathbf{l}_n^{i_n}$ are the respective vectors of circulating capital and of labor, used by process i_n in sector n to produce one unit of output. If a fraction $q_n^{i_n}$ of good n is produced by process i_n, then

$$\mathbf{a}_n = \sum_{i=1}^{I_n} q_n^{i_n} \mathbf{a}_n^{i_n}, \quad \mathbf{l}_n = \sum_{i=1}^{I_n} q_n^{i_n} \mathbf{l}_n^{i_n}$$

are the rows of A and L, respectively.

From equation (6.4) it then follows that prices are determined by average costs, since process i_n in sector n occasions unit costs

$$c_n^{i_n} = (1 + r)\mathbf{p}^T \mathbf{a}_n^{i_n} + w\mathbf{u}^T \mathbf{l}_n^{i_n}$$

The rate of extra profit $\rho_n^{i_n}$ of the respective process is then implicitly given by

$$(1 + r + \rho_n^{i_n})\mathbf{p}^T \mathbf{a}_n^{i_n} + w\mathbf{u}^T \mathbf{l}_n^{i_n} = p_n$$

A positive rate of extra profit of some process has different effects on producers: (1) Firms get encouraged to invest into growth, (2) new firms get convinced to enter the sector and to use this special process, or (3) firms within the sector change their mode of production and switch to the cheaper process. A negative rate of extra profit (losses) has the reverse effects: They make firms leave either the sector or this specific mode of production (by switching to another, more profitable process), or a firm has to shrink if it further on uses the unprofitable process. Positive extra profits can be earned by firms utilizing an innovation, a new, cheaper method of production. This approach thus shows parallels to

Vaona (2011) showed for Denmark that net and gross profit rate are highly correlated, i.e. accounting for the depreciation of capital does not change the overall trend of the profit rate.

[6] Following Vaona (2011), the computation of the aggregate gross profit rate was calculated as the relation between annual gross operating surplus (less mixed income) and real capital stock.

Schumpeterian *entrepreneurial profit*. The entrepreneur can reap extra profits by introducing some innovation, which offers the possibility to produce at lower costs (Schumpeter, 1934, 130). Subsequent competition and adaption of prices and wages lead to a decline of these profits, which finally vanish (Schumpeter, 1934, 131-132). The system is then in a new equilibrium position, where the incumbent method of production is replaced by the innovation, hence resembling the Schumpeterian notion of *creative destruction* (Schumpeter, 1954, ch. VII) A reconstruction of this pattern is shown in section 6.3, especially in context of figure 6.1.

By abstracting from the single firm, which only hosts some process, a *species* is defined by some technology as part of the population, the latter being defined by the respective sector. Each species is characterized by its input coefficients, leading to some *reproductive fitness*. Fitness in this context is a synonym for growth: "By absolute fitness is meant the expansion or contraction over some given time interval of the capacity output of a particular business unit" (Metcalfe, 2008, 30). It is influenced by three treats: (1) by rate of extra profit $\rho_n^{i_n}$, which are idiosyncratic for the process; (2) by the overall growth rate g of the economy due to savings; and (3) by the sectoral growth rate Δ_n, which corrects sectoral output according to changes in effective demand due to varying demand for production and final consumption. The growth rate of output $x_n^{i_n}$ produced by means of process i_n in sector n is then given by

$$g_n^{i_n} = \dot{x}_n^{i_n}/x_n^{i_n} = \rho_n^{i_n} + \Delta_n + g$$

As a consequence of $x_n = \sum_{i_n=1}^{I_n} q_n^{i_n} x_n^{i_n}$, this expression leads to the sectoral growth rate

$$g_n = (\rho_n + \Delta_n + g) \tag{6.6}$$

with average growth $\rho_n = \sum_{i_n=1}^{I_n} q_n^{i_n} \rho_n^{i_n}$ of sector n By differentiation of $q_n^{i_n} = x_n^{i_n}/x_n$, the dynamics of the system in the presence of technical change is described by the replicator dynamics

$$\dot{q}_n^{i_n} = q_n^{i_n} \left(\rho_n^{i_n} - \rho_n\right) \tag{6.7}$$

Different rates of extra profit of different processes producing the same homogeneous good consequently imply changing market shares. The dynamics of $q_n^{i_n}$ depends on the rate of extra profit and therefore on the price structure $(\mathbf{p}, w)$ and on the technical coefficients $\mathbf{a}_n^{i_n}$ and $\mathbf{l}_n^{i_n}$. Equation (6.7) hence describes a diffusion process, if within one sector several processes with different rates of extra profit are in use. Introducing new innovative (cheaper) processes consequently sets off a diffusion process of this innovation, gradually superseding the incumbent process.

6.3 Diffusion of GPTs

In this section, the diffusion of the influence of GPTs is analyzed by means of the just introduced multi-sector diffusion model. In subsection 6.3, a new GPT is introduced as a second sector in a former single-sector economy, making the emergence of one or more new processes in the first sector possible. Then, in subsection 6.3, technical change in the GPT sector is allowed for, and possible consequences on the first sector are investigated.

Introducing a New GPT

A new GPT is invented and introduced into the economic system at time $t = 0$. For $t < 0$ the economy is described by one sector, which reproduces itself with the net output used up for final consumption. The production process is characterized by the technical coefficients a^1_{11} and l^1_{11}. Gross production x_1 of this sector equals total production x^1_1 of this process. For $t \geq 0$, a second sector exists, producing a GPT, such that the old technology in sector 1 is now characterized by $\mathbf{a}^1_1 = (a^1_{11}, 0)^T$ and $\mathbf{l}^1_1 = (l^1_{11}, 0)^T$.

GPT as product innovation In the following, a new GPT will be introduced as a product innovation; in the context of ICT as the latest GPT, one might think in this regard of the development of products such as mainframe and microcomputers that replaced the former office machinery, or the Internet that opened up a new platform for communicating and trading goods and services. The GPT is produced by means of capital input from sector 1. The process utilized in sector 2 is characterized by technical coefficients $\mathbf{a}^1_2 = (a^1_{21}, 0)^T$ and $\mathbf{l}^1_1 = (0, l^1_{22})^T$. Hence the GPT is produced by high-skilled labor with wage premium $u > 1$. For $\mathbf{d} = (1, 0)^T$, taking the good of sector 1 as numéraire, price p of the GPT is given by

$$p = (1 + r)a^1_{21} + wl^1_{22}u \tag{6.8}$$

According to equation (6.3) the price of a GPT equals its production costs, i.e. the costs of commodity inputs (including interest, as they need to be available at the beginning of the production year) and the expenses for high-skilled labor. An introduction of the GPT sector with the produced good not being used for final consumption ($y_2 = 0$) only pays if similarly in sector 1 a second process is introduced, using the GPT as factor of production. If the GPT enters as circulating capital, the innovative process can be characterized by the technical coefficients $\mathbf{a}^2_1 = (a^2_{11}, a^2_{12})^T$ and $\mathbf{l}^1_1 = (0, l^2_{12})^T$. Let $q_1 > 0$ denote the share of the new process in sector 1. From goods market clearing (6.2), which now reads

$$(y_1, 0)^T = (x_1, x^2_1 q_1 a^2_{12})^T \left[\mathbb{I} - (\mathbb{I} + \hat{\mathbf{g}})A\right], \tag{6.9}$$

the growth rate g_2 of the GPT sector is given by $1+g_2 = q_1(t)(1+g_1)a_{12}/a_{21}$. From

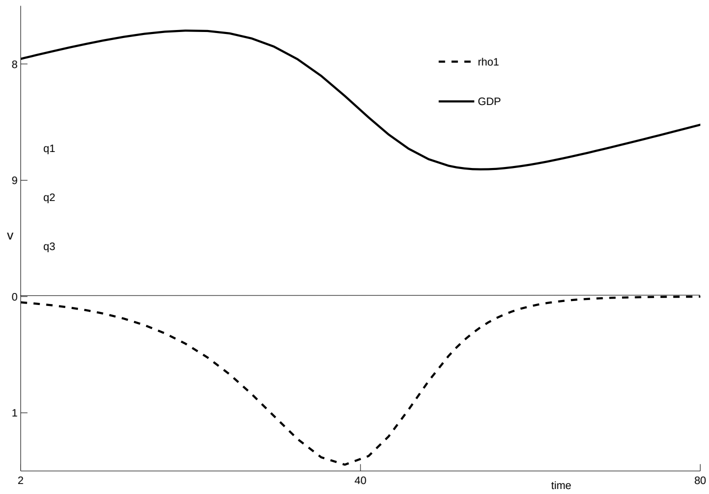


Figure 6.1: Negative growth and output slump

the first equation in (6.9), total output x_1 of the consumption sector exhibits a growth rate $g_1 = \rho_1 + r$ according to (6.6) with $g = r$. $\Delta_1 = 0$ holds because forced savings are assumed (y_1 equals net output) and no substitution of consumption exists due to $y_2 = 0$.

Diffusion of the GPT The dynamics of the system is driven by the rate of extra profit ρ_1^i of the two processes $i = 1, 2$ in sector 1, implicitly given by

$$\begin{array}{lcll} (1+r+\rho_1^1)\, a_{11}^1 & + & wl_{11}^1 & = & 1 \\ (1+r+\rho_1^2)(a_{11}^2 + a_{12}^2 p) & + & wl_{12}^2 u & = & 1 \end{array} \tag{6.10}$$

From (6.8), p can be replaced in (6.10) as well as in the now prevailing price equation $(1+r)[(1-q_1)a_{11}^1 + q_1(a_{11}^2 + a_{12}^2 p)] + w[(1-q_1)l_{11}^1 + q_1 l_{12}^2 u] = 1$ This problem is formally equivalent to a one-sector economy employing two processes: The first one is the same as above, characterized by technical coefficients $\tilde{a}_1 = a_{11}^1$ and $\tilde{\mathbf{l}}_1^1 = (l_{11}^1, 0)^T$; the second one is a combination of the GPT sector and the formerly defined second process, characterized by the technical coefficients $\tilde{a}_2 = a_{11}^2 + (1+r)a_{12}^2 a_{21}^1$ and $\tilde{\mathbf{l}}_2 = \left(0, (1+r)a_{12}^2 l_{22}^1 + l_{12}^2\right)^T$. In general, each two-sector economy with one innovative sector formally can be reduced to a one-sector diffusion problem, which is analytically solvable. This solution as well as further discussions of formal properties of the model are derived in Rainer (2013). Subsequent simulations are based on numerical solutions of the general replicator equation (6.7), adapted to the given numbers.

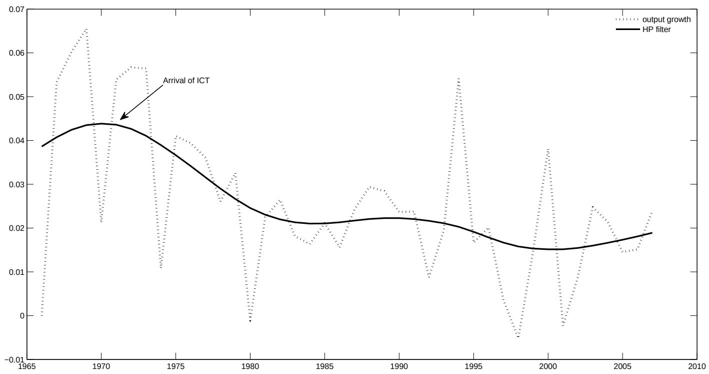


Figure 6.2: Growth of real output per man-hour

Output slump The development of total output is depicted in figure 6.1 for the technical coefficients $(a^1_{11}, l^1_{11}) = (0.3, 0.3)$, $(a^2_{11}, a^2_{12}, l^2_{12}) = (0.4, 0.1, 0.2)$ and $(a^1_{21}, l^1_{22}) = (0.1, 0.1)$. Since the average rate of extra profit is negative as a result of the capital using characteristic of the technical change, real GDP exhibits a recessive tendency throughout the diffusion process. Only in the long run the economic growth pattern given by $g = r = 0.01$ is restored. The reason for the output slump after introduction of some GPT is the following: By the market clearing condition (6.2), the growth component $\rho_1 + \Delta_1$ of the sectoral growth rate $g_1 = \rho_1 + \Delta_1 + r$ is obtained by savings of workers. Since $\Delta_1 = 0$, $\rho_1 < 0$ implies forced savings. Consumers therefore accept lower final consumption due to changing circumstances. This downturn cannot be compensated by the rising output of the innovative process and therefore leads to a regression of available goods for final consumption.

From an empirical perspective, looking at the output development over time, Jovanovic and Rousseau (2005b) showed that the emergence of the new information technology in 1971 was not able to reverse the decline of output growth in the U.S. that had been persisting since the 1960s. In their study, the arrival of IT was dated to 1971, because in this year Intel's 4004 processor came out and revolutionized the market for personal computers (PCs). We undertook a similar analysis for the Danish economy. The date of introduction was also fixed to 1971, as, on the one hand, PCs are the most important ICT product among all import goods; on the other hand, ICT equipment reached 1% of total capital stock[7] of the median sector in this year. Figure 6.2 presents the time series of real output per man-hour[8] in Denmark between 1966 and 2007. The solid line shows the long-term trend as obtained by the Hodrick-Prescott (HP) filter.

[7]The corresponding data was retrieved from the EU Klems database.

[8]Real output represents deliveries of final goods and services per sector to domestic households, investment, government and nonprofit institutions, as well as net exports to other countries, in constant prices of the year 2000. The total sum equals the gross domestic product.

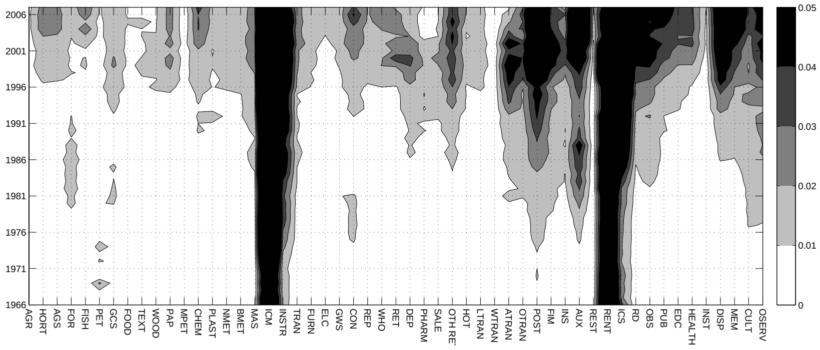


Figure 6.3: The diffusion of ICT products across sectors (intensive use)

While output growth shows a falling tendency throughout the whole period under study, figure 6.2 suggests that the emergence of ICT in 1971 did certainly not mitigate the slump. Differentiating between ICT goods and services, the decline in growth rates after 1985 coincides with the second wave of ICT services that started off after ICT-manufacturing products had pervaded the gros of industries (see Strohmaier (2013)).

Wage inequality Different skills which are differently remunerated imply wage inequality within the class of laborers. For two different skills, as assumed in this example, wage inequality can be estimated by the GINI index:[9]

$$GINI = q_h(1-q_h)\frac{u-1}{1+(u-1)q_h} \tag{6.11}$$

The share q_h of high skill labor is remunerated by some wage premium $u > 1$ relative to low skill labor. It is given by

$$q_h = \frac{x_1^2 l_{12}^2 + x_2^1 l_{22}^1}{x_1^1 l_{11}^1 + x_1^2 l_{12}^2 + x_2^1 l_{22}^1} = \left[1 + \frac{1-q_1}{q_1}\frac{l_{11}^1}{l_{12}^2 + a_{12}^2 l_{22}^1}\right]^{-1} \tag{6.12}$$

The last term in equation (6.12) accrues from $x_2 = x_1^2 q_1 a_{12}^2$ and by acknowledging $x_1^i = q_1^i x_1$ for $i = 1, 2$. In this case, the GINI index is independent of sectoral growth patterns, since growth of the GPT sector is coupled to the demand from sector 1.

The diffusion process described by (6.7) and the resulting transitional wage inequality calculated by (6.11) can also be analyzed empirically. The compound direct requirements matrix, which includes not only domestic and imported flows of intermediate products, but also of capital, is used in the following to derive the diffusion pattern of ICT.[10] Figure 6.3 depicts the diffusion of ICT throughout the

[9]The derivation of the GINI index for the case of K skills is conducted in Rainer (2013).

[10]Including investment flows is especially important in the case of ICT, as most of these products are of fixed-capital type.

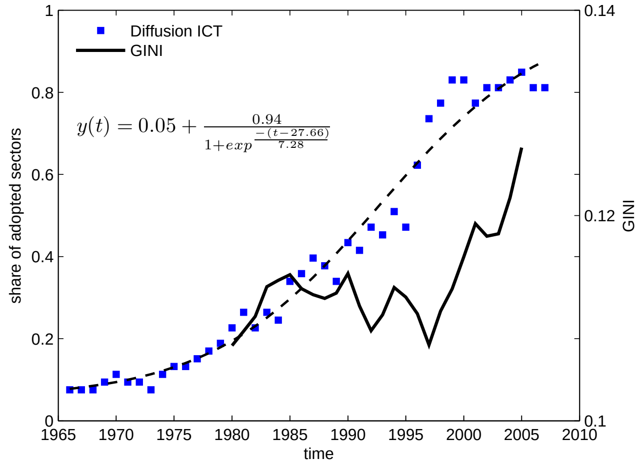


Figure 6.4: The diffusion of ICT products across sectors (left ordinate) and the GINI coefficient for low and high-skilled labor in ICT-using industries (right ordinate)

Danish economy from 1966 until 2007 (the industry classification is listed in the appendix). An input coefficient above 0.01 indicates that the corresponding sector has adopted ICT. The darker the color, the more intensive is the employment of ICT in the respective industry. The contour plot shows that ICT goods (ICM) and ICT services (ICS) initially spread over the neighboring industries, such as mfr. of machinery and equipment n.e.c. (MAS), mfr. of other electrical, medical and optical equipment (INSTR), as well as real estate activities (REST) and renting of machinery and equipment (incl. office computers) n.e.c. (RENT). In the mid-70s post and telecommunications (POST) and the financial markets (FIM) started to utilize ICT. Almost a decade later, one can see the beginning of online sale (OTH RET) and online auctioning (CONS), and the entry of ICT in research & development (RD). Afterwards, the technology spreads over most sectors in manufacturing and services, with the primary industries as the last sector to adopt it.

Furthermore, figure 6.4 links the diffusion of ICT to the dynamics of the wage rate[11] of low- and high-skilled labor in Denmark. The left ordinate presents the share of industries already using ICT, and the right ordinate gives the GINI coefficient as a measure of the dispersion of wages of low and high-skilled labor[12] in the ICT-using industries. Figure 6.4 shows that the diffusion path approaches the typical sigmoid curve with the adoption rate increasing around 1985 and again

[11]In order to take into account self-employed persons, wages and salaries per industry were re-estimated by assuming that self-employed and employees have the same wage rate.

[12]For the purpose of this paper, only between low-skilled and higher (i.e. middle and long cycle education)-skilled workers was discriminated. For Denmark, low-skilled labor refers to basic schooling, whereas middle and high-skilled labor comprises short, middle and long cycle higher education as well as vocational education and training (for further details on the labor accounts see the EU KLEMS manual, pp. 24–31).

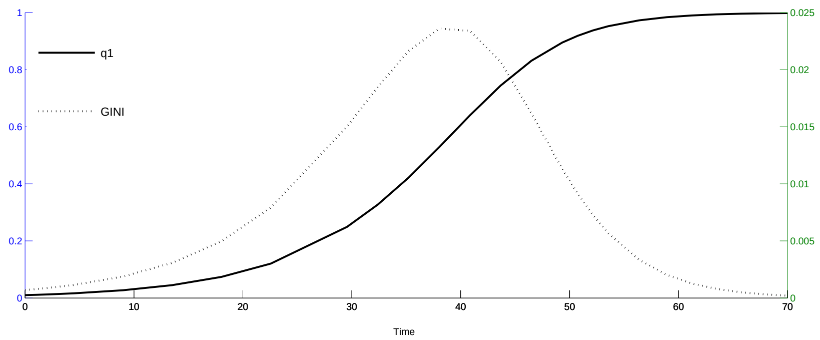


Figure 6.5: The diffusion of an innovative process and the resulting wage inequality

after 1995. After the dot.com-crash in 2000, the speed of diffusion slowed down significantly. Since not all industries that produce ICT goods and services could be taken into account (e.g. telecommunication services), the level of adoption is still below 100 per cent at the end of the period under study, even though the diffusion process has already reached its fade-out phase. Hence by that time, the vast majority of the Danish enterprises had implemented ICT for supporting their business processes, especially for finance and sales management, production and logistics, and human resource management (Statistics Denmark, 2006, 30).

With regard to the development of wage differentials, the GINI of ICT-using sectors is measured on the right-hand axis of figure 6.4. While the dispersion of wages and salaries in Non-ICT industries was constantly decreasing between 1966 and 2003, ICT-using industries exhibit a different pattern: The GINI as an indicator of wage dispersion peaked for the first time when the rate of adoption of ICT was about to take off in the early 1990s. At that time, the demand for qualified IT people was simply not possible to meet. This lack of e-skills, especially from incumbent employees, has been one of the major barriers to ICT adoption experienced by Danish enterprises (Statistics Denmark, 2006, 57). After 1990, the GINI was decreasing, since the labor market could adapt to the new order of skills that were required for efficient ICT usage: In the year 2000, 69,300 persons (about 2.4 per cent of the labor force) had an ICT-related education. Until 2004, this number was rising by 21 per cent to 83,500. From these persons, 83 per cent were employed; this rate is significantly higher than the average employment rate of 76.2 per cent in that year. The upward trend of the GINI since the beginning of this century can be attributed to the rapidly growing importance of ICT services which has been accompanied by a rising demand for persons with high ICT skills.

These empirically found diffusion patterns can be reconstructed by the model, as can be seen in figure 6.5 which, on the basis of (6.7), reveals a similar behavior of the share q_1 of the innovative process as suggested by figure 6.4. What gets apparent is the slow start of the diffusion of the innovative process due to the growth process based on the replicator dynamics, which is followed by a *takeoff* at $t \approx 25$. The respective course of the GINI index, also depicted in figure 6.5 for

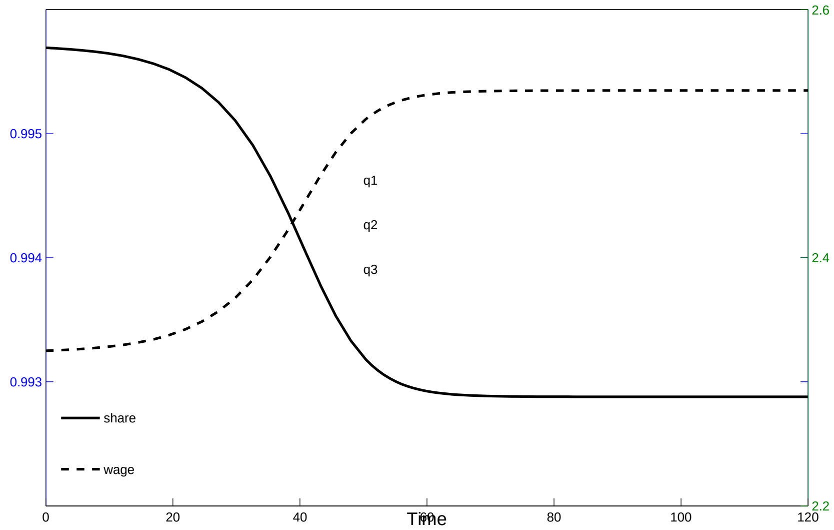


Figure 6.6: Changing wage rates and wage share

$u = 1.1$, can be explained as follows: At the beginning of the diffusion process, almost all workers perform low-skilled labor with wage rate w, whereas near the end of the process almost all workers are highly skilled with wage rate $wu > w$. Therefore the GINI index approaches zero at the beginning and towards the end of the process, whereas there is *transitional wage inequality* in between when high and low-skilled labor is concurrently employed.

Wage share Another measure touching on inequality and distribution is the wage share $\omega = W/(W + P)$ comprising total wages

$$W = w\mathbf{x}^T L\mathbf{u} = \mathbf{x}^T \left[\mathbb{I} - (1 + r)A\right] \mathbf{p}$$

and total profits $P = r\mathbf{x}^T A\mathbf{p}$. The changing wage share in the present example is depicted in figure 6.6. It is decreasing as a consequence of the capital *using* and labor *saving* nature of the technical change. An increasing wage rate is a general property of this model, indicating the tendency of the system towards higher labor productivity (Rainer, 2013). This, as a result of rising labor productivity, including the decline of the wage share, indicates *technical unemployment* or increasing leisure time.

Consequences of Technical Change in the GPT Sector

The model economy of the preceding subsection can be extended to the case of two different processes, which enter the first sector as a consequence of the occurrence of the new GPT in sector 2. Process 3 is characterized by the input coefficients

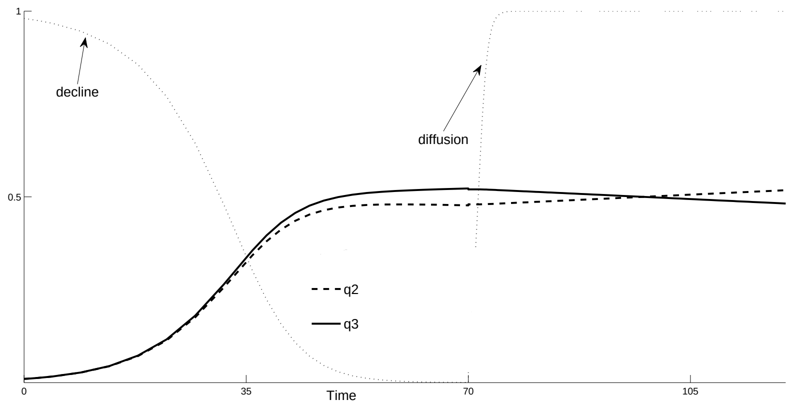


Figure 6.7: Two innovative processes

$(a^3_{11}, a^3_{12}) = (0.405, 0.085)$ and therefore uses less of the GPT as input (labor input is the same for processes 2 and 3 to keep matters simple). As depicted in figure 6.7 for $t < 70$, the incumbent process gets superseded and an advantage for the third process against the second process prevails. Without further incidents, for $t > 70$ the market share of process 3 would increase and finally take over the market due to its cost advantage compared to process 2. This scenario occasionally changes if technical change in the GPT sector reduces its unit costs, possibly (not necessarily) leading to a switch of profitability in sector 1 as indicated in figure 6.7 for $t > 70$: In sector 1 only the new processes 2 and 3 are depicted, and the new process in sector 2 is characterized by pure labor-saving technical change with $l^2_{22} = 0.05$.

Additionally, increasing labor productivity is indicated by a rising wage rate. This is a general property of the model: Whenever at least one commodity directly or indirectly enters the numéraire basket $\mathbf{d}$, the wage rate increases in the course of the diffusion process; it actually never decreases.[13]

This is all the more the case for a GPT sector, since a general purpose technology is *inter alia* characterized by its scope of improvement during its lifetime. After its arrival, the crude technology may take decades to mature and show its full potential. The relation between technical change in a GPT-producing sector and rising labor productivity in the application sectors is empirically studied by means of a structural decomposition analysis (SDA). Labor productivity growth is thereby measured as the relative change in the maximum wage rate as defined in (6.5). The SDA resembles growth accounting because the change in one macroeconomic variable – labor productivity growth– is broken down into its underlying sources (one of which is technical change). Subsequently, a cross-sectional analysis is applied and results are filtered for the ICT sector.[14] We thus

[13] A formal proof of this statement can be found in Rainer (2013).
[14] A detailed description of the SDA and further results can be found in Strohmaier and Rainer

trace the development in aggregate labor productivity back to its driving sectors on the mesoeconomic level and show which role technical change[15] *within* the ICT producing sector played in this development. The findings are shown in figure 6.8.

Technical change in the ICT-producing sector as measured from an input-output perspective is a improvable indicator for advances in the technology itself; especially since it does not consider capital goods, which embody the bulk of technological change in ICT. Nevertheless, input-output data are capable of tracking process changes on a mesoeconomic level. To underpin this analysis, the gray shades of the surface represent the degree of (local) innovation activity as given by the share of ICT patents in total patent applications.[16] The number of patents alone as a measure of technological change may be not satisfying either, first because the volume of patents just reflects the level of inventive activity, but does not say anything about how many of these inventions could be successfully introduced to the marketplace. Second, there have been important policy and institutional changes in the last decades that boosted incentives for filing patents. Nevertheless, a study by Kortum and Lerner (1998) shows that the increase in patent applications across the globe could be indeed attributed to technological change.

Turning back to figure 6.8, technical change in the ICT-producing industries manifests itself in labor productivity growth not earlier than from the mid-1990s onwards. Dating the arrival of this GPT at the beginning of the 70s, it thus took more than two decades for ICT to become a major source of productivity growth. Breaking down its effects on the sectoral level, ICT had its strongest impact on labor productivity growth in the following manufacturing industries: machinery and equipment, electrical, optical and medical instruments and transport equipment. It also significantly affected the construction sector. As regards the service sector, a high impact on post and telecommunications, real estate activities, other business activities, research & development and public administration can be observed.

With regard to inventive activities, figure 6.8 shows that the 1990s were not only characterized by productivity gains due to improvements in ICT, but also by a surge in ICT patents; however, most of the important innovations, which aim at facilitating its widespread use, were already developed between 1975 and 1990, outside of Denmark. For example, the first microcomputers – commonly known as personal computers – were developed in 1975 by the Massachusetts Institute of Technology. In the same year Bill Gates and Paul Allen founded Microsoft. The market of PCs rose quickly when Apple introduced its first microcomputer in

(2013).

[15]By technical change, we refer to the change in the production process of the respective industry, as opposed to technological change embodied in a new product. With regard to ICT, *technological* change means the emergence of this new GPT and the consequences for the economic system via its diffusion. *Technical change* refers to the changes in the input composition of the ICT sector over time, which in turn affect all other industries tied to the ICT sector upstream (due to the change in demand for intermediate products) and downstream (due to the change in the supply of ICT products).

[16]...filed by Danish applicants under PCT between 1977 and 2007. Data source: OECD.Stat.

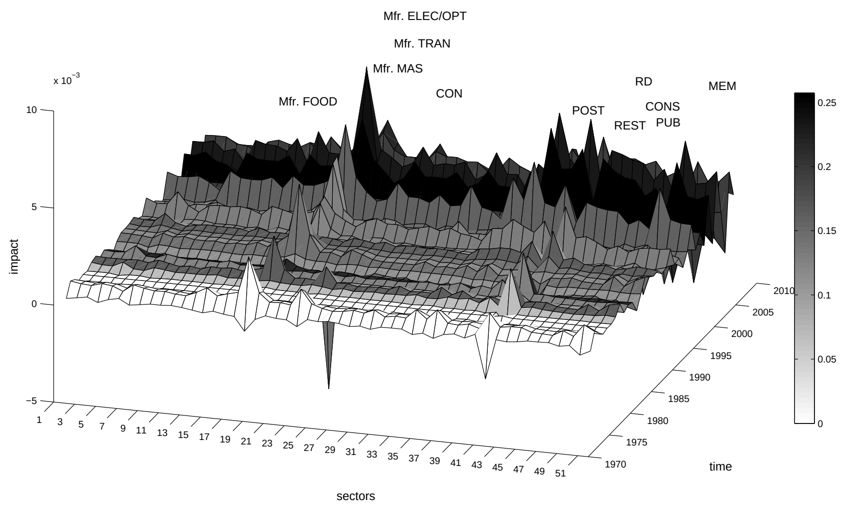


Figure 6.8: The contribution of technical change in the ICT sector to sectoral labor productivity growth
Mfr.: Manufacturing of; FOOD: Food, beverages and tobacco; MAS: Machinery and equipment n.e.c.; OPT: Optical and medical equipment; TRAN: Transport equipment; CON: Construction; POST: Post and telecommunications; REST: Real estate activities; RD: Research and development; CONS: Consultancy etc.; PUB: Public administration; MEM: Activities of membership organizations n.e.c.

1977 and even more, when IBM did so in 1981, equipped with DOS, the operating system by Microsoft. These developments in personal computers have been of particular importance for Denmark, since computers have been the most important import good for the economy when it comes to ICT products. The second half of the 80s was characterized by the emergence of the Internet that went viral from the 1990s onwards; In 1984, the domain name system was created, making the use of Internet way more customer-friendly. In 1987 followed the adaption of the TCP/IP standard protocol which gave a big boost to the number of users. All those innovations can be seen as an important step towards the era of e-commerce which started in 1995, when Amazon and Ebay went online. It is interesting to note that the *local* innovation activity[17] was highest between 1998 and 2003, at a late stage of the diffusion process. This indicates the long time span necessary for a GPT to reach maturity and for the economic system to adapt to the new technology, something which is resembled by the model results.

6.4 Conclusion

As concerns the theoretical part, the starting point for simulating diffusion patterns of GPTs is a multi-sector model. Its dynamics is based on differentiated growth due to diverse profitability of production processes. The following stylized

[17]as given by the number of patents from Danish enterprises.

facts are reconstructed: (1) The emergence of a new GPT sector (by a product innovation) and technical change in a GPT sector (by process innovations) induce changing productivity in related sectors. This includes negative output growth after the emergence of a new GPT, if technical change is capital-intensive. (2) By assuming a higher skill level necessary for processes which are related to the GPT sector, transitional wage inequality is demonstrated. (3) The S-shaped diffusion pattern, which prevails for successful innovations, is endogenized and feedback effects between output growth and prices (respectively wages) are considered.

Furthermore, the theoretical analysis was tested against empirical evidence from data of the ICT sector in Denmark from 1966 to 2007. The main purpose of the empirical part was to show that ICT was not only a sectoral revolution; it transformed processes throughout the whole economy. Since it took several decades for this technology to pervade the production system, its impact could only be observed recently. As regards the consequences of ICT for the labor market, the diffusion of this technology can be associated with transitional wage dispersion in the ICT-producing as well as ICT-using industries.

The analysis of the role of ICT for labor productivity change in the rest of the economy also reveals industry clusters: The ICT sector had its strongest impact on technology-intensive manufacturing industries, such as machinery and equipment or transport equipment as well as on neighboring service sectors such as post and telecommunications, real estate and other business activities. Likewise, the diffusion and intensity of utilization of ICT (depicted in figure 6.3) supports the hypothesis by Antonelli (2003) that a new technology diffuses at a higher rate, the more similar are the factor endowments between the place of origination and the place of adoption: This is the case, for example, of telecommunications, which represents a similar industry to the ICT services covered in our analysis (in fact, the new Danish industry classification from 2007 groups these two industries together). Thus our results cautiously suggest that the composition of factors determines the speed and order of adoption, and eventually the composition of the economic system as a whole. However, a profound statement would require further examination which is beyond the scope of this paper.

In general, findings promote the importance of the meso level as a unit of analysis, both from a theoretical and empirical perspective, as has been used, for example, by Dopfer and Potts (2008) and Saviotti and Pyka (2008); since it is the coordination among industries that determines the success or failure of a new technology regarding its impact on the economic system. A meaningful study of this sectoral interplay demands the differentiation of sectors according to their activities respective production processes. Such an analysis also represents a key tool for the design of effective policies fostering economic development via technological change.

Appendix

6.A Industry Classification

Table 6.A.1: Aggregation of Danish industries. The numbers in the third column indicate the assignment of the respective sector to the Danish 130-industry classification, the third column to ICT-producing, ICT-using and Non-ICT industries.

Code	Abbr.	Industry	Aggr.	ICT class
1	AGR	Agriculture	1	Non-ICT
2	HORT	Horticulture, orchards etc.	2	Non-ICT
3	AGS	Agricultural services; landscape gardeners etc.	3	Non-ICT
4	FOR	Forestry	4	Non-ICT
5	FISH	Fishing	5	Non-ICT
6	MPET	Extr. of crude petroleum, natural gas etc.	6	Non-ICT
7	GCS	Extr. of gravel, clay, stone and salt etc.	7	Non-ICT
8	FOOD	Mfr. of food, beverages and tobacco	8-18	Non-ICT
9	TEXT	Mfr. of textiles, wearing apparel, leather	19-21	Non-ICT
10	WOOD	Mfr. of wood and wood products	22	Non-ICT
11	PAP	Mfr. of paper prod.; printing and publish.	23-26	Non-ICT
12	PET	Mfr. of refined petroleum products etc.	27	Non-ICT
13	CHEM	Mfr. of chemicals and man-made fibres etc.	28-35	Non-ICT
14	PLAST	Mfr. of rubber and plastic products	36-38	Non-ICT
15	NMET	Mfr. of other non-metallic mineral products	39-41	Non-ICT
16	BMET	Mfr. and processing of basic metals	42-47	Non-ICT
17	MAS	Mfr. of machinery and equipment n.e.c.	48-52	ICT-using
18	ICM	Mfr. of ICT equipment	53,55	ICT
19	INSTR	Mfr. of electrical, optical and medical instruments	54,56	ICT-using
20	TRAN	Mfr. of transport equipment	57-59	ICT-using
21	FURN	Mfr. of furniture; manufacturing n.e.c.	60-62	Non-ICT
22	ELC	Electricity supply	63	Non-ICT
23	GWS	Gas and water supply	64-66	Non-ICT
24	CON	Construction	67-70	Non-ICT
25	REP	Sale and repair of motor vehicles etc.	71-73	ICT-using
26	WHO	Ws. and commis. trade, exc. of m. vehicles	74	ICT-using
27	RET	Retail trade of food etc.	75	ICT-using
28	DEP	Department stores	76	ICT-using
29	PHARM	Re. sale of phar. goods, cosmetic art. etc.	77	ICT-using
30	SALE	Re. sale of clothing, footwear etc.	78	ICT-using
31	OTH RET	Other retail sale, repair work	79	ICT-using
32	HOT	Hotels and restaurants	80-81	Non-ICT
33	LTRAN	Land transport; transport via pipelines	82-85	Non-ICT
34	WTRAN	Water transport	86	Non-ICT
35	ATRAN	Air transport	87	Non-ICT
36	OTRAN	Support. trans. activities; travel agencies	88-89	Non-ICT
37	POST	Post and telecommunications	90	ICT-using
38	FIM	Financial intermediation	91-92	ICT-using
39	INS	Insurance and pension funding	93-94	ICT-using
40	AUX	Activities auxiliary to finan. intermediat.	95	ICT-using
41	REST	Real estate activities	96-98	ICT-using
42	RENT	Renting of machinery and equipment etc.	99	ICT-using
43	ICS	Computer and related activities	100-101	ICT
44	RD	Research and development	102-103	ICT-using
45	OBS	Other business activities	104-109	ICT-using
46	PUB	Public administration etc.	110-113	Non-ICT
47	EDC	Education	114-118	Non-ICT
48	HEALTH	Health care services	119-120	Non-ICT

Continued on next page

Table 6.A.1 – continued from previous page

Code	Abbr.	Industry	Aggr.	ICT class
49	INST	Social institutions	121-122	Non-ICT
50	DISP	Sewage and refuse disp. and similar act.	123-125	Non-ICT
51	MEM	Activities of membership organiza. n.e.c.	126	ICT-using
52	CULT	Recreational, cultural, sporting activities	127-128	Non-ICT
53	OSERV	Other service activities	129-130	ICT-using

Chapter 7

Summary

The present thesis has focused on the pervasive character of general purpose technologies (GPTs) to fuel the technological 'engines of growth'. Since the impact of an innovation is primarily channeled through the diffusion process, a GPT – by affecting virtually all sectors of an economy – plays a particular role for long-term economic development. The other characteristics of a GPT, its scope of improvement and innovational complementarities, may have a similar or even more disruptive impact on the economy than the diffusion of the technology as such. But as Field (2011) points out, it is the latter criterion that distinguishes a GPT from other innovations that may only serve one purpose, but might be equally consequential.

To understand the full pervasiveness of GPTs, we have taken a multisectoral approach, in order to examine the technical complementarities between heterogeneous industries that produce different commodities by different means and modes of production.

In chapter 3 we show that an input-output framework is able to capture the main characteristics of GPTs. Moreover, it allows for investigating sectoral differences regarding the impact of a GPT, and thus the locus and direction of technical change. The underlying structural decomposition analysis represents a novel way of accounting labor productivity growth.

By operationalizing the term pervasiveness at the meso level, undertaken in chapter 4, the robustness of sectors as evidenced by diversified linkages to other industries is proposed as a measure for identifying GPT-producing sectors. The discussion also highlights the mutual dependence between the GPT-producing sector and user sectors, stressing the role of technical complementarities up and down the technology tree.

The latter was the central subject of chapter 5, in which industries have been represented in a hierarchical order. The 'technical tree' shows the core sectors for economic development and simultaneously presents intersectoral relations. GPT sectors were identified as the basic grid underlying the economic system. The method proposed is also an attempt to apply mesoeconomic concepts in evolutionary theory empirically.

Chapter 6 concludes by analyzing the empirical results in an evolutionary multi-sector model. Firms, not technology, thereby represent the unit upon which selection occurs, which causes population changes on the sectoral level. The framework is able to deal with the socio-economic consequences associated with the emergence of a new GPT, such as the output slump after the arrival of the technology or skill-induced wage dispersion. It thus extends the current literature on GPTs presented in chapter 2 that focus primarily on the role of R&D activities in growth and diffusion of pervasive innovations.

Based on these findings, we believe that national accounts provide a good source for uncovering both type and origins of major technological change. Our work thereby complements the empirical literature on GPTs that draws on patents: On the one hand, input-output tables are highly standardized, whereas figures on patents depend on the geographical location and the technology class in which they were filed, rendering cross-country and cross-sectional analyses difficult. On the other hand, technological complementarities that are derived from patents citing other patents as prior knowledge are not able to cover the full spectrum of spillover effects (Bresnahan, 2010); especially those that occur in the course of utilizing a specific technology (for instance, microcomputers) for developing another (e.g. wind turbines). These complementarities are to a certain extent captured in intersectoral commodity flows, assigning the meso unit an important analytical function for the study of technological change.

Specifying a new technology as a product innovation that triggers process innovations is particularly meaningful on the sector level, as industry classifications subsume similar products under one group so that a technology is sufficiently represented by the economic activities in one sector. This is especially the case of ICT for which the major industries producing this technology can be identified on the two-digit level in ISIC Rev. 3.1 (NACE Rev. 1.1); and more so in Rev. 4 (NACE Rev. 2.1), that was explicitly adjusted to better represent the new information and communication technologies. With regard to other GPTs, such as nanotechnology or also clean technology, a similar analysis would require a more disaggregated level of industry groupings.

For the investigation to give meaningful results, the inclusion of fixed capital in the analysis is essential, as the bulk of technology is embodied in commodities that endure longer than one production period. While in this regard, investments in ICT capital were studied as part of final demand in chapter 3, they were included in the intermediate matrix in chapter 4. Thus, the coefficients do not only represent current inputs, but also foreshadow future production trends. In chapter 5, capital consumption flows were used to estimate the annual deployment of fixed capital, which might picture best the actual production system. However, a more sophisticated approach to this problem would be to integrate a stock-flow concept into the input-output model by calculating so-called centre coefficients that take into account the actual degree of utilization of the different types of fixed capital during one period of time (see for example Kurz and Salvadori (1995) and Schefold (1989)).

Regarding the specific GPT under study, information and communication technology, empirical findings show that early adopters of the technological breakthrough have long-term benefits. Thus, experience with the technology matters, so that the risks involved in being a pioneer eventually pay off. Results from chapter 3 pictures the ICT revolution coming in two waves. The first started in the 1980s, induced by the ICT manufacturing sector, the second wave occurred in the mid-1990s and was triggered by ICT services. Chapter 4 indicates that the diffusion path between manufactured ICT and ICT services has been strongly interrelated, where the takeoff of the latter pushed the adoption rate of the former. These findings suggest a hierarchy of these subtechnologies, which becomes more evident in the technical tree that captures ICT services – but not the ICT-manufacturing sector – as a core of the Danish economy. The results differ though from the ones obtained in chapter 4 according to which ICT-manufacturing industries have evolved to occupy a crucial position in the economy. These discrepancies are partially attributed to the different methodological approach, and partially to the dataset applied; whereas in chapter 4 investment flows in constant prices of the year 2000 were used, the social network approach in chapter 5 was applied to chained prices and capital consumption data. Given the erosion in prices of ICT commodities and the volatility of capital formation flows, we believe the latter data to be even more informative about the impact of ICT.

The empirical evidence gathered throughout this work shows a somewhat different picture than has been drawn by common GPT models. Presenting GPTs as a single variable does not do justice to the complexity of radical technological change. The present work suggests that the generality of purpose should rather translate into a large spectrum of purposes serving distinctive economic processes that differ from each other by more than a productivity parameter. Due to the strong focus on innovational spillovers, the diffusion of a GPT was primarily modeled in the context of social learning. But evidently, technological proximity plays a role in the adoption process, since sectors neighboring the ICT-industry belonged to the first users. This distance to the locus of technical change has not been accounted for in the first generation of models. Likewise, the coevolution of (sub)technologies has found little attention, because industries in the intermediate sector are not technically related to each other. For instance, the present endogenous growth models cannot trace the interconnected development between manufacturing of ICT and ICT services without assigning each to a different GPT, which is clearly not the case.

We believe that the role of industries as interface between the micro and macroeconomic level has so far not been dealt with sufficiently in the literature on innovation, in particular on GPTs. By moving the analytical core onto the meso level, the present thesis also fills a gap between micro-founded concepts exploring innovation activities at the firm level and aggregate growth studies in this field. Relating the pervasive character of a technology to the notion of robust sectors further defines the part GPTs play for long-term economic development. From this perspective, the fitness of a technological breakthrough is reflected by the strength of robustness of those industries producing it in a structurally dynamic environment. Therefore, embedding the concept of GPTs into a multi-sector evolutionary framework contributes to a better understanding of the diffusion process of pervasive innovations and the complex relationship between technological progress and structural change.

STATISTICAL COMPANION

Annex A

Annex to Chapter 3

A.1 Composition and Fitness of the Numéraire

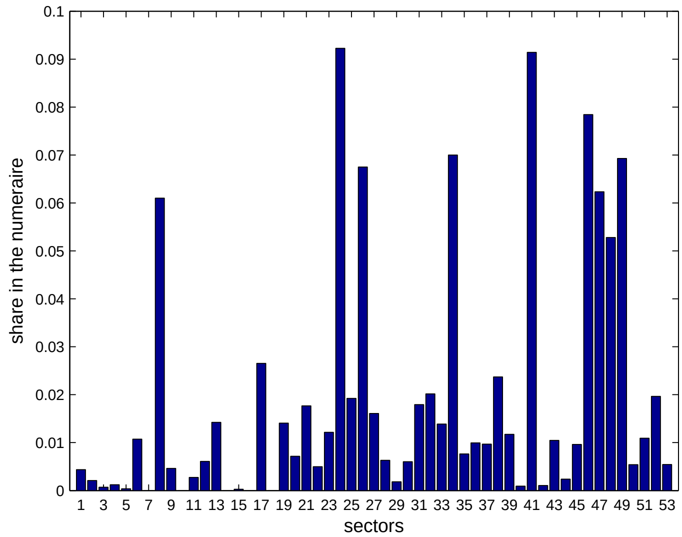


Figure A.1.1: Sectoral shares in the selected numéraire

Figure A.1.1 depicts the composition of the numéraire that was chosen for labor productivity growth accounting, while figure A.1.2 shows the growth of labor productivity obtained from the national accounts. More precisely, for each period we divided GDP at market prices (i.e. gross added value at basic prices + taxes on products (incl. VAT) - subsidies on products) by total hours worked in the respective period (depicted along the horizontal axis) against the productivity measure derived from the Sraffian system. A narrow scatter along the diagonal line through the origin shows a high correlation of the latter indicator to official productivity data. The figure exhibits two outliers – differing more than 1.5 percentage points from the other indicator – out of 39 data-points displayed. From 1980 onwards, both productivity indicators largely tend to match, so that the numéraire chosen leads to reliable results at an aggregate level (with a correlation coefficient of $\rho = 0.85$).

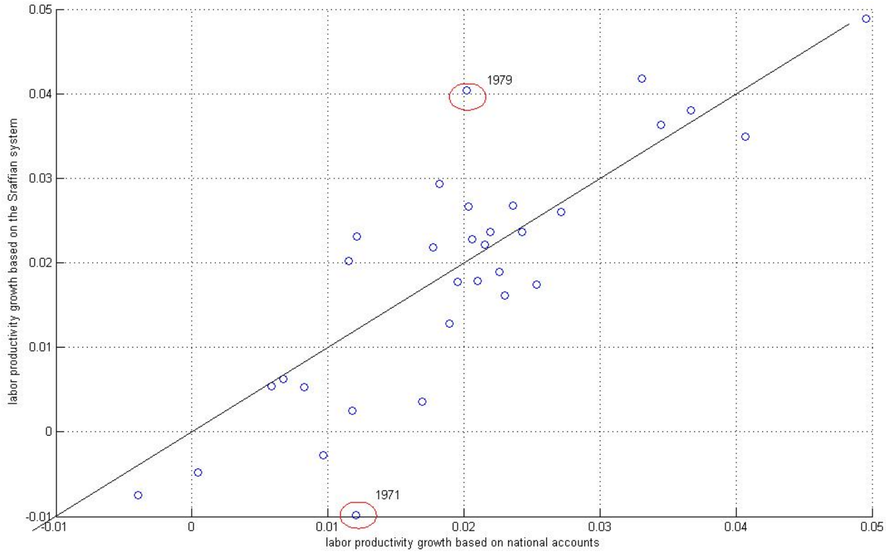


Figure A.1.2: Correlation of labor productivity growth obtained from national accounts and the Sraffian system

A.2 Annual Ranking Positions of Industries

Table A.1: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 1967 to 1973

		1967	1968	1969	1970	1971	1972	1973
1	Agriculture	16	14	18	36	30	24	50
2	Horticulture, orchards etc.	21	31	49	27	29	25	27
3	Agricultural services; landscape gardeners etc.	41	41	39	10	10	44	40
4	Forestry	30	32	32	7	7	47	52
5	Fishing	28	37	47	8	8	45	51
6	Extr. of crude petroleum, natural gas etc.	53	53	53	53	53	1	8
7	Extr. of gravel, clay, stone and salt etc.	40	49	46	5	5	49	46
8	Food, beverages and tobacco	1	2	1	51	51	3	3
9	Mfr. of textiles, wearing apparel, leather	20	20	11	18	21	33	22
10	Mfr. of wood and wood products	38	46	44	1	1	53	48
11	Mfr. of paper prod.; printing and publish.	31	45	29	13	14	40	34
12	Mfr. of refined petroleum products etc.	51	52	52	52	52	2	15
13	Mfr. of chemicals and man-made fibres etc.	10	7	23	42	43	11	6
14	Mfr. of rubber and plastic products	36	47	42	4	4	50	49
15	Mfr. of other non-metallic mineral products	33	43	40	6	9	46	42
16	Mfr. and processing of basic metals	37	50	45	3	2	52	47
17	Mfr. of machinery and equipment n.e.c.	13	5	14	30	37	17	5
18	Mfr. of ICT equipment	39	48	43	2	3	51	45
19	Mfr of electrical, optical and medical equipment	11	16	19	31	35	19	7
20	Mfr. of transport equipment	15	34	34	23	20	34	53
21	Furniture and other mfr. n.e.c.	6	6	7	28	34	20	14
22	Electricity	52	12	51	47	47	7	25
23	Gas and water supply	50	22	48	44	44	10	30
24	Construction	2	3	4	49	49	5	21
25	Sale and repair of motor vehicles etc.	22	18	15	25	28	26	4
26	Wholesale	18	8	10	48	48	6	2
27	Retail trade of food etc.	4	19	12	26	27	27	16
28	Department stores	25	35	24	20	17	37	23
29	Re. sale of phar. goods, cosmetic art. etc.	27	29	20	11	12	42	32
30	Re. sale of clothing, footwear etc.	8	15	8	17	19	35	20
31	Other retail sale, repair work	19	38	6	35	33	21	10
32	Hotels and rest	32	25	5	37	38	16	24
33	Land transport; transport via pipelines	42	23	28	38	39	15	19
34	Water transport	43	1	3	50	50	4	1
35	Air transport	14	27	50	39	40	14	29
36	Support. trans. activities; travel agencies	24	21	26	22	25	29	36
37	Post and telecommunications	17	17	9	19	26	28	28
38	Financial intermediation	49	24	17	32	24	30	26
39	Insurance and pension funding	23	30	27	29	23	31	18
40	Activities auxiliary to finan. intermediat.	34	44	37	9	6	48	41
41	Real estate	3	4	2	40	36	18	11

42	Renting of machinery and equipment etc.	44	39	36	12	11	43	44
43	Computer and related activities	45	36	30	34	32	22	31
44	Research and development	29	40	35	15	13	41	35
45	Consultancy etc. and cleaning activities	48	33	33	24	22	32	43
46	Publ. Administration	5	10	22	46	46	8	9
47	Education	9	13	16	41	41	13	13
48	Health	12	11	21	43	42	12	12
49	Social institutions	7	9	13	45	45	9	17
50	Sewage and refuse disp. and similar act.	35	42	41	16	15	39	39
51	Membership organizations n.e.c.	46	28	38	21	18	36	37
52	Recreational, cultural, sporting activities	47	51	31	33	31	23	38
53	Other service activities	26	26	25	14	16	38	33

Table A.2: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 1974 to 1980

		1974	1975	1976	1977	1978	1979	1980
1	Agriculture	2	50	52	7	12	23	6
2	Horticulture, orchards etc.	8	28	33	19	23	25	8
3	Agricultural services; landscape gardeners etc.	28	42	40	38	38	39	26
4	Forestry	18	39	37	48	35	34	30
5	Fishing	27	35	39	40	34	37	24
6	Extr. of crude petroleum, natural gas etc.	51	4	51	9	53	51	50
7	Extr. of gravel, clay, stone and salt etc.	22	47	47	44	43	45	22
8	Food, beverages and tobacco	1	2	53	1	1	2	2
9	Mfr. of textiles, wearing apparel, leather	9	20	17	36	26	17	13
10	Mfr. of wood and wood products	24	49	44	43	44	43	21
11	Mfr. of paper prod.; printing and publish.	17	34	31	37	31	32	17
12	Mfr. of refined petroleum products etc.	47	6	49	14	52	52	46
13	Mfr. of chemicals and man-made fibres etc.	45	13	14	11	29	9	12
14	Mfr. of rubber and plastic products	23	46	45	41	42	46	20
15	Mfr. of other non-metallic mineral products	26	43	41	39	39	41	23
16	Mfr. and processing of basic metals	21	48	46	45	41	44	19
17	Mfr. of machinery and equipment n.e.c.	3	8	10	16	32	13	4
18	Mfr. of ICT equipment	20	45	43	42	40	42	18
19	Mfr of electrical, optical and medical equipment	5	10	12	15	25	5	41
20	Mfr. of transport equipment	4	32	48	51	17	26	14
21	Furniture and other mfr. n.e.c.	40	24	9	22	15	8	3
22	Electricity	37	21	32	26	33	38	37
23	Gas and water supply	42	16	50	23	48	50	44
24	Construction	49	1	6	4	9	14	1
25	Sale and repair of motor vehicles etc.	10	19	20	34	21	16	5
26	Wholesale	53	3	4	50	51	3	47
27	Retail trade of food etc.	11	9	19	29	6	24	9
28	Department stores	34	29	24	30	22	48	33
29	Re. sale of phar. goods, cosmetic art. etc.	33	33	27	18	20	28	15
30	Re. sale of clothing, footwear etc.	30	11	13	21	45	21	7
31	Other retail sale, repair work	44	14	11	17	11	49	34
32	Hotels and rest	6	12	15	10	49	19	11
33	Land transport; transport via pipelines	48	18	28	31	13	12	39
34	Water transport	52	5	1	2	2	1	53
35	Air transport	12	25	29	20	50	29	43
36	Support. trans. activities; travel agencies	36	51	25	24	30	35	35
37	Post and telecommunications	16	23	16	13	47	18	10
38	Financial intermediation	50	31	7	35	16	53	42
39	Insurance and pension funding	32	52	21	52	10	31	40
40	Activities auxiliary to finan. intermediat.	25	44	42	47	37	47	28
41	Real estate	46	53	2	53	8	4	51
42	Renting of machinery and equipment etc.	29	37	38	46	28	40	29
43	Computer and related activities	41	15	22	25	19	10	38
44	Research and development	13	41	35	32	27	36	31
45	Consultancy etc. and cleaning activities	39	17	23	27	24	22	27
46	Publ. Administration	15	22	3	3	7	6	48
47	Education	35	26	8	6	4	7	49
48	Health	43	38	18	8	3	15	45
49	Social institutions	7	7	5	5	5	11	52
50	Sewage and refuse disp. and similar act.	31	40	36	49	46	33	25
51	Membership organizations n.e.c.	38	36	30	28	14	30	36
52	Recreational, cultural, sporting activities	14	30	26	12	18	20	16
53	Other service activities	19	27	34	33	36	27	32

Table A.3: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 1981 to 1987

		1974	1975	1976	1977	1978	1979	1980
1	Agriculture	9	10	49	5	20	12	49
2	Horticulture, orchards etc.	26	21	47	21	27	19	45
3	Agricultural services; landscape gardeners etc.	35	39	42	43	31	30	32
4	Forestry	27	47	31	45	33	41	27
5	Fishing	34	46	34	42	41	39	34
6	Extr. of crude petroleum, natural gas etc.	4	4	28	52	32	7	11
7	Extr. of gravel, clay, stone and salt etc.	40	42	41	39	40	34	39
8	Food, beverages and tobacco	2	1	46	1	3	4	52
9	Mfr. of textiles, wearing apparel, leather	25	30	18	31	22	42	29
10	Mfr. of wood and wood products	42	44	38	40	38	35	38
11	Mfr. of paper prod.; printing and publish.	32	33	32	30	34	27	35
12	Mfr. of refined petroleum products etc.	7	8	22	50	30	8	19
13	Mfr. of chemicals and man-made fibres etc.	15	29	7	47	12	10	18
14	Mfr. of rubber and plastic products	39	41	40	41	37	36	37
15	Mfr. of other non-metallic mineral products	38	37	36	36	35	31	41
16	Mfr. and processing of basic metals	43	40	39	38	39	37	40
17	Mfr. of machinery and equipment n.e.c.	46	13	6	12	16	53	20
18	Mfr. of ICT equipment	41	43	37	37	36	33	36
19	Mfr of electrical, optical and medical equipment	13	28	4	18	17	46	10
20	Mfr. of transport equipment	22	22	16	10	51	47	50
21	Furniture and other mfr. n.e.c.	10	14	5	17	19	49	43
22	Electricity	53	5	48	32	13	23	31
23	Gas and water supply	18	15	27	49	14	20	46
24	Construction	5	2	2	15	1	3	2
25	Sale and repair of motor vehicles etc.	20	16	15	46	48	48	53
26	Wholesale	3	3	8	6	2	2	3
27	Retail trade of food etc.	12	32	10	51	49	11	9
28	Department stores	36	36	44	35	47	44	14
29	Re. sale of phar. goods, cosmetic art. etc.	33	35	30	44	42	18	16
30	Re. sale of clothing, footwear etc.	48	27	25	13	11	45	12
31	Other retail sale, repair work	49	11	35	25	44	13	6
32	Hotels and rest	8	12	50	19	15	29	47
33	Land transport; transport via pipelines	50	31	53	14	10	9	23
34	Water transport	1	9	3	28	53	1	1
35	Air transport	24	26	26	27	46	25	13
36	Support. trans. activities; travel agencies	29	25	19	20	18	40	21
37	Post and telecommunications	28	23	52	3	9	22	7
38	Financial intermediation	51	6	1	2	7	5	51
39	Insurance and pension funding	52	17	20	9	52	6	17
40	Activities auxiliary to finan. intermediat.	47	38	45	29	45	32	44
41	Real estate	44	53	29	53	23	52	48
42	Renting of machinery and equipment etc.	31	52	23	26	28	43	28
43	Computer and related activities	11	20	13	16	24	21	22
44	Research and development	37	45	43	34	29	28	30
45	Consultancy etc. and cleaning activities	19	24	17	23	25	24	24
46	Publ. Administration	6	7	9	7	6	50	8
47	Education	16	18	14	8	5	38	5
48	Health	23	49	24	48	8	15	33
49	Social institutions	17	51	11	4	4	51	4
50	Sewage and refuse disp. and similar act.	30	48	33	33	43	17	42
51	Membership organizations n.e.c.	45	34	12	22	21	26	26
52	Recreational, cultural, sporting activities	14	50	51	11	26	14	15
53	Other service activities	21	19	21	24	50	16	25

Table A.4: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 1988 to 1994

		1988	1989	1990	1991	1992	1993	1994
1	Agriculture	15	7	17	30	36	5	25
2	Horticulture, orchards etc.	30	45	28	22	13	37	49
3	Agricultural services; landscape gardeners etc.	45	36	35	43	32	27	38
4	Forestry	44	29	49	23	19	42	40
5	Fishing	36	33	47	38	15	28	42
6	Extr. of crude petroleum, natural gas etc.	35	27	30	29	12	38	41
7	Extr. of gravel, clay, stone and salt etc.	40	42	41	34	28	33	47
8	Food, beverages and tobacco	2	1	2	12	51	1	3
9	Mfr. of textiles, wearing apparel, leather	21	21	34	19	37	41	31
10	Mfr. of wood and wood products	41	39	42	33	30	31	44
11	Mfr. of paper prod.; printing and publish.	46	43	32	42	33	29	48
12	Mfr. of refined petroleum products etc.	50	20	46	40	20	21	50
13	Mfr. of chemicals and man-made fibres etc.	28	12	24	20	10	22	15
14	Mfr. of rubber and plastic products	39	41	39	35	26	32	46
15	Mfr. of other non-metallic mineral products	43	35	44	39	25	35	39
16	Mfr. and processing of basic metals	37	40	40	31	29	30	45
17	Mfr. of machinery and equipment n.e.c.	5	10	48	17	49	9	5
18	Mfr. of ICT equipment	38	38	38	32	27	34	43
19	Mfr of electrical, optical and medical equipment	19	15	52	4	6	44	8
20	Mfr. of transport equipment	11	17	22	47	35	17	23
21	Furniture and other mfr. n.e.c.	12	9	51	5	46	52	7
22	Electricity	33	31	29	28	16	23	34
23	Gas and water supply	16	23	26	10	21	47	33
24	Construction	3	2	53	8	34	53	2
25	Sale and repair of motor vehicles etc.	25	47	20	49	18	46	9
26	Wholesale	8	53	9	1	53	3	10
27	Retail trade of food etc.	49	16	7	18	4	45	14
28	Department stores	17	50	11	21	11	19	53
29	Re. sale of phar. goods, cosmetic art. etc.	24	37	25	15	41	16	28
30	Re. sale of clothing, footwear etc.	14	24	4	16	22	36	22
31	Other retail sale, repair work	9	51	3	13	8	7	12
32	Hotels and rest	10	8	14	53	42	49	21
33	Land transport; transport via pipelines	13	14	50	27	43	20	16
34	Water transport	1	49	1	7	23	12	4
35	Air transport	20	48	21	52	7	43	30
36	Support. trans. activities; travel agencies	29	13	43	41	38	15	29
37	Post and telecommunications	32	22	12	25	9	13	20
38	Financial intermediation	7	5	13	6	5	39	13
39	Insurance and pension funding	6	4	15	48	48	26	17
40	Activities auxiliary to finan. intermediat.	42	30	45	26	31	25	37
41	Real estate	47	11	16	14	45	51	24
42	Renting of machinery and equipment etc.	31	44	31	37	24	10	35
43	Computer and related activities	23	18	10	51	2	11	18
44	Research and development	34	34	37	24	14	24	27
45	Consultancy etc. and cleaning activities	22	19	19	36	44	18	32
46	Publ. Administration	18	6	8	9	52	14	52
47	Education	53	3	27	3	3	50	11
48	Health	4	26	23	11	50	4	6
49	Social institutions	51	32	36	2	1	2	1
50	Sewage and refuse disp. and similar act.	48	46	33	44	17	48	36
51	Membership organizations n.e.c.	27	52	6	45	47	40	51
52	Recreational, cultural, sporting activities	26	28	5	46	39	8	19
53	Other service activities	52	25	18	50	40	6	26

Table A.5: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 1995 to 2001

		1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
1	Agriculture	22	14	14	13	18	16	18
2	Horticulture, orchards etc.	19	35	18	31	36	40	42
3	Agricultural services; landscape gardeners etc.	29	31	27	26	32	24	19
4	Forestry	21	32	24	25	24	45	11
5	Fishing	38	30	26	23	21	36	24
6	Extr. of crude petroleum, natural gas etc.	17	18	22	22	15	25	36
7	Extr. of gravel, clay, stone and salt etc.	33	26	33	18	31	32	26
8	Food, beverages and tobacco	3	9	1	41	3	8	2
9	Mfr. of textiles, wearing apparel, leather	18	17	16	29	12	20	37
10	Mfr. of wood and wood products	31	29	29	19	29	31	28
11	Mfr. of paper prod.; printing and publish.	26	22	23	33	22	21	33
12	Mfr. of refined petroleum products etc.	10	20	36	12	16	22	35
13	Mfr. of chemicals and man-made fibres etc.	11	15	6	32	6	13	39
14	Mfr. of rubber and plastic products	32	27	31	20	28	33	29
15	Mfr. of other non-metallic mineral products	35	23	28	24	26	29	30
16	Mfr. and processing of basic metals	34	28	32	17	30	30	27
17	Mfr. of machinery and equipment n.e.c.	40	52	5	49	52	5	46
18	Mfr. of ICT equipment	30	25	30	21	27	34	25
19	Mfr of electrical, optical and medical equipment	43	46	12	10	46	9	20
20	Mfr. of transport equipment	20	44	46	6	25	18	16
21	Furniture and other mfr. n.e.c.	51	43	9	48	9	12	43
22	Electricity	42	16	35	39	10	37	14
23	Gas and water supply	25	13	15	36	17	41	10
24	Construction	46	2	50	30	51	50	53
25	Sale and repair of motor vehicles etc.	50	50	49	3	47	46	4
26	Wholesale	6	1	53	51	1	1	50
27	Retail trade of food etc.	47	53	37	50	37	52	51
28	Department stores	28	34	10	28	23	48	38
29	Re. sale of phar. goods, cosmetic art. etc.	12	41	19	9	11	23	23
30	Re. sale of clothing, footwear etc.	9	39	17	8	45	42	3
31	Other retail sale, repair work	8	12	40	40	53	15	13
32	Hotels and rest	23	51	7	47	8	53	40
33	Land transport; transport via pipelines	15	47	25	44	44	43	12
34	Water transport	5	4	2	53	2	3	1
35	Air transport	39	21	38	15	41	17	31
36	Support. trans. activities; travel agencies	41	33	42	35	19	14	44
37	Post and telecommunications	16	11	11	37	20	19	7
38	Financial intermediation	53	10	4	7	49	11	8
39	Insurance and pension funding	44	8	21	4	14	39	47
40	Activities auxiliary to finan. intermediat.	36	36	20	16	33	35	22
41	Real estate	4	49	52	43	50	7	45
42	Renting of machinery and equipment etc.	37	24	34	27	35	27	32
43	Computer and related activities	52	42	3	38	42	49	9
44	Research and development	45	19	41	14	34	28	21
45	Consultancy etc. and cleaning activities	48	48	13	46	39	38	34
46	Publ. Administration	13	6	47	5	5	4	52
47	Education	2	3	51	1	4	10	49
48	Health	7	5	44	2	7	6	6
49	Social institutions	1	7	48	52	48	2	5
50	Sewage and refuse disp. and similar act.	24	37	39	34	40	44	41
51	Membership organizations n.e.c.	27	38	8	11	38	26	15
52	Recreational, cultural, sporting activities	14	45	45	45	13	51	48
53	Other service activities	49	40	43	42	43	47	17

Table A.6: Annual ranking positions of Danish industries with regard to their impact on labor productivity growth from 2002 to 2007

		2002	2003	2004	2005	2006	2007
1	Agriculture	33	20	26	19	40	21
2	Horticulture, orchards etc.	42	32	25	20	23	19
3	Agricultural services; landscape gardeners etc.	39	31	36	25	38	28
4	Forestry	15	42	27	36	28	49
5	Fishing	36	45	37	22	26	35
6	Extr. of crude petroleum, natural gas etc.	18	48	28	35	48	44
7	Extr. of gravel, clay, stone and salt etc.	29	40	44	28	32	31
8	Food, beverages and tobacco	53	2	1	1	47	7
9	Mfr. of textiles, wearing apparel, leather	13	24	23	38	15	23
10	Mfr. of wood and wood products	31	36	41	29	36	33
11	Mfr. of paper prod.; printing and publish.	24	25	21	17	31	22
12	Mfr. of refined petroleum products etc.	27	49	19	43	43	40
13	Mfr. of chemicals and man-made fibres etc.	51	14	33	7	25	46
14	Mfr. of rubber and plastic products	32	38	42	27	35	30
15	Mfr. of other non-metallic mineral products	26	34	40	24	30	34
16	Mfr. and processing of basic metals	30	39	43	30	34	32
17	Mfr. of machinery and equipment n.e.c.	4	12	5	31	4	2
18	Mfr. of ICT equipment	28	37	45	26	33	29
19	Mfr of electrical, optical and medical equipment	19	18	16	47	6	5
20	Mfr. of transport equipment	23	6	48	41	12	41
21	Furniture and other mfr. n.e.c.	11	15	3	9	7	15
22	Electricity	47	29	53	45	29	36
23	Gas and water supply	41	47	11	42	42	42
24	Construction	3	1	8	48	2	53
25	Sale and repair of motor vehicles etc.	16	3	12	12	50	10
26	Wholesale	7	7	6	2	1	50
27	Retail trade of food etc.	45	26	4	5	16	3
28	Department stores	12	11	14	13	14	11
29	Re. sale of phar. goods, cosmetic art. etc.	38	27	18	16	46	26
30	Re. sale of clothing, footwear etc.	34	17	46	8	17	38
31	Other retail sale, repair work	9	19	39	4	5	14
32	Hotels and rest	40	53	13	51	10	12
33	Land transport; transport via pipelines	17	50	31	37	9	45
34	Water transport	8	4	20	32	18	6
35	Air transport	49	23	22	3	11	18
36	Support. trans. activities; travel agencies	43	21	24	49	13	16
37	Post and telecommunications	6	8	30	21	44	9
38	Financial intermediation	2	5	7	6	22	17
39	Insurance and pension funding	20	10	29	14	8	4
40	Activities auxiliary to finan. intermediat.	44	46	34	23	27	25
41	Real estate	52	33	49	44	53	52
42	Renting of machinery and equipment etc.	25	30	35	33	37	27
43	Computer and related activities	22	9	15	46	19	20
44	Research and development	37	44	50	34	41	37
45	Consultancy etc. and cleaning activities	48	35	17	15	45	48
46	Publ. Administration	1	13	51	18	3	39
47	Education	10	16	2	53	24	1
48	Health	46	51	10	52	51	51
49	Social institutions	5	52	9	50	52	13
50	Sewage and refuse disp. and similar act.	35	43	38	40	20	43
51	Membership organizations n.e.c.	21	41	52	10	49	8
52	Recreational, cultural, sporting activities	14	28	32	11	39	24
53	Other service activities	50	22	47	39	21	47

A.3 Additional Figures

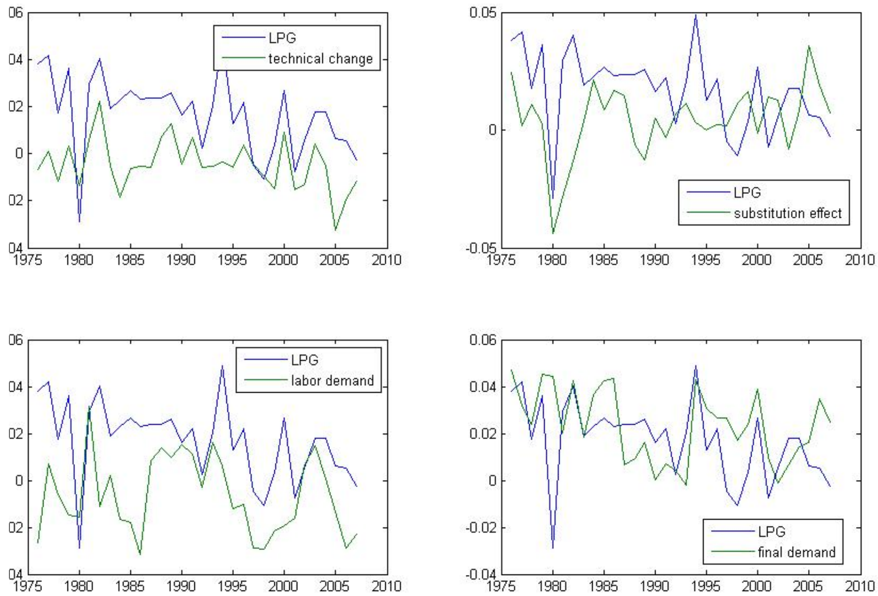


Figure A.3.1: Contribution of technical change, employment, factor substitution and final demand to annual labor productivity growth

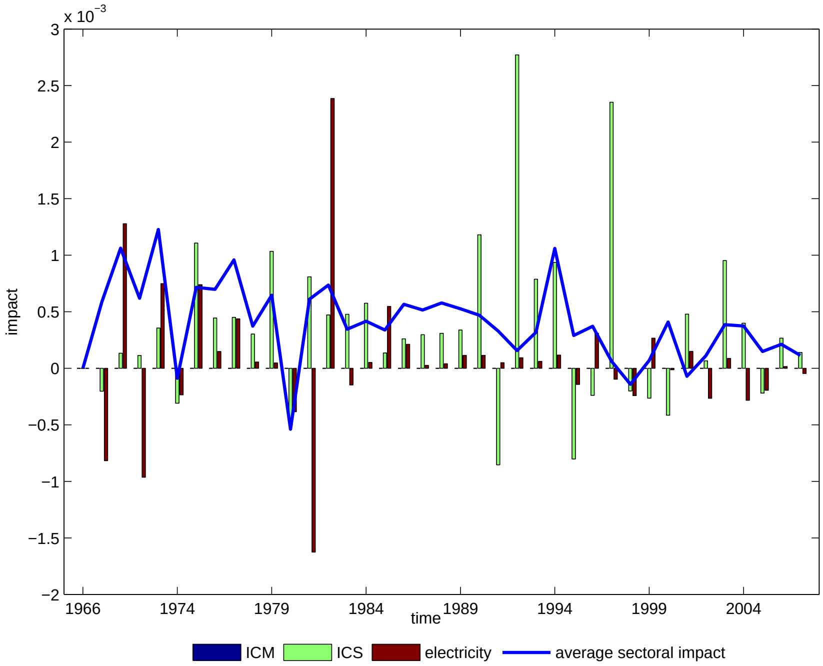


Figure A.3.2: Contribution of ICT manufacturing (ICM), computer-related services (ICS) and electricity to labor productivity growth.

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Total													
no. of enterprises	84 197	83 236	83 228	107 424	178 873	183 100	183 250	182 936	182 953	187 444	194 782	200 290	205 075
average	1619	1 601	1 601	1 821	2 264	2 378	2 320	2 287	2 287	2 343	2 435	2 504	2 563
no. of persons/EP	8	8	9	8	7	7	7	7	7	7	7	7	7
ICT													
no. of enterprises	1 760	1 692	1 613	1 613	6 529	7 774	7 821	7 780	7 555	8 172	8 660	9 111	9 424
industry average	880	846	807	807	2 176	2 591	2 607	2 593	2 518	2 724	2 887	3 037	3 141
no. of persons/EP	15	16	16	17	9	9	10	9	9	8	8	8	9
ICT-using													
no. of enterprises	35 604	35 278	35 052	58 175	99 236	100 686	101 472	102 239	103 962	106 403	110 729	113 457	115 911
industry average	2 374	2 352	2 337	2 644	2 919	2 961	2 899	2 921	2 970	3 040	3 164	3 242	3 312
no. of persons/EP	6	7	7	7	6	6	6	6	6	6	6	6	6
Non-ICT													
no. of enterprises	46 833	46 266	46 563	47 636	73 108	74 640	73 957	72 917	71 436	72 869	75 393	77 722	79 740
industry average	1 464	1 446	1 455	1 401	1 741	1 866	1 761	1 696	1 661	1 695	1 753	1 807	1 854
no. of persons/EP	10	10	10	10	8	8	8	8	8	8	8	8	8

Table A.1: Number and size of enterprises in ICT-producing, ICT-using and Non-ICT industries from 1995 until 2007. The size refers to the number of persons employed per enterprise (EP). Industry average gives the average number of enterprises per industry in the respective sector. Note that the table only covers the private sectors and furthermore does not include the agricultural sector, financial institutes and insurance. Furthermore, data for wholesale and service industries are only recorded from 1999 onwards. Data source: Statistics Denmark. Own calculations.

Annex B

Annex to Chapter 4

B.1 Comparing the Ghosh and Leontief Model

The following section deals with the development of the ICT sector among the industry network according to conventional linkage measures based on the Ghosh and Leontief model. We further analyze how results change with different prices (current versus constant) and when capital flows are taken into account.

ICT and related industries	**Ranking**									
	Constant Prices					Current Prices				
	1966	1976	1986	1996	2006	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	24	19	8	3	3	6	5	2	3	4
Mfr. of other electrical machinery and apparatus	17	12	18	24	29	19	13	20	23	29
Mfr. of radio and communicat. equipm. etc.	11	9	31	18	7	22	10	27	16	11
Mfr. of medical and optical instrum. etc.	32	32	56	57	20	26	29	48	48	26
Computer activities excl. software consultancy and supply	37	37	34	33	41	40	38	37	32	39
Software consultancy and supply	31	36	29	31	36	34	34	28	31	35

Table B.1: Ranking position of total forward linkages (TFL) for ICT industries in the Ghosh model (constant and current prices)

ICT and related industries	**Ranking**									
	Constant Prices					Current Prices				
	1966	1976	1986	1996	2006	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	6	5	2	3	4	12	21	28	37	16
Mfr. of other electrical machinery and apparatus	19	13	20	23	29	99	108	112	97	104
Mfr. of radio and communicat. equipm. etc.	22	10	27	16	11	21	18	26	6	6
Mfr. of medical and optical instrum. etc.	26	29	48	48	26	4	5	7	15	5
Computer activities excl. software consultancy and supply	40	38	37	32	39	22	20	9	19	15
Software consultancy and supply	34	34	28	31	35	67	63	41	55	51

Table B.2: Ranking position of total forward linkages (TFL) of ICT industries in the Leontief model (constant and current prices)

(a) TFL of ICT incl. capital flows in constant prices

ICT and related industries	**Ranking**				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	24	19	8	3	3
Mfr. of other electrical machinery and apparatus	17	12	18	24	29
Mfr. of radio and communicat. equipm. etc.	11	9	31	18	7
Mfr. of medical and optical instrum. etc.	32	32	56	57	20
Computer activities excl. software consultancy and supply	37	37	34	33	41
Software consultancy and supply	31	36	29	31	36

(b) TFL of ICT without capital flows in constant prices

ICT and related industries	**Ranking Number**				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	27	26	40	18	6
Mfr. of other electrical machinery and apparatus	31	27	30	35	44
Mfr. of radio and communicat. equipm. etc.	35	32	58	32	9
Mfr. of medical and optical instrum. etc.	60	62	82	74	63
Computer activities excl. software consultancy and supply	33	30	32	55	54
Software consultancy and supply	22	22	33	73	66

(c) Change in positions with respect to Table (a)

ICT and related industries	**Change in Ranking**				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	-3	-7	-32	-15	-3
Mfr. of other electrical machinery and apparatus	-14	-15	-12	-11	-15
Mfr. of radio and communicat. equipm. etc.	-24	-23	-27	-14	-2
Mfr. of medical and optical instrum. etc.	-28	-30	-26	-17	-43
Computer activities excl. software consultancy and supply	4	7	2	-22	-13
Software consultancy and supply	9	14	-4	-42	-30

(d) ICT *direct* forward linkages (DFL) including capital flows

ICT and related industries	**Ranking Number**				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	17	13	5	2	2
Mfr. of other electrical machinery and apparatus	24	16	19	31	52
Mfr. of radio and communicat. equipm. etc.	35	23	45	26	10
Mfr. of medical and optical instrum. etc.	43	46	60	57	14
Computer activities excl. software consultancy and supply	38	24	27	23	35
Software consultancy and supply	31	28	24	29	37

(e) Change in positions of DFL with respect to Table (a)

ICT and related industries	**Change in Ranking**				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	7	6	3	1	1
Mfr. of other electrical machinery and apparatus	-7	-4	-1	-7	-23
Mfr. of radio and communicat. equipm. etc.	-24	-14	-14	-8	-3
Mfr. of medical and optical instrum. etc.	-11	-14	-4	0	6
Computer activities excl. software consultancy and supply	-1	13	7	10	6
Software consultancy and supply	0	8	5	2	-1

Table B.3: Comparison of forward linkages of the ICT sector and related industries in the Ghosh model

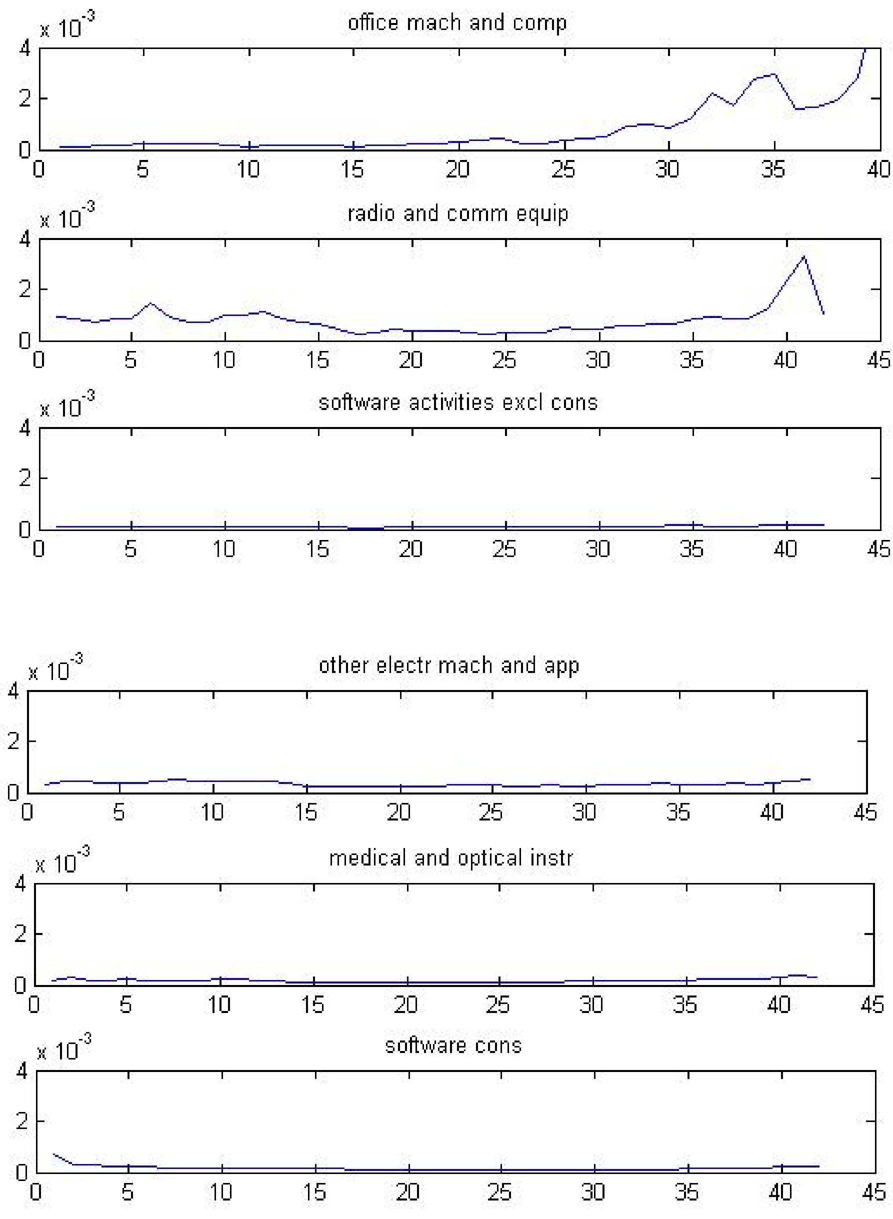


Figure B.1.1: Change in row variance for the ICT sector and related industries between 1966 and 2007 (Ghosh model). Note: The x-axis denotes time (1965=0, 2010=45).

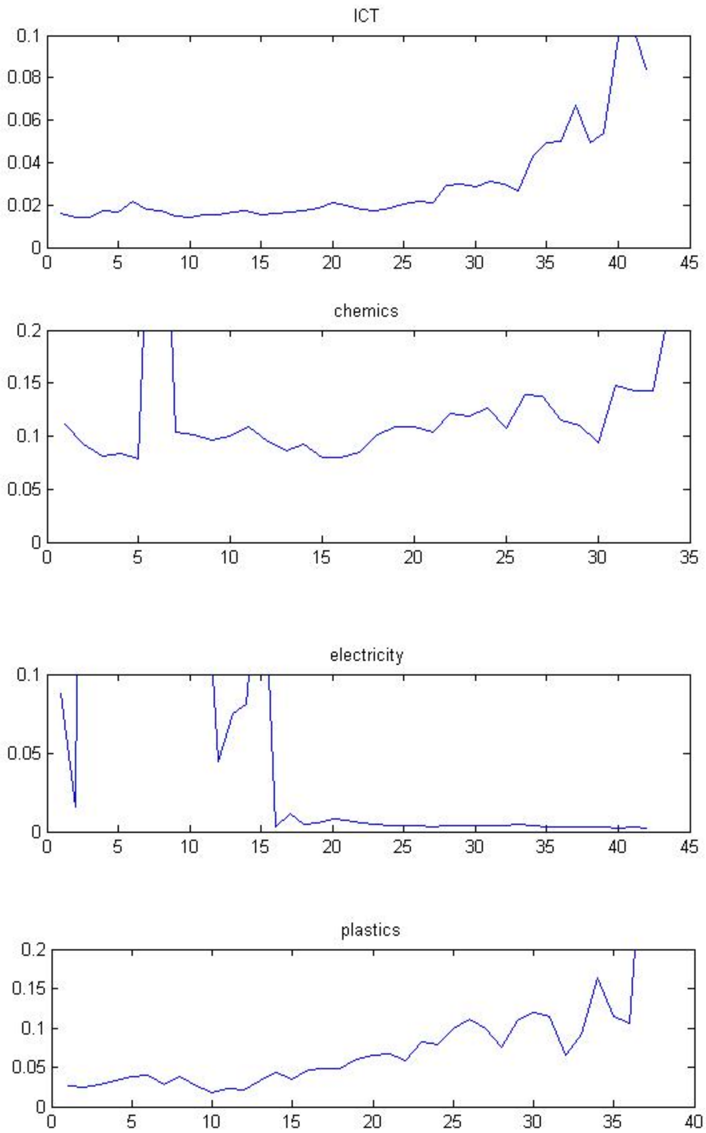


Figure B.1.2: Change in row variance for selected sectors between 1966 and 2007 (Ghosh model). Note: The x-axis denotes time (1965=0, 2010=45).

(a) TFL of ICT incl. capital flows in constant prices

ICT and related industries	Ranking				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	98	101	78	54	27
Mfr. of other electrical machinery and apparatus	10	10	12	11	4
Mfr. of radio and communicat. equipm. etc.	35	16	34	22	13
Mfr. of medical and optical instrum. etc.	47	33	42	34	14
Computer activities excl. software consultancy and supply	105	87	67	40	32
Software consultancy and supply	102	74	58	47	7

(b) ICT *direct* forward linkages (DFL) including capital flows

ICT and related industries	Ranking Number				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	25	26	30	30	33
Mfr. of other electrical machinery and apparatus	23	23	25	18	9
Mfr. of radio and communicat. equipm. etc.	14	21	13	21	23
Mfr. of medical and optical instrum. etc.	11	10	9	8	20
Computer activities excl. software consultancy and supply	12	20	23	22	14
Software consultancy and supply	19	17	24	20	12

(c) Change in positions of DFL with respect to Table (a)

ICT and related industries	Change in Ranking				
	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	73	75	48	24	-6
Mfr. of other electrical machinery and apparatus	-13	-13	-13	-7	-5
Mfr. of radio and communicat. equipm. etc.	21	-5	21	1	-10
Mfr. of medical and optical instrum. etc.	36	23	33	26	-6
Computer activities excl. software consultancy and supply	93	67	44	18	18
Software consultancy and supply	83	57	34	27	-5

Table B.4: Comparison of forward linkages of the ICT sector in the Leontief model

ICT and related industries	Ranking									
	With respect to the Ghosh model, forward linkages based on the Leontief model moved in ranking by ... positions									
	Direct Forward Linkages					Total Forward Linkages				
	1966	1976	1986	1996	2006	1966	1976	1986	1996	2006
Mfr. of office machinery and computers	-8	-13	-25	-28	-31	-74	-82	-70	-51	-24
Mfr. of other electrical machinery and apparatus	1	-7	-6	13	43	7	2	6	13	25
Mfr. of radio and communicat. equipm. etc.	21	2	32	5	-13	-24	-7	-3	-4	-6
Mfr. of medical and optical instrum. etc.	32	36	51	49	-6	-15	-1	14	23	6
Computer activities	26	4	4	1	21	-68	-50	-33	-7	9
Software consultancy and supply	12	11	0	9	25	-71	-38	-29	-16	29

Table B.5: Comparison of direct and total forward linkages in the Ghosh and Leontief models (constant prices)

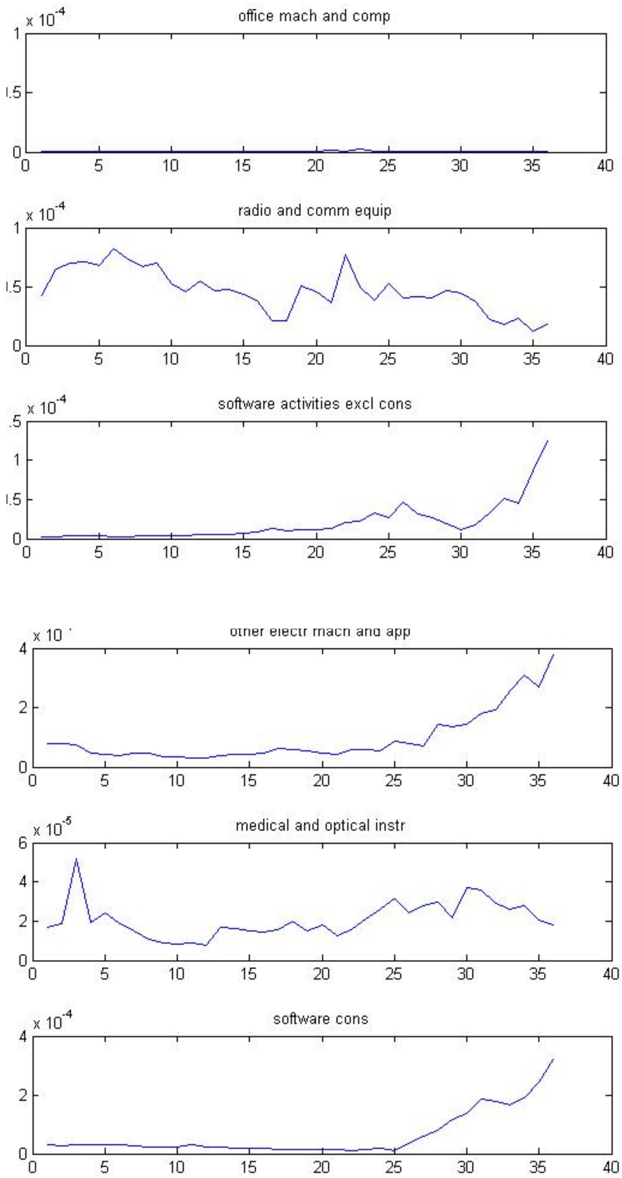
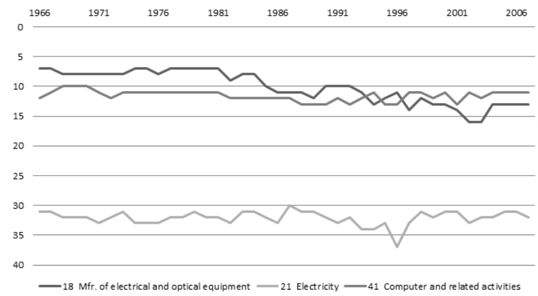


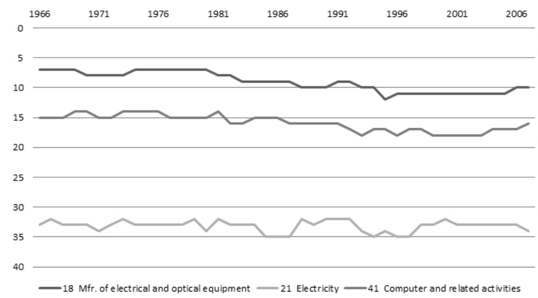
Figure B.1.3: Change in row variance for ICT-sector and related industries between 1966 and 2007 (Leontief model). Note: The x-axis denotes time (1965=0, 2010=45).

	1966	1976	1986	1996	2006
	Ghosh				
	Direct Forward Linkages				
18 30009 Mfr. of electrical and optical equipment	7	8	11	11	13
41 72000 Computer and related activities	12	11	12	13	11
21 401000 Electricity	31	33	33	37	31
	Total Forward Linkages				
18 30009 Mfr. of electrical and optical equipment	7	7	9	11	10
41 72000 Computer and related activities	15	14	15	18	17
21 401000 Electricity	33	33	35	35	33
	Leontief				
	Direct Forward Linkages				
18 30009 Mfr. of electrical and optical equipment	13	11	12	12	14
41 72000 Computer and related activities	40	31	24	15	4
21 401000 Electricity	30	22	20	19	17
	Total Forward Linkages				
18 30009 Mfr. of electrical and optical equipment	12	12	12	12	11
41 72000 Computer and related activities	28	27	25	21	13
21 401000 Electricity	34	30	29	30	31

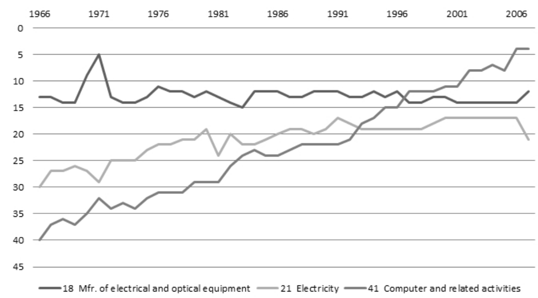
Table B.6: Ranking position of the ICT manufacturing and service sector and the electricity sector from 1966 to 2006



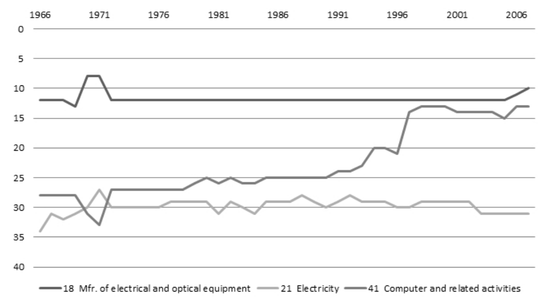
B.1.4.1 Direct Forward Linkages Ghosh Model



B.1.4.2 Total Forward Linkages Ghosh Model



B.1.4.3 Direct Forward Linkages Leontief Model



B.1.4.4 Total Forward Linkages Leontief Model

Figure B.1.4: Rank change over time in the Ghosh and the Leontief models

Annex C

Annex to Chapter 5

C.1 A Note on Knowledge Spillovers in an R&D Network

The focus in chapter 5 lies on the pervasive character of a GPT and not on its potential to trigger phases of strong innovative activity. However, it is possible to extend the framework to further factors of production, such as investments in R&D or the employment of heterogeneous labor, by letting the algorithm search for the most innovative industries among the supplier network. Introducing R&D expenditures for the period between 1987 and 2006, gives further insights into Denmark's high position among innovation leaders in Europe. For this sake, we incorporate R&D intensity into the analysis of direct and indirect commodity flows in order to measure the total knowledge embodied in the sectoral product. The existing framework is modified by using instead of the sectoral constribution to annual output the industrial share in total domestic R&D expenditures as scaling parameter in eq. (5.4). Furthermore, we premultiply the fundamental matrix of the absorbing Markov chain (based on commodity flows) in eq. (5.6) by the direct R&D intensity per industry (i.e. sectoral R&D expenditures per gross output). This gives the mean number of times the embodied knowledge flow originating in one sector passes through other industries in the domestic producer network[1] before the corresponding product reaches final demand.

Data on annual R&D expenditures were retrieved from the OECD Analytical Business Enterprise Research and Development database (ed. 2009 based on ISIC Rev. 3.1). The 20 sectors listed in this database were disaggregated according to our 66-sector classification by assuming an equal distribution of R&D investments across subindustries. Furthermore, for those industries that do not report any R&D activity, we assume minimum expenditures in the amount of 1.5% per cent of sectoral value added. The analysis was undertaken for parameter values $\beta = 1$,$\gamma = 1$, this means that coupling is taken into account and the resulting hierarchical order is presupposed to be flat. Figure C.1.1 shows that by the late 1980s, a great share of R&D resources went to the ICT manufacturing sector, indicating the early efforts made to adjust the production system to the new technology. In fact, this sector spanned the bulk of industries in manufacturing and services at that time and acted as the second innovation pillar besides the chemical industry with its

[1] Note that in the following analyis only domestic transaction flows were taken into account. For more elaborated approaches that consider differences in R&D spending between the exporting and importing country see, e.g., Hauknes and Knell (2009) and Papconstantinou et al. (1998).

focus on biotechnology. Comparing this figure to the technical tree of 1997, one can observe that the machinery sector has become a core of the network. This increasing dominance in research activities can be associated with wind power generation and to a lesser extent to biotechnology. Since the machinery sector belonged to the ICT-manufacturing community before, its evolution reveals the role of ICT as an enabling technology. However, in the mid-1990s R&D became more and more directed towards ICT services, which also shows the significance of the latter activity in domestic production (see Fig. C.1.3).

Table C.1: Evolution of the technical tree based on the R&D network 1988–2006. The first column gives the sector ID, the second and third column indicate the economic activity and corresponding abbreviation, respectively, the columns 4-12 record the ranking of each industry according the robustness score in descending order (pos), the parent industry (par), as well as the number of desc (desc). The value 0 in par denotes the root node, parameter α in the tree learning algorithm was set to 0.5.

					1988			1997			2006
ID	Activity	Label	pos	par	desc	pos	par	desc	pos	par	desc
			pos 1988	par	desc	pos 1997	par	desc	pos 2006	par	desc
			pos	par	sub	pos	par	sub	pos	par	sub
1	Agriculture and horticulture	AGR	65	11	0	65	11	0	65	11	0
2	Forestry	FOR	60	17	0	62	19	0	63	39	0
3	Fishing	FISH	66	17	0	66	19	0	66	11	0
4	Mining and quarrying	MIN	63	17	0	63	19	0	64	11	0
5	Manufacture of food, tobacco	MFOOD	43	11	0	42	11	0	46	11	0
6	Textiles and leather products	MTEXT	22	11	0	22	11	0	15	11	0
7	Manufacture of wood etc.	MWOOD	50	11	0	50	11	0	57	11	0
8	Manufacture of paper etc.	MPAP	29	11	0	26	11	0	25	11	0
9	Printing etc.	MPRINT	37	11	0	47	11	0	30	11	0
10	Oil refinery etc.	OIL	64	17	0	64	19	0	59	11	0
11	Manufacture of chemicals	MCHEM	13	0	9	6	0	16	2	39	26
12	Pharmaceuticals	MPHARM	19	11	1	15	11	2	14	11	0
13	Manufacture of rubber etc.	MRUB	15	11	0	16	11	0	13	11	0
14	Manuf.of glass, concrete etc.	MGLASS	58	11	0	60	11	0	61	11	0
15	Manufacture of basic metals	MBMET	33	17	0	36	11	0	35	11	0
16	Manufact. of fabricated metal	MFMET	23	17	0	27	19	0	27	11	0
17	Manufacture of ICT	ICT	4	0	50	2	0	23	5	11	15
18	Electronic/Electrical equipment	MELTR	10	17	0	12	17	0	17	17	0
19	Manufacture of machinery	MMACH	7	17	0	3	17	9	4	0	0
20	Manuf. of motor vehicles etc.	MVEH	53	17	0	55	19	0	33	11	0
21	Mf. of ships, transport equip.	MTRAN	24	17	0	49	19	0	60	11	0
22	Manuf.of furniture,other manuf	MOTH	5	17	0	7	11	0	7	11	0
23	Repair, inst. of machinery etc	RMACH	26	17	0	38	19	1	58	17	0
24	Electricity, gas and steam	ELC	21	17	0	14	19	0	19	17	0
25	Water collect.purification etc	WAT	45	17	0	33	17	0	34	39	0
26	Sewerage, waste collection etc.	WASTE	28	17	0	18	17	0	22	17	0
27	Construction	CON	32	17	0	37	17	0	41	17	0
28	Sale, repair of motor vehicles	SRVEH	25	17	0	21	11	0	24	11	0
29	Retail sale	RET	30	17	0	31	17	0	28	39	0
30	Land transport, pipelines	LTRANS	11	17	0	10	17	0	16	11	0
31	Water transport	WTRANS	56	17	0	53	23	0	51	17	0
32	Air transport	ATRANS	38	17	0	46	17	0	52	11	0
33	Support activities for transp.	STRANS	31	17	0	35	39	0	32	39	0
34	Postal and courier activities	POST	9	17	0	13	17	0	10	17	0
35	Accommodation, food service	HOT	14	17	0	20	11	0	21	11	0
36	Publishing activities	PUBL	35	17	0	51	11	0	47	39	0
37	Radio,TV, movie,video,sound pub	RADIO	17	17	0	29	39	0	26	39	0
38	Telecommunications	TELE	8	17	0	9	17	0	11	17	0
39	IT and information service	ICS	2	0	1	1	0	11	1	0	23
40	Financial service activities	FIS	42	17	0	28	39	0	23	39	0
41	Insurance and pension funding	INS	39	17	0	11	39	0	12	39	0
42	Other financial activities	OFIS	61	17	0	43	39	0	45	39	0
43	Buying, selling of real estate	REAL	62	17	0	54	17	0	53	39	0
44	Renting of resident. buildings	RENTRB	46	17	0	45	17	0	40	17	0
45	Owner-occupied dwellings	OWNB	36	17	0	34	17	0	29	17	0
46	Legal, account., cons.activit.	BUS	1	0	0	4	17	0	6	39	0
47	Architecture and engineering	ARCH	48	17	0	52	39	0	48	39	0
48	Research and developm.(market)	RD	52	12	0	32	12	0	54	11	0
49	Research and dev. (non-market)	RD (nm)	49	17	0	25	17	0	55	39	0
50	Advertising, market research	ADV	6	17	0	8	39	0	9	39	0
51	Oth.techn.serv.,veterinary act	OTSERV	57	17	0	58	39	0	44	39	0
52	Rental and leasing activities	RLACT	44	17	0	41	17	0	38	17	0
53	Employment activities	EMPL	18	17	0	23	39	0	31	39	0

Continued on next page

Table C.1 – continued from previous page

ID	Activity	Label	1988 pos	1988 par	1988 sub	1997 pos	1997 par	1997 sub	2006 pos	2006 par	2006 sub
54	Travel agent activities	TRAV	40	17	0	39	17	0	43	17	0
55	Cleaning, other business serv.	OBUS	3	0	0	5	0	0	3	11	0
56	Rescue service ect. (market)	RESC	59	39	0	61	39	0	62	39	0
57	Public administration ect.	PUB	12	17	0	17	17	0	20	39	0
58	Adult-,other education(market)	OEDU	47	17	0	40	17	0	39	39	0
59	Education (non-market)	EDU	27	17	0	30	17	0	37	39	0
60	Human health activities	HEALTH	54	17	0	59	12	0	50	39	0
61	Residential care	RCARE	55	17	0	57	11	0	56	11	0
62	Arts,entertainm.,other culture	CULT	51	17	0	56	39	0	49	39	0
63	Sports, amusement, recration	RECR	41	17	0	48	17	0	42	17	0
64	Activities of membership org.	MEMB	16	17	0	19	17	0	18	17	0
65	Repair of personal goods	RPERS	20	17	0	24	17	0	8	17	0
66	Other personal services	OPSERV	34	17	0	44	11	0	36	11	0

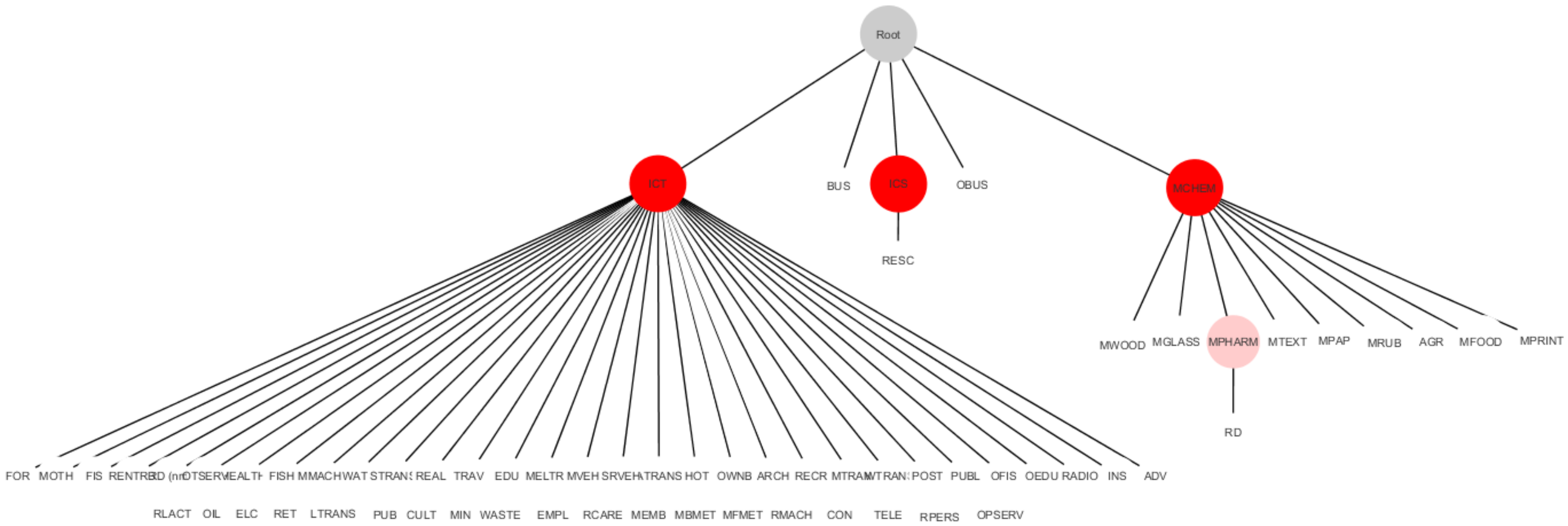


Figure C.1.1: R&D network in 1988

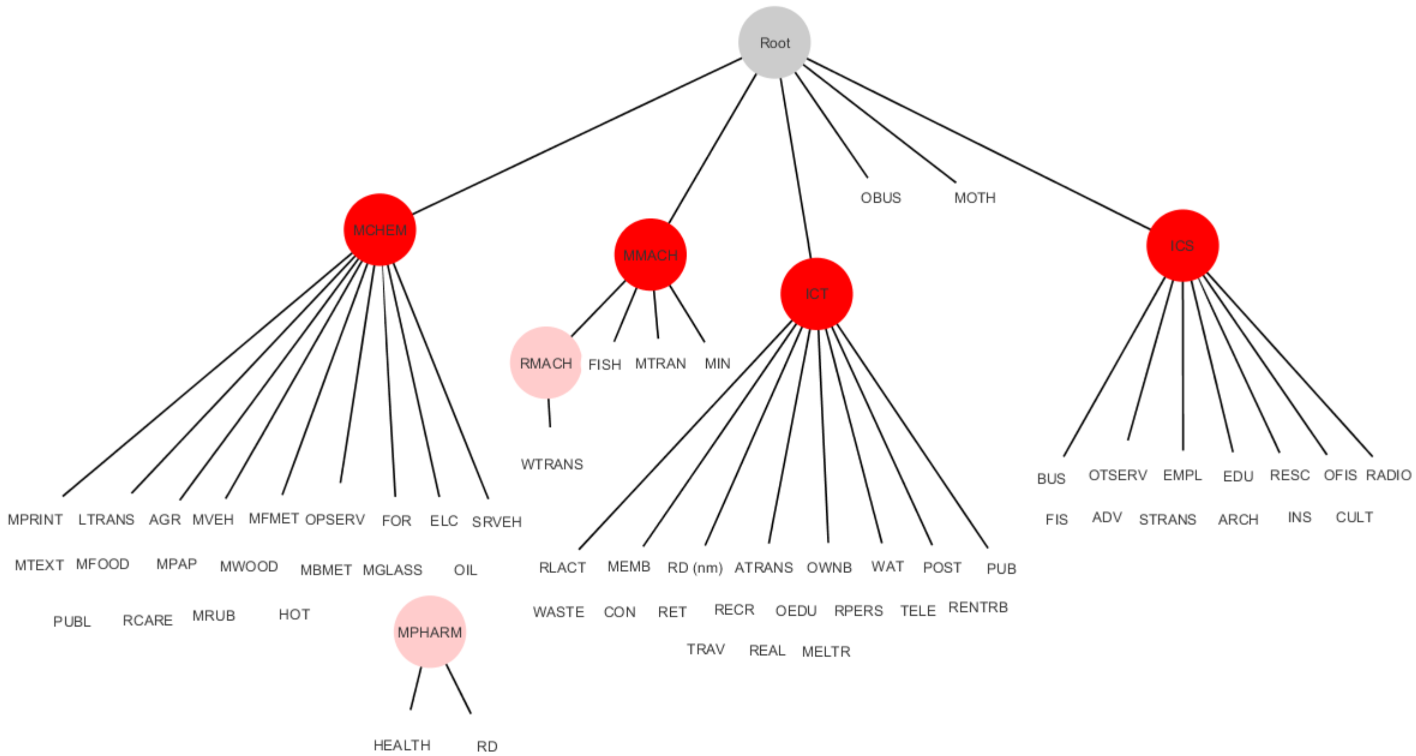


Figure C.1.2: R&D network in 1997

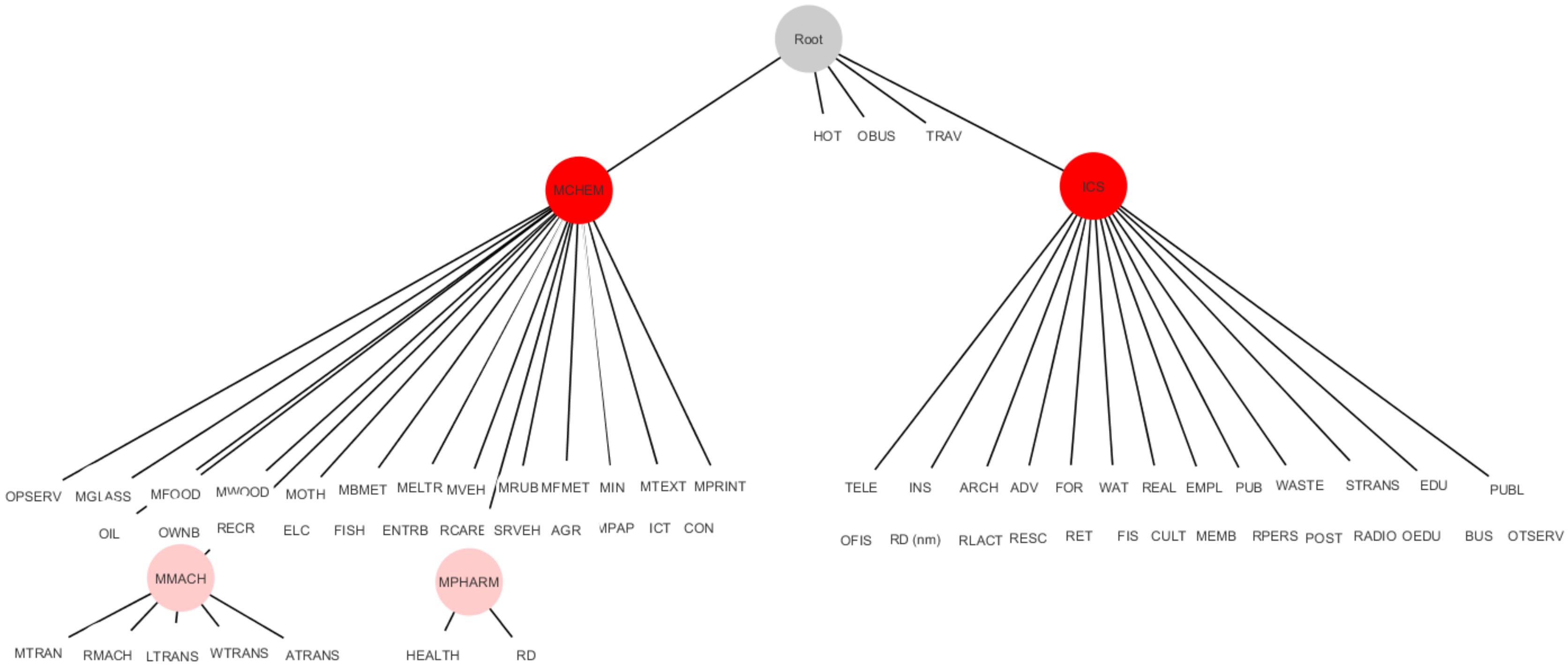


Figure C.1.3: R&D network in 2006

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