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Essays on General Purpose Technologies

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Sapere aude!

Preface

Writing a PhD thesis is a long and winding path and I'm happy that I had many people around me on whose support I could rely throughout the whole time. I would like to start my thesis by thanking all those people.

First of all, I would like to thank my supervisor Lucas Bretschger, who hired me as student assistant and later gave me the opportunity to write this thesis and work at his chair at ETH Zurich, for his kind support during the whole time.

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Zurich, January 2009 Roger Wehrli

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Thesis Summary

A small number of breakthrough technologies drove economic development in every major era of mankind: The first ones, over 10'000 years ago, were the domestication of plants and animals. The industrial revolution was facilitated by James Watt's steam engine, and later electricity not only altered the production of goods dramatically, but also the lifestyle of consumers. Finally, today's economic landscape has been transformed by the introduction of the computer. These breakthrough technologies are called General Purpose Technologies (GPTs). A GPT is generally characterised by its pervasiveness (demonstrated by its use as input in a wide range of sectors); by its potential for continued technological advancement (manifested as sustained improvements in productivity ex post); and by the presence of complementarities arising in manufacturing and in R&D technology.

This PhD thesis consists of four different papers, all illuminating some aspect of GPTs: a broader survey of GPT growth models is followed by two sections with two Schumpeterian GPT growth models. The final paper presents empirical estimations that take a closer look at the interplay between the diffusion of a GPT and R&D expenditures.

The initial impact of GPTs on overall productivity is empirically shown to be minimal, with the realisation of its full potential often taking several decades. This observed delay between the introduction of a new key technology and the emergence of significant economic growth implies that a growth process induced in this way may be subject to economic cycles. Most of the models presented in the literature survey are in line with that fact. The existing GPT growth models are discussed in a two-dimensional framework. First, the models are categorised according to their growth model type. Second, the models are differentiated along a further dimension according to their growth pattern: While some models need new GPTs in order to sustain long-term

growth, in other models the economy shows steady-state growth without the arrival of a new GPT. The effect of a new GPT in these latter models is to increase the long-term steady state growth rate.

Both theoretical models developed in this thesis are Schumpeterian growth models in which GPTs are introduced. The first model concentrates on the passage from an old to a new GPT. In contrast with most of the other models, which focus on the time *after* the arrival of a new GPT, our model focuses on the events *before* the arrival, if R&D firms know the point of time and the technological impact of the new GPT. In this framework the economy goes through three main phases: First, the economy is in its old steady state. Second, there are transitional dynamics, which are characterised by oscillating cycles: In the time immediately before the arrival of a new GPT, there is an increase in R&D activities and growth even going beyond old steady state levels. This is followed by a large slump in R&D activities using the old GPT. In a third phase, as the new GPT becomes active, the economy is in a new steady state with higher growth rates.

The second model focuses on long-term growth with a sequence of GPTs in order to fit two stylised historical facts: First, GPTs arrive at ever decreasing time intervals. Second, new GPTs usually use previously invented technologies and knowledge. Therefore, the arrival of a new GPT is not determined by exogenous factors in this model. The stochastic arrival now depends on the currently available applied knowledge stock. Through this modelling approach we obtain, as a result of the model, the first stylised fact.

In most GPT models users and producers first have to adapt to the new technology before its impact on productivity and economic growth can be realised. This adaptation is mostly done by reallocating resources to the R&D sector, i.e. increases in R&D expenditures after the arrival of a new GPT, and decreases once the new technology can be fully applied in the economy. Our empirical study provides evidence for this reallocation of R&D expenditures. Furthermore, we find that the share of basic R&D expenditures decreases during the diffusion process. This indicates that basic R&D is the basis for applied R&D to be productive on a new GPT.

Kurzfassung

Einige bahnbrechende Technologien bestimmten das Wachstum in jeder Epoche der modernen Menschheit, beginnend vor über 10'000 Jahren mit der Domestizierung von Pflanzen und Tieren. Während die industrielle Revolution stark durch James Watts Dampfmaschine geprägt war, hat später die Elektrizität nicht nur die Produktion radikal verändert sondern auch den Lebensstil der Konsumenten. Heutzutage wird das ökonomische Leben durch den Computer stark beeinflusst. Diese bahnbrechenden Technologien werden Universaltechnologien (General Purpose Technologies oder GPTs) genannt. GPTs werden über ihre weite Verbreitung (z.B. durch ihren Gebrauch als Einsatzfaktoren in zahlreichen Sektoren), über ihr inhärentes Potential für weiteren technologischen Fortschritt (welches sich ex post durch anhaltende Verbesserungen manifestiert) und über das Vorhandensein von Komplementaritäten sowohl in der Produktion als auch in der Forschung und Entwicklung (F&E) definiert.

Diese Dissertation besteht aus vier Artikeln, die unterschiedliche Aspekte von GPTs behandeln: Nach einem umfassenden Literaturüberblick über existierende GPT-Wachstumsmodelle folgen zwei Kapitel mit zwei Varianten Schumpeterischer GPT-Wachstumsmodelle. Als letztes werden empirische Schätzungen präsentiert, die den Zusammenhang zwischen der Diffusion eines GPTs und der Allokation von F&E-Ausgaben untersuchen.

Der positive Einfluss von GPTs auf die Produktivität und das Wachstum macht sich typischerweise erst Jahrzehnte nach ihrer Erfindung bemerkbar. Diese Verzögerung führt zu Zyklen. Die meisten GPT-Wachstumsmodelle, die im Literaturüberblick diskutiert werden, bilden diese empirische Evidenz ab. Die existierenden Modelle werden im ersten Kapitel in einem zweidimensionalen Raster diskutiert. In einer ersten Dimension werden die Modelle gemäss ihrem Wachstumsmodelltyp kategorisiert. In

einer zweiten Dimension werden sie gemäss dem Einfluss der GPTs auf das Wachstum eingeteilt: In gewissen Modellen ist anhaltendes Wachstum nur durch das nimmer ersiegende Erscheinen von neuen GPTs möglich. In anderen Modellen werden die Ökonomien durch gleichgewichtiges Wachstum charakterisiert und das Erscheinen einer neuen GPT bewirkt einen Anstieg dieser gleichgewichtigen Wachstumsrate.

Das erste für diese Arbeit entwickelte Modell betrachtet den Übergang von einem GPT zu einem neuen. Wir fokusieren dabei auf die Zeit *vor* der Ankunft eines neuen GPTs falls die F&E-Firmen dessen Ankunftszeitpunkt und dessen Einfluss abschätzen können. Dies steht im Gegensatz zu den meisten existierenden Modellen, welche die Zeit *nach* der Ankunft betrachten. Es werden drei Hauptphasen unterschieden: Zuerst ist die Ökonomie im alten Gleichgewicht. Danach sind oszillierende Zyklen zu beobachten: Die F&E-Ausgaben und das Wachstum steigen dabei vor der Ankunft des neuen GPTs sogar über das alte Gleichgewichts-Niveau. Darauf folgt ein deutlicher Einbruch der F&E-Aktivitäten. In einer dritten Phase, in der nun das neue GPT aktiv ist, befindet sich die Ökonomie in einem neuen Gleichgewicht mit höheren Wachstumsraten.

Das zweite Modell betrachtet langfristiges Wachstum über eine Sequenz von GPTs. Dabei werden zwei stilisierte historische Fakten berücksichtigt: Erstens werden neue GPTs über die Zeit in immer kürzeren Abständen erfunden. Zweitens bauen neue GPTs auf existierenden Technologien auf. Deshalb ist die stochastische Ankunft eines GPTs in diesem Modell nicht exogen, sondern hängt vom aktuell vorhandenen Wissensstock ab. Dieser Modellierungsansatz stellt u.a. sicher, dass wir den ersten stilisierten Fakt als Resultat des Modelles erhalten.

Die Konsumenten und Produzenten müssen sich zuerst an ein neues GPT anpassen, bevor sich dessen positiver Einfluss bemerkbar macht. Dies geschieht zumeist über die Reallokation von Ressourcen im F&E Sektor, z.B. durch eine Erhöhung der F&E-Ausgaben nach der Ankunft eines GPTs und einer Senkung, sobald die Möglichkeiten der neuen Technologie ausgeschöpft werden können. Die hier präsentierte empirische Studie zeigt Evidenz für diese Reallokation. Zusätzlich finden wir, dass der Anteil der Grundlagenforschungsausgaben über die Zeit des Diffusionsprozesses abnimmt. Dies kann dahingehend interpretiert werden, als dass Grundlagenforschung die Basis bildet, um angewandte Forschung im Bereich eines neuen GPTs produktiv werden zu lassen.

Chapter 1

Introduction

The domestication of plants in 9000 - 8000 BC and the domestication of animals in 8500 - 7500 BC were great innovations that dramatically changed the way humans lived. These changes were so fundamental that North (1981) calls this era "the first economic revolution": Humans could settle down in villages and alter their social organisation, which also lead to the birth of the notion of private property. Agricultural productivity and living standards increased greatly. However, despite this great technological progress, sustained economic growth in the Western Hemisphere only started during the industrial revolution in the late 18th century, and not 10'000 years ago.

In this introduction we present several reasons why economic growth is only a recent phenomenon: First, technological progress does not have diminishing returns anymore since institutions exist which facilitate research and rendered the expansion of an ever growing knowledge stock possible. There is not a single breakthrough technology or General Purpose Technology to which the emergence of sustained economic growth can be attributed. However, it was during the industrial revolution for the first time possible to exploit large complementarities between so-called macroinventions and microinventions which are follow-up inventions. Before we elaborate the above mentioned reasons, a short discussion of General Purpose Technologies is presented. Finally, at the end, we briefly introduce the literature on GPTs and give a short outlook over possible future GPTs, with a focus on the energy sector.

1.1 General Purpose Technologies

There is a small number of outstanding breakthrough technologies that had a big impact on the economic development in every economic era. Crafts (2004) states that electricity, steam, and information and communication technologies (ICT) are the most important technological breakthroughs of the last two centuries. Bresnahan and Trajtenberg (1995) are among the first to call these types of breakthrough technologies General Purpose Technologies (GPTs) and to introduce this concept in a formal model. They define GPTs by their pervasiveness (demonstrated by their use in a wide range of sectors for a large variety of purposes); by their potential for continual technological advancement (manifested as sustained improvements in productivity ex post); and by the presence of complementarities arising in manufacturing or in R&D technology (documented by the impact of a GPT on existing technologies that creates the demand to alter some of them, and the impact of a GPT on new technologies that creates a larger portfolio of profitable investments).

Lipsey et al. (2004) identify twenty-four GPTs that are listed in Table 1.1. This list is not exhaustive since other authors include other GPTs and/or exclude some. Langlois (2002), for example, also lists semiconductors. It is generally agreed that the first GPT of mankind is the domestication of plants in 9000 - 8000 BC mentioned above (Lipsey et al., 2005). However, although this and the subsequent GPTs increased productivity greatly, they did not boost growth in the long term before the industrial revolution. The average growth rate of income per capita was negligible, as Galor (2005) shows.

1.2 Economic Growth in a Historical Perspective

Growth was historically only a temporary and local phenomenon that was never sustained (Mokyr, 2005). During the early mediaeval period in Europe, for example, the achievements of the classic antiquity (Greeks and Romans) lost their impact and the economic and cultural situation was primitive compared to the Roman period (Mokyr, 1990). Nevertheless, the Middle Ages saw the invention of a lot of new technologies such as the stirrup for horse riders, windmills, buttons for clothing, spinning wheels,

No.	GPT	Date
1	Domestication of plants	9000 - 8000 BC
2	Domestication of animals	8500 - 7500 BC
3	Smelting of ore	8000 - 7000 BC
4	Wheel	4000 - 3000 BC
5	Writing	3400 - 3200 BC
6	Bronze	2800 BC
7	Iron	1200 BC
8	Waterwheel	Early medieval period
9	Three-masted sailing ship	15th century
10	Printing	16th century
11	Steam engine	Late 18th to early 19th century
12	Factory system	Late 18th to early 19th century
13	Railway	Mid 19th century
14	Iron steamship	Mid 19th century
15	Internal combustion engine	Late 19th century
16	Electricity	Late 19th century
17	Motor vehicle	20th century
18	Airplane	20th century
19	Mass production, continuous process, factory	20th century
20	Computer	20th century
21	Lean production	20th century
22	Internet	20th century
23	Biotechnology	20th century
24	Nanotechnology	Sometime in the 21st century

Table 1.1: Historical GPTs as listed in Lipsey et al. (2005, p. 132)

etc. (Clark, 2007). Some regions even experienced temporary economic growth during the Middle Ages: For example, Italy went trough a short period of significant economic growth in the 14th century with its important trade cities Venice and Genoa and the manufacturing and financial center Florence, as well as Portugal in the 15th, Spain in the 16th, Holland in the 17th, and Britain in the 18th century (Monteiro and Pereira, 2006). The reasons for these short periods of growth were mostly due to development of trade and an increasing size of markets, as well as to resource abundance. Italy dominated long-distance trade in the Mediterranean sea in the 14th century and profited from the innovations of the commercial revolution such as banks and insurances. But after engaging in several conflicts and after the discovery of a new sea route to India in the early 15th century, the economies of the Italian cities stagnated. The 15th and 16th centuries were the centuries of the Iberian economies. The Portuguese utilisation of the new sea route to India and the discovery of America by Spain boosted trade and opened up completely new markets. Between 1570 and 1670, the Netherlands experienced economic prosperity thanks to commercial expansion, which was achieved by adopting and improving foreign commercial-related innovations as well as by generating new innovations.

All these periods of prosperity and growth were, however, only transient, and it was not until the onset of the so-called industrial revolution that growth was finally transformed into a lasting phenomenon. Britain, the homeland of the industrial revolution, soon outperformed the Netherlands, hitherto Europe's leading economy. Soon, the Netherlands were far behind Britain and "by 1825 or so, the Netherlands had been transformed from a paradise of technological ingenuity to a museum" (Mokyr 2000, p. 508).

The question arises why early GPTs and technological progress never succeeded in sustaining long-term growth before the industrial revolution, as we have already mentioned in the first paragraph of this introduction. Looking at the literature, a number of reasons for this development are identified. These reasons are of a technical as well as a non-technical nature and will be discussed in the following. We start with the non-technical aspects, before turning to the technical reasons, which will lead us to the discussion of GPTs, the main subject of this PhD dissertation.

1.3 Institutions and Useful Knowledge

In general, the take-off of sustained growth during the industrial revolution in the West was not such a revolutionary event as the word "industrial revolution" might indicate. Mokyr (2002b, p. 23) calls the word revolution "overused and abused by historians" because the impact of a dramatic invention took decades to be felt. Gregory Clark (2001, p. 69) has a radical view: "It [the industrial revolution] can then be interpreted as just another isolated technological advance as European economies had been witnessing since at least the fifteenth century." The industrial revolution and the consequential emergence of sustained growth was the culmination of a lot of events and innovations that happened over the centuries before. These innovations were facilitated by the development of the concept of a corporation that is distinct of its members and the development of a pluralistic society in Europe during and after the mediaeval period (Lipsey et al., 2005).

Guilds were the first corporate institutions that were independent of the state and the church. Later, universities (in the thirteenth century) and cities with their own jurisdiction arose. The pluralistic society in Europe facilitated science and allowed scientists to work more independently. The division between lay and religious areas of jurisdiction facilitated research that was not in line with religious belief, and finally lead to the separation of science from religion.[1] This division was reinforced by the reformation, which allowed scientist to emancipate themselves from the more strict Catholic church. Furthermore, the rise of nation states and independent cities and the competition between them allowed scientists to express different views and work more freely than ever before. The foundations of universities where the new knowledge was taught, and the attached libraries that recorded the knowledge, created an institutional memory for scientific knowledge. Universities institutionalised research and development (R&D) even before industrial research became significant in the early 20th century (Lipsey et al., 2005).

The creation of these independent institutions fostered, amongst others, the foundation and expansion of what Mokyr (2002a) calls “useful knowledge”, which is primarily the knowledge of natural phenomena. Science played an important role during all phases of the industrial revolution. The leading sectors were always the ones that were the most influenced by science. During a first phase (1770 - 1880), innovations were based on mechanical knowledge built on the findings of Newtonian mechanical science. Later, non-mechanical sectors, such as chemicals and steel, took the lead. Before the industrial revolution, economic growth had always reached a limit because technological

[1] One of the reasons why the industrial revolution did not occur in China or in the Islamic World is that this division was not allowed in their hemispheres. In the Islamic world, which was leading in exact sciences such as optics, astronomy, geometry, trigonometry and medicine in the thirteenth century, no independent lay institutions were developed (Lipsey et al., 2005). As a result, there were no institutions that pursued research in natural philosophy because the Islamic religious leaders considered it blasphemous. This is part of the reason why the Islamic World lost its technological advantage: natural philosophy set the cornerstone for Newtonian mechanics, which was crucial for the industrial revolution.

progress had diminishing returns. The findings of science in natural philosophy did not immediately produce technological applications and were not done in a directed way, but more by trial and error and luck. Only in the fifteenth, sixteenth and seventeenth centuries, a new kind of science emerged that considered experiments as important in order to debate empirical subjects. This helped to finally overcome the diminishing returns during the industrial revolution, as is explained in more detail below.

Mokyr (2002a) argues that science before 1800 mainly created singleton techniques that were not linked to other techniques and hardly led to incremental and sustained improvements. Other authors agree on the general argumentation of Mokyr (2002a) but not on the timing. Lipsey et al. (2005) state that several lines of cumulative scientific and technological advances already existed from 1450 - 1750.

According to Mokyr (1990), there are two kinds of useful knowledge. One is the so-called propositional knowledge that describes *what* is known and that builds the epistemic base of knowledge. The other is the so-called prescriptive knowledge that describes *how* to do things and that pools all the techniques that are known in an economy, i.e. it is what is sometimes also called “the book of blueprints”. Before the industrial revolution, the epistemic base was very narrow. This means that it was normally only known that the specific singleton technique works, but there was little knowledge about the reasons why a technology worked. Therefore, new technologies were not developed further, did not give rise to complementary innovations, and, as a consequence, did usually not lead to sustained growth. Only during the industrial revolution in Britain was the epistemic base expanded, which allowed to overcome the diminishing returns of technological progress (Mokyr, 2002b). This was caused by the so-called “knowledge revolution” that established standards in open science. These standards eased the accessability of knowledge, together with more efficient storage of knowledge due to textbooks and encyclopedias, and better search engines thank to indices and experts. These falling access costs to knowledge allowed for important positive feedback mechanisms between the two types of knowledge, which led to mutual reinforcements. Scientist could on the one hand employ the propositional knowledge to build new techniques, i.e. to increase the prescriptive knowledge. On the other hand, the limits of the prescriptive knowledge showed the direction in which the propositional knowledge should be expanded. Furthermore, the falling access costs meant that the accumulation of knowledge turned irreversible. In the antiquity, many of the great inventions were lost to subsequent generations because the knowledge did not diffuse throughout society but remained within a small circle of scientists due to the high access costs (Mokyr, 2005). Scientist are now better informed, are faced with well-defined problems, and can therefore direct and concentrate their research efforts towards promising fields.

We sum up the findings by stating that the rise of useful knowledge thanks to the widening epistemic base; the irreversibility of its accumulation and the growing complementarities in research; together with falling access costs to knowledge, were crucial for the technological and economic development that led to today's sustained economic growth. However, returning to the main subject of this PhD thesis - General Purpose Technologies - we might ask which technologies were crucial for the emergence of sustained growth in the West.

1.4 Breakthrough Technologies and Growth

In general, newly invented technologies were important for the industrial revolution, and technological progress is seen to be the central driving force of modern economic growth (De Vries, 2002). However, it is hard to identify the impact of a specific innovation on the process. Mills and Crafts (1996), who show that trend growth of industrial output accelerated gradually over several decades in the 18th and 19th centuries, agree on that. They have "no strong priors about the precise path of the growth process. Even dating of famous macroinventions does not help because their impact on growth will not be immediate and might be quite long delayed" (Mills and Crafts, 1996, p. 292).

The industrial revolution cannot be attributed to a sole major technology, but to a combination of technologies that evolved over a longer time period. Lipsey et al. (2005) name the most important innovations: They argue that the advances made in mechanical science and the ensuing innovations are the main reasons why the industrial revolution took place in Great Britain and not somewhere else in the world. They identify the organisational GPT "factory system" and the two evolutionary technologies “textile machinery” and “high-pressure steam engine” as the most important innovations in this period.

Mokyr (1990) offers the concept of macro- and microinventions, which is helpful for understanding technological development and which shares some similarities with the concept of GPTs: A macroinvention is an invention that is not an improvement of existing technologies, but a new breakthrough technology without clear precedent. Microinventions are incremental and small improvements of existing technologies. The definition of macroinventions does not fully coincide with the definition of GPTs. Mokyr (2002b), for example, does not count the invention of the Personal Computer (PC) as a GPT, but argues that the semiconductor is the macroinvention of ICT. The information revolution and the subsequent innovations such as the PC and the internet are seen as follow-up microinventions. The main difference between the two concepts is that macroinventions are technology-radical, because they do not have a clear technological precedent and present a complete new technology, whereas GPTs are use-radical. Use-radical means that the innovation “could not have emerged out of the technologies that preceded it in that specific use” (Lipsey et al., 2005, p. 90).

Galor (2005) states that the trifling growth before the industrial revolution, the period he calls the “Malthusian period”, was caused by the slow pace of technological progress. The rate of technological progress rose during the industrial revolution from a rate that has never been higher than 0.05% per year before the industrial revolution to a rate around 1% or higher for the successful economies (Clark, 2007). Mokyr’s (1990) explanation of this phenomenon, which centers on negative feedbacks and diminishing returns before the industrial revolution, is substantiated by the complementarity of macro- and microinventions: Without new macroinventions the marginal productivity of research decreases, and without microinventions most macroinventions would not be implemented and no economic rents could be earned. However, these complementarities were never fully exploited due to the small epistemic base and lack of fertile ground for the development of complementary microinventions. During the industrial revolution, this complementarity could for the first time be fully exploited, and macroinventions were followed by a huge number of microinventions thanks to the above mentioned institutional and other changes.

The time path of the arrival of new GPTs shows the typical pattern of all main economic indicators over the last 10'000 years: it is characterised by a very slow acceleration over time and an explosion of the number of new GPTs during the last three centuries. Solely ten of the twenty-three historical GPTs as listed in Table 1.1 were discovered before the eighteenth century. The first GPT of the industrial revolution was the steam engine. The steam engine and its inventor James Watt are - together with the factory system, the automation of textile manufacturing and the railway - often seen as the great symbols of the industrial revolution. The steam engine not only allowed textile manufacturers to automate production and increase the speed of operation, but also enabled such important new technologies as the railway and the iron steamship. The new factory system that relied heavily on mechanisation, which is an organisational GPT, started in the textile sector. It was adopted rapidly in many other sectors, and by the end of the nineteenth century factories with some degree of mechanisation existed throughout the manufacturing sector (Lipsey et al., 2005). The railway only transported coal to ports and did not compete with canals for cargo transportation before a larger railroad network was build and before it was used for more purposes such as long-distance cargo transportation and transport of people.

Although the above mentioned GPTs spread successfully through the whole British economy, we might ask if GPTs really increase productivity. The Railway, e.g., is traditionally seen as important for industrialisation in general and a prerequisite for the rise of the first mass production-mass consumption economy in the United States (Lipsey et al., 2005). Fogel (1964) challenges this view. He calculates that the social savings thanks to railways in the United States was only 0.6% of the GDP in 1890. However, already Rosenberg (1982, pp. 58 - 59) observes that "the growing productivity of industrial economies is the complex outcome of large numbers of interlocking, mutually reinforcing technologies, the individual components of which are of very limited economic consequences by themselves". Therefore, we cannot measure the total impact of GPTs with technological complementarities whose effects are widespread over space and time by simply calculating the impact of removing one technology. The sum of the effects of complementary technologies will always be larger than the isolated effect of one individual technology. Technological complementarities cannot be measured by statistical studies of the type conducted by Fogel (1964). The railway is a good example of such complementarities: It would have developed very differently - if at all - without the steam engine GPT, and later without the internal combustion engine and electricity (Lipsey et al., 2005). Only the complementarity with the steam engine allowed the railway to become an important GPT. Moreover, the railway was also an important starting technology for many other complementary technologies, for example diesel engines.

The line of reasoning just presented for the case of railways and steam engines can easily be adapted to the other historical GPTs of Table 1.1. All of these GPTs had a large impact on productivity, although their effect can hardly be exactly quantified.

1.5 GPTs in the Economic Literature

The historical analysis presented on the preceding pages has proved to be very useful in understanding technological progress and the role of GPTs for economic growth. By characterising different GPTs and their impact on development, Lipsey and co-authors provided the groundwork for a descriptive theory as well as formal modelling of the phenomenon. In this introduction, we only give a short overview of analytical approaches employed in the analysis of GPTs. An extensive literature survey will be presented in Chapter 2.

In principle, the literature on formal models of GPTs can be distinguished into two strands. One strand builds on the neoclassical paradigm, while the other is based on evolutionary economics. First attempts to integrate GPTs into endogenous growth models of the neoclassical tradition were undertaken in the volume of Helpman (1998) with the models of Helpman and Trajtenberg (1998a and 1998b) and Aghion and Howitt (1998a). They integrate the notion of GPTs in a standard endogenous growth framework and concentrate on steady state solutions. This kind of modelling was criticised by the evolutionary school represented by Carlaw and Lipsey (2006). They suggest what they call a "structuralist-evolutionary" approach that, according to them, does not use an equilibrium concept leading to the high technical complexity in modeling as in the neoclassical models. This kind of approach allows them to endogenise the arrival of new GPTs, but they can tackle the problem only with numerical simulations. In their view, it is important to incorporate what Geoffrey Hodgson (2001) calls "historical specificity" and to reproduce stylised facts from economic history with their model.

Papers in the neoclassical tradition often concentrate on building general models (the so-called "theoretical generality" that is opposed to "historical specificity") that are not bound to some specific region, type of country or epoch. In these growth models, technological progress is modelled as an increase in a knowledge stock, an increase in the quality of goods, or an increase in the variety of goods. This implies that technological progress leads to an immediate increase in productivity measured by total factor productivity (TFP) and economic growth. These kinds of models do typically not take into account that technological progress might not always be symmetric, where symmetric means that a given input always leads to the same expected amount of technological progress. In the theory on GPTs, however, it is often argued that GPTs lead to innovational complementarities. Therefore, a given research input can lead to a higher outcome after the arrival of a new GPT. Endogenous growth models in the neoclassical tradition also neglect that technological progress does not directly equal TFP growth because it takes time until a new technology can successfully and productively be applied in the economy. David (1990) explains this phenomenon with the example of the electric dynamo and the computer. The lack of a visible productivity effect of the computer in the eighties is often called the "Solow Paradox". However, it is now commonly agreed that the computer has had a large impact on productivity. Oliner and Sichel (2000), for example, show that ICT had a significant impact on productivity in the second half of the nineties. The reasons for this delay are manifold: Diffusion itself takes time, as innovators first have to build up a critical mass of complementary components for a new GPT (e.g. software for computers), and new GPTs require the acquisition of specific skills and the related learning processes can take a considerable amount of time.

Although Carlaw and Lipsey (2006) believe their model to be the first GPT model that meets historical specificity, we think that even the first contributions in the seminal volume of Helpman (1998) started to approach historical specificity. Although still in a neoclassical framework, Aghion, Howitt, Helpman and Trajtenberg already begin to contest that technological progress always appears in a symmetric and rational way and try to integrate some of their empirical or anecdotal evidence on GPTs in their respective endogenous growth models.

1.6 Potential Future GPTs

Table 1.1 lists not only historical GPTs, but with nanotechnology also a recent technology that could become a GPT. Nanotechnology offers a wide variety of potential applications in different sectors such as material production, medicine, electronics and energy production. This view of nanotechnology being a next GPT is strengthened by studies from Shea (2005), Palmberg and Nikulainen (2006) and Youtie, Iacopetta and Graham (2008).

Looking at the growing resource scarcity, pollution and climate change menacing mankind in the long term, it seems obvious that large technological progress which helps to save resources and energy and mitigate the environmental impacts is indispensable in order to keep at least the present level of wealth in developed countries and not hinder developing countries from catching up.

The last GPT that directly affected the supply of energy was the invention of electricity in the late 19th century, which offered an alternative to the existing animate and mechanical power systems and finally lead to today's dominance of electronics and to the ICT revolution. The key invention for electricity was the dynamo in 1867 that converts mechanical power into flows of electrons. These flows of electrons can be used for a large amount of applications.

In a first period, electricity was produced with large steam turbines fed with coal. This kind of electricity production that generates a lot of pollution still dominates in many countries today (Victor, 2002). Over time, the method of electricity generation has seen many innovations, of which the construction of large dams was one of the most important innovations that allows to run water at a fast speed through turbines (Lipsey et al., 2005). Modern atomic physics has enabled the rise of a new milestone technique, nuclear power, which has become very important in most Western economies. In France, which is the country with the highest share of nuclear power in electricity generation, 77% of electricity is produced by nuclear power plants (Victor, 2002).

Natural gas technologies have become more important in the 1990s thanks to low-cost, flexible and efficient gas turbines. Today, building gas power plants is even discussed in Switzerland, a country with good conditions for water powers.

The major concern about coal and gas power stations is their high emission of CO2 and their impact on the climate. Some alternative renewable power sources could provide a solution to that issue: Wind energy has a current share of 0.5% in world electricity production, biomass has a share of 1.3%, geothermal has 0.3%, and solar energy, which still plays a marginal role in global electricity production (IEA, 2006). All these renewable technologies have the potential for improvements and could be used on a larger scale in the future.

Besides these alternative technologies that are already produced in the market, there are some interesting future energy technologies such as nuclear fusion, superconductors to reduce losses in power transmission, and hydrogen and fuel cells. Hydrogen can be produced from a wide variety of resources, among them also some renewable resources such as hydro, wind, solar, biomass and geothermal resources. Hydrogen and fuel cells are widely seen as one of the key energy sources in the future, because they are expected to contribute significantly to a reduction in environmental pollution and enhanced energy security and diversity, and because they can be used in transportation, heat and power generation and in energy storage systems (Edwards et al., 2008). The storage of energy is also a big issue, because most of the existing alternative technologies do not provide base load. If the electricity could be stored at off-peak times, less conventional energy power stations providing base load would be needed.

Another promising new technology for generating electricity is nuclear fusion. It is estimated to produce 200'000 kWh "with the lithium in one laptop battery plus half a bath of water" at possible costs between 0.05 - 0.09 Euro per kWh (Smith and Ward, 2008, p. 4332). The main advantages over the existing power sources are that it does not emit any greenhouse gases, it does not largely pollute the environment, major accidents seem to be impossible and there is no long-term radio-active waste. The greatest advantage is that it could offer essentially unlimited fuel because there is enough lithium to produce electricity for the whole world for millions of years.

We actually do not know which one of these technologies related to energy supply will become a powerful GPT, nor when the possible productivity gains will appear, since there are still a lot of substantial challenges remaining that can only be solved by large technological development. And, once all technical problems are solved, it may still take a long time until the new technology is successfully applied in the economy. David (1990) shows that it took four decades until substantial productivity gains thanks to the electric dynamo were realised. On one hand, it took some time until factories were redesigned in order to fully exploit the advantages offered by the new power source. On the other hand, electricity was first only applied for very few uses in street lighting, street railways, and some specific industries, before new applications were invented for households such as washing machines and dishwashers, and in communication technology such as the pathbreaking telegraph. Electricity is one of the most pervasive GPT the history has ever seen: Most of the later GPTs such as mass production, continuous process and factory, computer, lean production and the internet rely on the complementarity with electricity. Looking back in a historical perspective at the evolution of a GPT, its development always appears inevitable (Lipsey et al., 1998). However, during the first years of a new technology, it is in the best case only known what the impact in its core purpose and sector might be, but it is mostly uncertain if it will have a larger impact.

A new GPT that leads to a less energy-intensive economy could also arrive on the demand side of energy. The energy consumption and the damaging pollution could be reduced if a next GPT needs less energy and resources than the GPT it replaces. Therefore, it is important that R&D is not only done in order to find and develop promising alternative power sources, but R&D should in general be directed into the development of less energy-intensive and less polluting technologies, so that a new GPT might help to reduce the energy demand.

1.7 Outline of the Study

The present study consists of four different papers, all illuminating some aspects of GPTs: a broader survey of GPT growth models is followed by two sections on a quality-ladder GPT growth model. The first of these two theoretical sections introduces a Schumpeterian growth model that concentrates on the passage from an old to a new GPT, while the second shows a model with a sequence of GPTs. Finally, empirical estimations that have a closer look at the interplay between the diffusion of a GPT and R&D expenditures are presented. This interplay is poorly modelled in the existing theoretical literature.

The literature survey in Chapter 2 discusses existing GPT growth models, which are classified in a two-dimensional framework in order to make comparison clearer. First, the models are categorised according to their growth model type. We distinguish between models using a quality ladder approach, models using an increasing variety approach and models with human capital/knowledge driven growth. Second, the models are differentiated according to their growth pattern. We identify models that need new GPTs in order to sustain long-term growth, and models where the economy displays steady-state growth without the arrival of a new GPT. The only effect of a new GPT in these latter models is to increase the long-term steady state growth rate.

The GPT models where long-term growth can only be sustained by the continuing arrival of new GPTs have horizontal substitutability, i.e. the different components of a GPT or the different intermediate goods belonging to one GPT generation are substitutes for each other. The marginal productivity of each new incremental innovation belonging to a specific GPT, i.e. of each new component of a GPT, is decreasing in the number of components. Without a new GPT, which leads to a higher marginal productivity of its incremental innovations compared to the incremental innovations of the old GPTs, growth would asymptotically approach zero.

Chapter 3 and Chapter 4 develop two theoretical Schumpeterian quality-ladder growth models based on the model of Barro and Sala-i-Martin (2004). The models study the impact of new GPTs where the arrival of a new GPT increases research efficiency. The models represent general theoretical analysis, yet we derive our motivation from some recent historical evidence. Although we don't think it useful to build a model for every specific historical event because it runs the risk of becoming descriptive and loses the power of modeling, we still wanted to show that our models explain some empirical facts.

Chapter 3 presents a model that analyses the transition from an old to a new GPT.

The main focus lies on the events *before* the arrival of a new GPT, in contrast to most existing models which focus on the time *after* the arrival. In our model, it is assumed that agents can foresee the near future and anticipate the arrival of the new GPT, i.e. R&D firms know the point of time and the technological impact of the new GPT.

The firms are able to anticipate the arrival of new GPTs, which can be observed in numerous instances in economic history. The United States, for example, adopted the steam engine long after its introduction in Britain. And even in Britain, the arrival of the steam engine GPT could be anticipated because it was not a GPT from the beginning: it was first a single purpose technology that was mainly used for pumping out water from mine shafts before it turned into a general purpose technology.

In our quality-ladder growth framework, we can show that the anticipation of a new GPT makes the economy pass through three main phases: Initially, the economy is in its old steady state with constant growth rates in output and R&D expenditures. Second, as the arrival of a new GPT comes closer, there are transitional dynamics which are characterised by oscillating cycles around the steady state levels. The amplitude of these cycles becomes larger and larger, and during the last cycle before the arrival of a new GPT, R&D activities and growth even go beyond the old steady state levels. Immediately before the arrival of the new GPT, however, we observe a large slump in R&D activities using the old GPT as well as lower growth rates. In a third phase, as the new GPT becomes active, the economy is in a new steady state where the growth rate is higher than in the old steady state because the increase in research efficiency makes investments in R&D more attractive.

The result of increasing R&D activities in the old GPT before the arrival of a new GPT is in line with historical examples: During the nineteenth century, for example, the replacement of water power as the main source of power by the steam engine seemed to be obvious. Nevertheless, some of the greatest innovations in water power were achieved during this time. And the spread of steam as a source of power for marine ships led to new innovations that increased the efficiency of sail.

In Chapter 4 the model presented in Chapter 3 is extended. Since this model focuses on long-term growth, it has a longer time horizon than the model in Chapter 3 and not only looks at the transition from an old to a new GPT, but at a longer sequence of GPTs. The arrival of a new GPT is not determined by exogenous factors because the stochastic arrival now depends on the currently available applied knowledge stock, which is in line with a stylised fact from economic history: New GPTs usually use previously invented technologies and knowledge. This kind of modelling allows to capture another historical stylised fact: The time interval between the arrival of new GPTs has become ever shorter.

Empirical evidence for the latter stylised fact can already be found in Table 1.1. While millennia passed between GPTs in the early times, seven GPTs can be observed in the twentieth century alone. Nevertheless, none of the existing models account for this fact: On one hand, models that focus on the impact of new GPTs on the course of a single economic cycle, as our model in Chapter 3, are by definition not concerned with a sequence of GPTs. On the other hand, long-term models where growth is driven by a sequence of GPTs either assume fixed time intervals between the arrival of new GPTs, or a stochastic pattern with no long-term trend in either direction. By assuming exogenous arrival patterns, the existing models also miss the second stylised fact which can be observed for all the existing GPTs: None of them was an invention from scratch, but relied heavily on previous technologies and knowledge.

The numerical simulations in Chapter 4 show that our model allows for a better reproduction of the historical facts regarding the frequency as well as the economic conditions for the discovery of new GPTs. Furthermore, the model includes an interesting combination of features: Not only is the arrival of new GPTs stochastic, but we also model economic cycles within the lifetime of a single GPT, assuming that the economic impact of such a new technology decreases over time.

Whereas the first part of this thesis focuses on theoretical approaches and models, Chapter 5 presents an empirical study that estimates the influence of the diffusion of a new GPT on per capita R&D expenditures and the share of basic R&D expenditures. For this purpose, diffusion data on the PC and the internet are included in a panel of nineteen OECD countries over the time period 1981 - 2004, which are analysed with both single equation estimations and a system of simultaneous equations using three-stage least squares.

There are only very few empirical studies on GPTs: Jovanovic and Rousseau (2005) present the broadest empirical study. They discuss the identifying features of a GPT and test them empirically for electricity and information technology (IT). However, Jovanovic and Rousseau (2005), as well as all other studies to our knowledge, do not study the impact of a GPT on research and development and on other general macroeconomic variables. In this chapter, we try to close this gap by studying the impact of the diffusion of GPTs on R&D expenditures for the example of the PC and the internet.

The theoretical literature on GPTs proposes that users and producers first have to adapt to a new GPT. This adaptation is done by developing templates, and learning and reallocating resources to the R&D sector, which leads to increases in R&D expenditures after the arrival of a new GPT and decreases once the new technology can be fully applied in the economy, i.e. once the diffusion process has stopped. Although this pattern is quite intuitive, it has not yet been confirmed by larger empirical studies. Therefore, the first tested main hypothesis is that we expect per capita R&D expenditures to increase after the arrival and during the first period of the diffusion process of a new GPT.

Endogenous growth theory normally only considers one homogenous type of R&D and does not distinguish between basic and applied R&D. Evenson and Kislev (1976), without modeling GPTs, and Carlaw and Lipsey (2006), who model GPTs, are exceptions that allow for these different types of R&D. From these models stems the second main hypothesis: The diffusion of a GPT should influence the share of basic R&D. However, from a theoretical point of view, the direction of the effect is not clear: The share is expected to decrease during the diffusion of a GPT if basic R&D is a prerequisite for applied R&D: After the arrival of a new GPT, a new fundamental knowledge base has to be accumulated in order to make applied R&D on the new GPT more productive, as it follows from Evenson and Kislev (1976). Conversely, the share of basic R&D is expected to increase if the purpose of basic R&D is to find new GPTs, as in the model of Carlaw and Lipsey (2006).

We find that per capita R&D expenditures increase and the share of basic R&D expenditures declines during the diffusion process. This indicates that basic R&D is needed for applied R&D on a new GPT to be productive and to fully exploit possible productivity gains of the new GPT. This is a unique result that adds to the existing theoretical and empirical literature and that indicates possible directions for the further development of GPT growth models that consider the different types of R&D.

Chapter 2

General Purpose Technologies and Endogenous Growth: Modelling Approaches and Conclusions*

We overview the existing GPT growth models and classify them in a two dimensional framework. First, the models are categorised according to their growth model type. Second, the models are differentiated along a second dimension according to their growth pattern. While some models need new GPTs in order to sustain long-term growth, in other models the economy shows steady-state growth without the arrival of a new GPT. The effect of a new GPT in these latter models is to increase the long-term steady state growth rate.

*This chapter represents joint work together with Gay Saxby (ETH Zurich).

2.1 Introduction

Economic history often shows that in any given time period a handful of key technologies has been responsible for widely fostering technological change and thereby bringing about sustained and pervasive productivity gains. These key technologies are qualitatively different from anything previously experienced and have caused deep structural adjustments in the economy. Relevant historical and current examples of this type of technological change are the steam engine, electricity and information and communications technology (Crafts, 2004). Bresnahan and Trajtenberg (1995) and Helpman (1998) were among the first to refer to these types of radical technological phenomena as General Purpose Technologies (hereafter GPTs) and to broadly characterise them by their pervasiveness (demonstrated by their use as inputs in a wide range of sectors); by their potential for continual technological advancement (manifested as sustained improvements in productivity ex post); and by the presence of complementarities with their user sectors arising in manufacturing or in R&D technology.

Jovanovic and Rousseau (2005) test empirically the extent to which the three defining characteristics of GPTs set out by Bresnahan and Trajtenberg (1995) are applicable to two technologies commonly regarded as GPTs, namely electricity and information technology (IT). Their findings show, firstly, that within thirty years electricity had overtaken steam as the most import power source and was very pervasive among all sectors. The diffusion of computers has been slower but is still increasing. In order to control for the second characteristic of the definition, the improvements in the efficiency of the technologies are measured by the price of a unit of quality over time. For both technologies the prices declined much faster than the general equipment price index, with the changes for computers being more revolutionary. This further supports the classification of both technologies as GPTs. Finally, the authors also find evidence to support the third part of the definition: new firms invest more during the eras in which these technologies were active than at other times, indicating that both technologies have the ability to spawn innovation.

In the context of economic growth, the initial impact of General Purpose Technologies on overall productivity growth is empirically shown to be typically minimal, with the realisation of its eventual potential often taking several decades. This observed delay between the introduction of a new key technology and the emergence of significant economic growth effects implies that a growth process induced in this way may be subject to episodes of sharp acceleration and deceleration (Crafts, 2004) giving identification of this type of drastic technological change particular relevance for the theory of economic growth.

Although technological change has long been accepted as the single most important force driving the process of economic growth the early neoclassical models of economic growth assume that technological progress occurred in an exogenous manner. This assumption is made in order to reconcile the theoretical models - which predict that without continuing improvements in technology, per capita growth must eventually cease - with empirical evidence of a positive, possibly constant, per capita growth rate in the long run. Dissatisfaction with these models arose because the exogeneity of technological progress means that the models in fact provide no explanation for the empirically observed process of long-run growth.

This led to attempts to include a theory of technological progress within the neoclassical framework. However, technological advance involves the creation of new ideas, which are partially non-rival and therefore have aspects of public goods. This results in non-convexities in the production structure of firms, making the maintenance of the standard competitive assumptions used in neoclassical models all but impossible. In particular, the competitive framework breaks down if technological discoveries depend in part on purposive R&D efforts - that is, investment in R&D activities with the intention to earn a return from those investments - and if an individual's innovations spread only gradually to other producers. Beginning with Romer (1990) and with significant contributions by Grossman and Helpman (1991) and Aghion and Howitt (1992), theories of R&D and imperfect competition were incorporated into the growth framework. In these models, technological advance results from purposive R&D activity, which is rewarded by some form of ex post monopoly power.

While this new generation of endogenous growth models pays closer attention to empirical implications and to the relationship between theory and data, they mostly still tend to treat all forms of technological change in the same, simplified manner. However, if one considers in detail the concept of GPTs, it should be obvious that the impact of such a drastic new innovation should differ from normal technological progress. Empirical studies of GPTs give rise to the stylised fact of an observed delay between the appearance of such technologies and their impact on economic growth. Several of these studies (e.g. Griliches, 1957; Helpman and Trajtenberg, 1998b, Jovanovic and Rousseau, 2005) document the cross-industry pattern of diffusion for a number of GPTs. These studies have established that the diffusion pattern of GPTs is generally governed by standard S-curve dynamics, suggesting the ability of these drastic innovations to generate growth fluctuations and even business cycles. Other studies (e.g. Nahuis, 1998; Jacobs and Nahuis, 2002; Crafts, 2004) support David's (1990) assertion that the dynamic effects of GPTs can take a long time to materialise, with a period of several decades passing before any significant impact on macroeconomic activity is felt (Petsas, 2003).

The overall aim of this paper is to compare the various approaches to the theoretical modelling of GPTs and to have a closer look at the representation of the empirical facts on GPTs. To this end, the existing models are classified in a two dimensional framework. Firstly, the models are grouped according to their type in the context of endogenous growth theory, i.e. we distinguish between models using a quality ladder approach, models using an increasing variety approach and models with human capital/knowledge driven growth. The second dimension classifies the models according to the growth pattern. The first category of models displays steady state growth without the arrival of a new GPT, with the arrival of a new GPT serving to increase this steady state growth rate. The other category of models in this dimension requires the arrival of new GPTs in order to exhibit a positive growth rate.

We will determine the extent to which each model category complies with the essential definition of GPTs as given above and we will examine the manner in which each theory deals with the following: how GPTs arise in the economy, how incremental innovations arise, the manner in which GPTs impact economic growth, and how uncertainty is dealt with in the model. Our focus will be on highlighting the differences among these interrelated factors in each model. In doing so we hope to develop a clearer picture of the scope and focus of the existing approaches and of the main advantages and disadvantages of each model category. This will allow us to identify any areas of the literature which might be improved in representing useful and relevant models of GPTs and economic growth.

This article is organized as follows: In Section 2.2 the contextual background to the theory of GPTs is explained. Section 2.3 introduces the different model categories and provides a general discussion of the models belonging to each one. Finally, Section 2.4 considers how these different modelling approaches represent the impact of a GPT on economic growth. In this Section we also offer some conclusions on our findings, and make some suggestions for the most fruitful directions for future research.

2.2 Theory of GPTs

Endogenous growth models typically view R&D as the main origin of technological change. R&D is defined as profit-motivated intentional actions; that is, investment in knowledge with the intention of obtaining a financial return on that investment. Within the GPT literature it is thought that certain of these investments lead to drastic innovations, i.e. to a new GPT.

Lipsey et al. (1998) consider in detail how to define a GPT, using both historical examples, from which they draw a set of stylised facts, and an analysis of contemporaneous theoretical literature. Their definition is based on the underlying opinion that any useful theory of GPTs need not necessarily provide an explanation for all relevant empirical observations, but should at least not contradict them. Further, they suggest that a theory that predicts the effects of GPTs requires a definition stated in terms of technological characteristics, rather than in terms of the impacts of such technologies on the economy. Based on their theoretical and empirical analysis and their underlying concept of the requirements of a working definition of GPTs, the authors identify four characteristics which they suggest, taken together, provide the necessary and sufficient conditions for a technology to be delineated as a GPT. In summary, and with the characteristics enumerated in brackets for clarity, the authors propose that a GPT is a technology that starts off in a fairly crude state with a limited number of uses and (1) evolves into a much more complex technology with (2) dramatic increases in the range of its uses across the economy and in the number of economic outputs it produces. As a mature technology, a GPT becomes (3) widely used for a number of different purposes, and (4) has many complementarities with existing or potential new technologies.

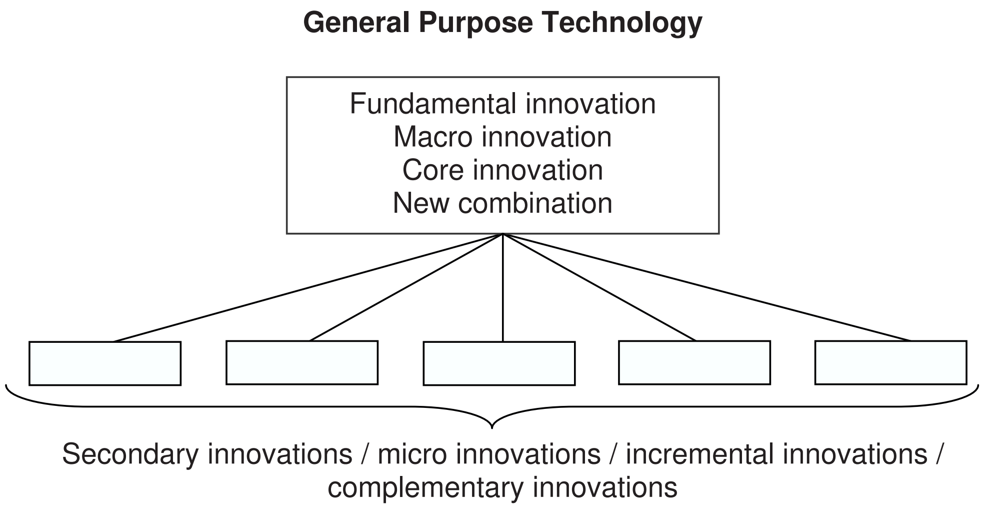

Figure 2.1: The Components of a GPT and its Different Names

While the process used by Lipsey et al. to reach this definition is perhaps more rigorous and methodical than that used by previous authors, the final characterisation of GPTs is the same. In essence, they are pervasive technologies with an inherent capacity for technological improvement, giving rise to many complementarities which bring about increasing returns to scale.

These drastic innovations due to a new GPT are considered to manifest as a new technology core, which in turn gives rise to a whole new technology that completely replaces the previous dominant technology while also opening up new opportunities for further expansion and development. The idea of such a drastic new innovation is referred to variously in the literature as a "new combination" (Schumpeter, 1934), a "macro-innovation" (Mokyr, 1990), a "fundamental innovation" (Aghion and Howitt, 1998a) and a "core innovation" (van Zon et al., 2003). Generally, the arrival of a new fundamental innovation is thought to be an uncertain event arising from basic research. It is commonly associated with high risks and costs, but also with the possibility of significant financial returns (Van Zon et al., 2003). These financial returns result from the monopoly status achieved by the inventor, by virtue of the fact that the new innovation is so different from what has come before that previous patents hardly provide any competition.

Once a new fundamental innovation comes into being, it gives rise to economic and technological complementarities, which result in incremental innovations related to the core technology. Profit-oriented entrepreneurs carry out applied research that refines existing knowledge in a predictable manner to produce non-revolutionary or incremental innovations, or improvements in the technology. These innovations stemming from the core technology are also referred to in the literature as "micro-innovations" (Moykr, 1990), "secondary innovations" (Aghion and Howitt, 1998a) and "incremental innovations" (Van Zon et al., 2003). They are typically highly path-dependant, following a specific technological trajectory and, as a result, are said to belong to the same technology family. For this reason, GPTs are also sometimes referred to more generically as "enabling technologies" (Lipsey and Bekar, 1994). In contrast to the invention of a new technology core, the development of incremental innovations is typically associated with greater levels of certainty with regards to the outcome of the R&D effort. The development of incremental innovations is consequently characterised by relatively low costs and risks.

It is important to note that the GPT itself consists of the entire package of core technology plus related incremental innovations as illustrated in Figure 2.1. Since the process of technological change is considered a path-dependent, evolutionary one occurring under conditions of uncertainty, even a definition as comprehensive as that provided by Bresnahan and Trajtenberg or Lipsey et al. allows for definitive identification of GPTs ex post only, once the extent of incremental innovations and improvements to which the technology gives rise are known. As far as predicting ex ante which technologies will become GPTs, this is only likely to be possible for those GPTs well enough along their development trajectories to be clearly developing into GPTs, or for some technologies early on their development trajectories that have a clear potential to become GPTs.

2.3 Overview of the Theoretical Models

The following analysis categorises existing models within a two-dimensional framework. The first dimension distinguishes between some of the main approaches in endogenous growth theory; specifically between models using an increasing varieties approach, mod-

	Level Effects	Growth Effects
Quality Ladder	**QLLE** Petsas (2003) Schiess, Wehrli (2008a)	**QLGE** Helpman, Trajtenberg (1998a, 1998b) Aghion, Howitt (1998a) Eriksson, Lindh (2000)
Increasing Variety	**IVLE**	**IVGE** Van Zon, Fortune, Kronenberg (2003) Van Zon, Kronenberg (2006)
Human Capital / Knowledge Driven	**KDLE** Jacobs, Nahuis (2002) Nahuis (2004) Carlaw, Lipsey (2006)	**KDGE**

Table 2.1: Classification of GPT Growth Models

els using a quality ladder approach and models with human capital / knowledge driven growth. In models using the first approach (increasing variety of products), technological progress is modelled by an increase in the number of products available either for production or consumption. In the first case, these products are the intermediate inputs for the production of final goods, as modelled for example by Romer (1990), while Grossman and Helpman (1991) provide an example for modelling in the consumption case. Quality ladder models such as Aghion and Howitt (1992) are characterised by a fixed number of products with individual variable quality attributes. Technological progress is modelled by an increase in the quality of a specific existing product. The third category called "human capital / knowledge driven growth" groups those models where growth stems from the accumulation of knowledge capital and/or from the allocation of skilled labour in the different sectors, such as the production sector, the applied R&D sector and the basic R&D sector. These models follow the tradition of the models of Uzawa (1965) and Lucas (1988) in which accumulated knowledge stocks and the allocation of human capital to the education and production sectors are crucial for economic growth.

The second dimension considers the growth pattern of GDP. In the first category "level effects", there is steady state growth that is sustained without the arrival of new GPTs. The sole long-run effect of a new GPT is to increase the steady state growth rate. The models in the "growth effects" category need the arrival of a new GPT in order to exhibit long-term positive growth rates.

Based on the categorisations just outlined, the models discussed in this paper can be grouped into six model classes which are named according to the abbreviation in the first line in each box in Figure 2.1. The abbreviation "QLLE", for example, stands for "quality ladder model with level effects".

A more detailed discussion of these categorised (growth) models would, however, be incomplete, without some prior attention being given to the seminal article of Bresnahan and Trajtenberg (1995). Since their model is a partial equilibrium model, in which the implications for aggregate growth are due to effects on the supply side only, it is not classified in one of the above growth model categories. Nevertheless, this paper should not be neglected since it was the first serious attempt to model the phenomenon of GPTs on a conceptual basis.

2.3.1 The Conceptual Model of GPTs

The central idea of the paper by Bresnahan and Trajtenberg (1995) is that there are a handful of GPTs, which, as they evolve and advance throughout the economy, bring about generalised productivity gains. This effect results from the existence of "innovational complementarity", by which the authors mean strategic complementarities between the owners of GPTs and the sectors applying GPTs. When an innovational complementarity exists "(t)he productivity of R&D in a downstream sector increases as a consequence of innovation in the GPT technology. These complementarities magnify the effects of innovation in the GPT, and help to propagate them throughout the economy" (Bresnahan and Trajtenberg, 1995, p. 84). GPTs are thus considered to play the role of "enabling technologies", i.e. they open up new opportunities rather than providing final solutions in themselves.

These innovational complementarities create both opportunities and problems for economic growth. On one hand, the development of GPT-using applications in many application sectors raises the return to innovations in the GPT sector for the specific GPT used in the application sectors, which in turn leads to further new opportunities for these applications. This results in increasing returns to scale that reinforce the process of technological progress. On the other hand, however, these complementary innovational activities are widely dispersed in the economy, making it difficult to co-ordinate, and provide appropriate innovation incentives to the GPT and application sectors. This results in too little innovation taking place too late in both sectors. Bresnahan and Trajtenberg suggest that this reflects a number of real world phenomena that surround innovation, such as uncertainty and asymmetric information in new knowledge creation, and time gaps and sequencing problems which make alignment of agents located far from each other along time and technology dimensions difficult.

The model of Bresnahan and Trajtenberg essentially describes the structure of technological change in the economy. It looks at the relationship between the sector in which a GPT is developed and the downstream application sectors that make use of this technology, as well as the relationships among the application sectors themselves. They suggest that technologies in general have a treelike structure, with a few prime movers at the top and all other technologies radiating from them. Their model describes a stylised set of related industries, with highly decentralised technical progress centred around the GPT. The GPT itself is therefore not represented by an actual good, but rather by a level of technology which is perceived by users of the technology in the application sector (who are actual or potential users of the GPT as an input) as quality attributes (represented by a scalar value in the model).

The single, perpetual GPT is owned by a monopolist, who optimally chooses how fast to improve its general productivity, while users of the GPT in the application sectors choose how fast to improve their own specific application of that GPT. The economic return to improving the technology of the GPT itself comes from selling an undifferentiated good embodying that technology in markets where the GPT firm exercises some monopoly power. The economic incentives for innovation in the GPT itself therefore depend on the prevailing market structure, the level of appropriability, and on the demand function in the application sectors.

Within each application sector, sellers purchase the GPT good, combine it with their own technology and sell their output to buyers. Each application sector also engages in its own innovative activity, leading to its own level of technology. A dual inducement mechanism ensures that an improvement in the level of technology of any application sector increases the incentives for the GPT to upgrade its own technology, just as the marginal value of enhancing the application sector's own level of technology rises with the quality of the GPT.

2.3.2 Quality Ladder Models - A Schumpeterian Approach

Although Joseph Schumpeter did not formally deal with the theory of GPTs and their impact on economic growth, his ideas of creative destruction and economic cycles form a basis for the notion of economic growth driven by R&D-based technological innovation. In his 1934 work, he argued that economic growth occurs through a process of "creative destruction", a term he used to describe the concept that new inventions render old technologies or products obsolete. Schumpeterian growth is sometimes also known as R&D-based growth, and can be used to refer generally to economic growth that is generated by the endogenous introduction of new goods or processes which leads to vertical innovations (as opposed to growth based on physical or human-capital accumulation).

Schumpeter's ideas gave rise to the quality-ladder framework for modelling economic growth, based on the notion that innovative entry by entrepreneurs was the force that sustained long term economic growth, even as it destroyed the value of established companies that enjoyed some degree of monopoly power. According to these ideas, successful innovation is a source of temporary market power, eroding the profits and positions of old firms, yet ultimately succumbing to the pressure of new inventions commercialised by competing entrants. This idea is central to many modern theories of endogenous long-run growth, e.g. Grossman and Helpman (1991, Chapter 4) and Aghion and Howitt (1992).

The link between GPTs and Schumpeter's ideas of innovation-driven economic growth is most apparent in his explanation of so-called "Schumpeterian cycles" in the economy. These cycles are represented by technological waves caused by the arrival of major technological breakthroughs that influence all sectors and involve discontinuities in the process of technological innovation - something akin to a GPT. According to Schumpeter, new cycles are the result of basic innovations, but before such an innovation arrives, the old system has to break down. This transformation accompanying radical innovation is the essence of Schumpeter's idea of creative destruction.

The basic Schumpeterian growth model provides the simplest macroeconomic model of a GPT. We reproduce here a quality-ladder version developed by Aghion and Howitt (1992) as a basis for comparison with what follows.[1] In this model, final output Y is produced using a flow of intermediate inputs $F(x)$, the quality of which is represented by a productivity parameter A, as follows:

$$Y = AF(x) \tag{2.1}$$

The intermediate input x is itself produced with labour according to a one-to-one linear production technology, so that x represents also the flow of manufacturing labour services. Growth results from vertical innovations by means of which each innovation provides a new method for producing final output throughout the economy (a new GPT) while at the same time also producing a new intermediate good by means of which the new method can be implemented. New innovations increase the current productivity factor A by a multiplicative factor $\gamma > 1$. Innovations are themselves the random outcome of research. The more labour services are allocated to research, the higher the probability of an arrival of a new innovation.

In the steady state, labour services do not move from manufacturing to research or in the other direction. They remain constant because the expected marginal outcome of labour in both sectors is equal. This arbitrage condition indicates that the optimal amount of labour employed in research rises when the expected discounted profit of research increases.[2]

The flow of final output produced between the tth and (t+1)th innovation is:

$$y_t = A_t F(L - n) \tag{2.2}$$

where x in equation (2.1) is replaced with $L - n$. L is the fixed amount of labour in the economy and n labour employed in research. It follows from this equation

[1] Cheng and Dinopoulos (1996), while not explicitly addressing GPTs, have also built a quality-ladder model, where cycles can arise due to a sequence of technological breakthroughs and subsequent improvements.

[2] The mathematical formulation of this arbitrage equation and the arbitrage equations of the other models presented in this paper is shown in the technical appendix 2.5.1 for the interested reader.

that growth in this model can be uneven according to the allocation of labour. If the expected marginal profitability of research increases, some of the labour employed in manufacturing switches to research until the respective marginal productivities of research and manufacturing return to equality. The labour that switches over is then missing as an input in the manufacturing sector which results in less growth compared to the previous period. If L and n are constant, as is the case in the steady state with constant exogenous variables, the amount of output over time is influenced only by the multiplicative factor γ. Because $A(t+1) = \gamma A(t) > A(t)$ the amount of output rises with every new technological invention.

However, although the time path of aggregate output as represented above can fluctuate, it does not involve a slump. Rather, every implemented innovation will provide a one-off burst to total output. An innovation arrives with probability λn, where $\lambda > 0$ is an exogenous research productivity factor. Therefore, the average growth rate is given by the following equation:

$$g = \lambda n \ln \gamma \tag{2.3}$$

The model described here is the base model for the quality ladder models discussed in Section 2.3.2 and Section 2.3.2. The key feature of these models is that the production functions exhibit horizontal substitutability between the components of a GPT; in other words the components developed for a specific GPT are substitutes for each other. The model class "quality ladder models with growth effects" will be explained in Section 3.1.1 in more detail. Section 3.1.2 discusses the model class "quality ladder models with level effects". This order has also been chosen because Helpman and Trajtenberg (1998a and 1998b) and Aghion and Howitt (1998a) were among the first who integrated Bresnahan and Trajtenberg's notion of GPTs into a growth model.

Quality Ladder Models with Growth Effects (QLGE)

Our more detailed comparison of the models in this and the next Sections shows a key difference between the Schumpeterian model of economic growth through creative destruction and the models of GPT-driven economic growth presented in this Section. In Schumpeter, newly developed technology is immediately represented by more or less spontaneous economic growth, while other models normally distinguish an initial phase of lowered output followed by a phase of net output growth once the GPT is fully implemented. Accounting for the existence of slumps requires another stage to be added in the innovation process.

In this Section we discuss quality ladder models that need the ongoing arrival of new GPTs in order to sustain a positive growth rate in the long term. In these models, the quality level of intermediate goods is linked to the GPT regime under which they were invented. Therefore a certain number of new intermediate goods have to be invented before the productivity gains due to the new GPT can be realised. Helpman and Trajtenberg (1998a and 1998b) were the first to build a QLGE model. They were followed by Aghion and Howitt (1998a) who introduced Helpman and Trajtenberg's modelling of GPTs using the quality ladder model explained before.

Helpman and Trajtenberg (1998a and 1998b)

The basic model presented in Helpman and Trajtenberg (1998a) endeavours to explore the economy wide dynamics that a GPT might generate by tracking the effects of a new GPT on macroeconomic aggregates. The main idea put forward by this paper is that a GPT can only be implemented in production through the development of intermediate goods that embody the GPT technology. The development of these intermediate goods is costly and some critical mass of them must be developed before final output firms will switch from using the old technology to using the new GPT technology. This model is extended in Helpman and Trajtenberg (1998b) in order to analyse the economy wide implications of the diffusion of new GPTs among multiple final goods sectors where each is characterised by a set of parameters that determines how fast that sector is likely to adopt the GPT. This allows them to capture additional horizontal complementarities.

The final good is produced with the aid of a GPT i and an assembly of components $x_i(j)$ that have to be compatible with the particular GPT in use. The productivity of the GPT depends on the number of supporting components which are specific to that GPT. This is modelled using a Dixit-Stiglitz function, which displays the property that as more components are added to a particular GPT, the total output increases. Thus final output is given by:

$$Y_i = A_i F(x_i) \tag{2.4}$$

Compared to the baseline model of Aghion and Howitt (1992) in Section 2.3.2, Helpman and Trajtenberg introduced the index i for GPT generation i in equation (2.4). This indicates that the production function is specific for one single GPT. Again A_i is a productivity parameter. In the general quality ladder approach A increases with every innovation. In this GPT approach, A_i only increases by $\gamma > 1$ if a new GPT arrives and it only increases the productivity of that specific GPT i and not of the existing GPTs.[3]

The manufacturing part $F(x_i)$ of the production function is given by:

$$F(x_i) = (\int_0^{n_i} x_i(j)^\alpha dj)^{1/\alpha} \tag{2.5}$$

where n_i is the number of components and $0 < \alpha < 1$. This imposes a finite limit on the development of the GPT, and implies vertical complementarity between the GPT and its components, and horizontal substitutability among the components themselves, which means that the different components of a GPT are all substitutes to each other. Only one GPT is in use at any point in time, and GPTs arrive exogenously at predetermined time intervals of equal length and are immediately recognised as such when they arrive.

The economy passes through a series of cycles, each consisting of two phases. The arrival of a new GPT marks the beginning of a new cycle. In the first phase of this cycle, resources shift from final production output (or from R&D to develop components for the old GPT if this is still taking place), into R&D to develop supporting components for the new GPT. This shift occurs because resources in the latter type of R&D become relatively more productive. A critical mass of these intermediate goods is required before the GPT can be used in production.

[3] We have changed the original notation in order to be able to compare directly the different modelling strategies. The original notation of equation (2.4) is:

$$Q_i = \lambda^i D_i$$

where λ^i stands for the productivity of GPT i and D_i corresponds to $F(x_i)$ in equation (2.5).

When enough components have been developed so that the productivity of the new GPT exceeds that of the old GPT, all workers are allocated to manufacturing, and final goods producers switch from using the old to using the new GPT. According to Helpman and Trajtenberg the diversion of labour out of component production (where it earns monopolistically competitive rents) and into R&D (where it earns no rents) leads to an "output slowdown" which they model as a fall in measured output. Their model thus gives rise to a two-phase growth cycle. In the first phase, output and productivity experience negative growth, the real wage stagnates and the share of profits in GDP declines. After enough complementary inputs have been developed for a particular GPT, the benefits of the new GPT begin to manifest themselves, leading to a second phase of the growth cycle characterised by rising output, real wages and profits. Over both cycles, the economy grows at rate of advancement of the GPT itself:

$$g = ln\gamma/\triangle \tag{2.6}$$

This expression is similar to the growth equation in the basic model from Aghion and Howitt (1992) presented above. $\triangle$ represents the predetermined time interval at which new GPTs arrive. For a Poisson process, $\triangle$ equals *1/probability of arrival of a new GPT*, which leads to the same expression as in equation (2.3).

Eriksson and Lindh (2000) extend the model of Helpman and Trajtenberg (1998a). They do not assume that all old components become worthless when a new GPT arrives. A fraction of the old components is also valuable for a new GPT. Furthermore, they endogenise the time of the arrival of a new GPT: The accumulation of social knowledge gained during the innovation process using the most recent GPT finally leads to the invention of a new GPT. Therefore, the more components are invented, the nearer the replacement of the old GPT with a new one.

Aghion and Howitt (1998a)

Looking more closely at the question of how the adoption of new technological paradigms gives rise to cyclical growth patterns, including long recession periods, Aghion and Howitt (1998a) derive a simple version of the Helpman and Trajtenberg model within the Schumpeterian endogenous growth framework of their 1992 paper by adding a second stage - that of component building in Helpman and Trajtenberg - to the innovation process. Furthermore, the arrival of GPTs is modelled by a Poisson process and treated as a by-product of the collective experience of using the old GPT.

This model again shows how the economy passes through a series of 2-phase cycles. The difference between the basic Schumpeterian model and the Helpman and Trajtenberg version of the model can be seen in the equation for output, which is equal to $A_{(t-1)}F(L-n)$ during phase one of the cycle (when the amount n of labour is devoted to researching new intermediate goods for the new GPT) and $A_tF(L)$ during phase 2 (when an intermediate good to implement the GPT has been found and all labour is allocated to manufacturing). The switch in labour out of manufacturing and into research therefore causes the output to fall each time a new GPT is discovered by an amount $A_{(t-1)}(F(L)-F(L-n))$. Like the Helpman and Trajtenberg model, this model therefore also gives rise to per capita GDP growth cycles resulting from the adoption of a new GPT.

The allocation of labour is again determined by the expected profit that can be realised due to successful research and must equal the input costs. In contrast to the standard quality ladder approach, profit optimising innovators have to take account of two separate phases with different expected profit values. In phase 2 they have to consider the possibility of the arrival of a new GPT and therefore of being driven to phase 1, while in phase 1, they have to take into account that they will sooner or later loose their monopoly position.

Aghion and Howitt also partially address the unsatisfactory feature in previous models of exogenous arrival times of the GPTs by allowing these to be governed by a simple Poisson process that is endogenously determined by the instantaneous flow of labour services. In addition, the productivity of new technologies is also endogenously determined in this model, and is, like the arrival times, constant in the stationary equilibrium. This is because the innovation rate is derived from the expected value of the Poisson distribution with a parameter determined by the equilibrium flow of labour services into research (Carlaw and Lipsey, 2006).

The equation for the average growth rate reflects the frequency of (GPT) innovations times the size of the jump as in the basic model of Aghion and Howitt (1992) in equation (2.3):

$$g = \ln \gamma \frac{\mu \lambda n}{\mu + \lambda n} \tag{2.7}$$

As can be seen in equation (2.7) the frequency shown in the fraction looks more complicated due to the change from one to two phases. The additional variable μ reflects the probability of the arrival of a new GPT, i.e. the probability of moving to phase 1, developing components for the new GPT.

Aghion and Howitt suggest two aspects of the Helpman and Trajtenberg theory that are questionable on empirical grounds, namely the size of the slump that may be caused and the timing of slowdowns. With regard to the latter issue, Aghion and Howitt point out that the Helpman and Trajtenberg model implies an immediate slump as soon as a new GPT arrives, while empirical evidence suggests that it may take several decades before major technological innovations have any impact on macroeconomic activity (David, 1990). Aghion and Howitt argue that measurement error, complementarities and social learning are all factors that are likely to contribute to this delayed reaction. Social learning, and in particular technology spillovers, whereby firms gradually learn from each other how to implement the new technology, are of major interest. At first nobody knows how to use a new technology, but as individual firms begin to experiment with the new technology, a point is finally reached where almost everyone can see enough firms using the new technology to make it worthwhile to experiment with it. More generally, there is a minimum amount of applied knowledge that must be accumulated after the GPT appears but before it can be used productively, and the accumulation of this knowledge is subject to a random process.

Aghion and Howitt also criticise Helpman and Trajtenberg's representation of falls in measured output, arguing that the reallocation of labour to the R&D sector is not enough to account for the size of observed slowdowns, as the Helpman and Trajtenberg model suggests. To the contrary, they propose that adjustment and coordination problems associated with the introduction of a new GPT, and its accompanying higher rates of innovation, might increase the rate of obsolescence and the rate of job turnover.

Since Aghion and Howitt's model presented above suffers from the same drawbacks, they develop a three-sector model in which resources are allocated between the production sector and an R&D sector that develops components that are complementary with each new technology as above, and a third sector that contains a set of resources that are confined to it. These special resources produce templates that are needed before each new GPT can be useful.

Social learning implies that each sector has to develop a specific intermediate good before anyone in the sector can profitably make components for the GPT. In other words, once a GPT has made its appearance, firms then set about developing sector-specific templates using fixed endowments of specialised R&D labour that has no other use. Success occurs with low probability to start with, increasing as more and more sectors acquire templates. When each sector has its own template, resources shift from producing final output, to R&D to create components for the GPT. Only when enough components have been created, does the economy finally switch to using the new GPT in production. This part of the model is explained above. An autonomous system of two ordinary differential equations is derived to represents firstly the flow of the sector from the state of not having a template for the new GPT to the state of having a template but not having discovered the a way to implement the GPT; and secondly the flow from the second state to the successful transition to the new GPT.

Numerical simulations of their second model show the desired time path of GDP. Growth is not affected directly after the arrival of a new GPT. After some time, however, there is a slump in output which is followed by growth which increases GDP to a level above the old level. The delay in the slump is solely caused by the introduction of social learning in the model.

Quality Ladder Models with Level Effects (QLLE)

Quality ladder models with level effects (QLLE) do not need ongoing arrivals of new GPTs in order to sustain a positive growth rate in the long term, since in this setting newly invented intermediate goods always have a higher quality level compared to the older intermediate goods. A new GPT increases the size of the quality jumps of intermediate goods, and, in doing so, also increases the steady state growth rate.

Petsas (2003)

Early models of Schumpeterian growth suffer from the drawback of exhibiting scale effects in terms of long run growth. This is a result of the assumption that the rate of technological change depends positively on the level of R&D resources devoted to innovation at each point in time. Population growth causes the size of the economy to expand exponentially over time, with a concomitant increase in R&D resources, and in the long-run rate of growth of per capita real output.

Petsas (2003) attempts to abstract from the scale effects that affect similar models, and also takes into account evidence of long diffusion lags associated with the adoption of a new GPT. He analyses the effects of a GPT on short-run and long-run economic growth in a contemporary model of Schumpeterian growth without scale effects, i.e. in the quality-ladder model of Dinopoulos and Segerstrom (1999). The diffusion of a new GPT across the industries is exogenous, being modelled by a differential equation which states that the diffusion is only dependent on time. The arrival of innovations is governed by a memoryless Poisson process, the intensity of which depends positively on R&D investments and negatively on the level of difficulty of conducting R&D. The productivity of R&D declines as the size of the population increases, reflecting the fact that it is harder to introduce new products and replace old ones in large markets. This last assumption is crucial for the result of non-existent scale effects due to population growth.

In addition to the QLGE models presented above, households maximise their discounted utility which is not a linear utility function. They can determine their consumption and saving shares by means of an intertemporal optimization. The households consume final goods that are produced at a certain quality level. The goods q of quality j enter into the utility function as follows:

$$\ln u(t) = \int_0^1 \ln[\sum_j \gamma(\theta)^j q(j,\theta,t)]d\theta \tag{2.8}$$

where $\gamma(\theta)$ is the size of the quality improvement which increases for the θ sectors that have adopted the new GPT. The effect of the arrival and adoption of a new GPT is to increase the size of the quality jumps. It follows from the solution of the optimal control problem that only the state-of-the-art product is demanded.

The final consumption goods are produced by a continuum of structurally identical industries, within each of which labour, the only factor of production, can be allocated between the manufacture of high-quality goods, and R&D services used to discover new products of higher quality. The firms in each industry are competing for the best quality product, since they only achieve a monopoly position if they produce the state-of-the-art product. A new GPT affects the R&D sector by means of an increase in the efficiency of R&D labour. Next to an increase in the quality jumps of final goods, this is the second effect of GPTs in this model.

The long-run growth rate in the model is shown to depend positively on the magnitude of quality innovations and the probability of the discovery of a higher quality product $I(\theta, t)$:

$$g = \frac{\dot{u(t)}}{u(t)} = I(\theta, t) \ln \gamma(\theta) \tag{2.9}$$

The model exhibits transitional growth cycles of per capita GDP. In contrast to other GPT-based models that generate similar cyclical results, but where the results are not robust to the introduction of positive population growth, in Petsas' model the long-run growth rate does not reduce to zero in the absence of the arrival of a new GPT, as can be seen in equation (2.9), where growth is dependent on the quality jumps of the final good. This is the main difference between quality-ladder models with growth effects and quality-ladder models with GPT showing level effects. In QLGE models, goods of one GPT generation are all using the same technology, i.e. are on the same quality-ladder, and the quality jumps appear in the form of a new GPT. In the approach presented in this Section, every new product is on a higher quality level, which directly impacts economic growth. A new GPT merely increases this growth rate.

Schiess and Wehrli (2008a)

Schiess and Wehrli (2008a) build a quality-ladder model in which a new GPT increases the efficiency of research. They use a different model framework from Petsas (2003), basing their model instead on the Schumpeterian growth model in chapter 7 of Barro and Sala-i-Martin (2004). In contrast to all other models discussed in this survey, they focus on the events that occur before the arrival of a new GPT. As such, they do not present their model as a rival to existing theories, but rather as complementary to those, in that it illustrates an additional channel through which a GPT affects the economy. One of the critical assumptions of this model is the ability of firms to anticipate the arrival of a new GPT. This assumption is defended by empirical evidence showing that the arrival of a new GPT is most often not entirely unpredictable - the steam engine, for example, was first used in the UK before it made its way to the United States.

The production of the final good uses labour and intermediate goods as inputs. The intermediate goods have quality attributes, while the final goods do not; this differs from Petsas (2003) where the final goods contain the quality attribute. The main mechanism of the model lies in the R&D sector where intermediate good producers compete for the next quality level. In contrast to Petsas, the quality jumps do not increase because of a new GPT; new GPTs result only in the second of Petsas' effects, namely that of increasing the research efficiency. Agents have to decide whether they want to consume, produce intermediate goods or invest in R&D through the stock market. The model is solved by using a free-entry condition that is well-known from industrial organisation theory. This condition states that firms invest in R&D as long as the expected return is greater than zero.

Once again, the steady state growth rate is dependent on the probability of research success and on the size of the quality jump as in (2.9). The effect of a GPT is that this growth rate rises due to the improved efficiency in R&D.

The model is also solved for transitional dynamics. Using numerical simulations the authors show that the anticipation of a new GPT can induce cyclical behaviour between the old and the new steady state: As the arrival of a new GPT becomes increasingly imminent, the growth rate starts to oscillate around the old steady state level which leads to an increase in R&D and growth exceeding the old steady state levels. Directly before the arrival of the new GPT, there is a large slump in R&D activities and therefore also in growth.

2.3.3 Increasing Variety Models with Growth Effects (IVGE)

In the increasing variety models the intermediate goods are accumulated into the capital stock. Growth is then generated by increasing the variety of the capital stock, i.e.

by increasing the number of intermediate goods. The quality of these intermediate goods is typically constant in standard endogenous growth theory. The IVGE models presented below introduce a so-called "volume" of each GPT which assigns a quality dimension to each innovation. This allows to distinguish between core and peripheral innovations and to introduce asymmetries between them. Because of the asymmetries the impact of each GPT decreases the longer its regime lasts and growth asymptotically approaches zero.

Van Zon, Fortune and Kronenberg (2003) and Van Zon and Kronenberg (2006)

Van Zon, Fortune and Kronenberg (2003) and Van Zon and Kronenberg (2006) are the only GPT models using an increasing variety approach. Both belong to the growth effects category of models. As we shall demonstrate later, there are no models using the increasing variety approach with level effects which follows straightforward from the basic model assumptions.

The first of these two related papers presents a simple endogenous growth model that allows for the occurrence of innovations that can develop into GPTs, whereas Van Zon and Kronenberg (2006) apply this stochastic GPT growth model to study the effects of different energy policy schemes.

Modelling final output production, they follow Romer (1990) in using a multi-levelled Ethier function, but do not include human capital:

$$Y = L_y^{1-\alpha} K_e^{\alpha} \tag{2.10}$$

It is important to understand in detail the structure of the production of capital. The effective capital K_e consists of N different GPTs which are indexed by j:

$$K_e = [\sum_{j=1}^{N} z_j^{\alpha}]^{1/\alpha} \tag{2.11}$$

Where z_j is the volume of GPT j. Equation (2.11) together with equation (2.10) would lead to the same representation of the impact of capital on final good production as the seminal endogenous growth model of Romer (1990). Every new type of capital has the same effect and leads to an increase in Y since the production function is additively separable.

Van Zon et al. (2003) interpret each new type of capital j as a new GPT. Growth is therefore caused firstly by symmetrical horizontal innovation that increases the number of GPTs in existence. Growth is then further influenced by a breakdown of this symmetry through what the authors term "quasi-vertical innovation" which occurs within each GPT. This is made feasible by representing each GPT j as consisting of a single core ($x_{i,j}$'s with $i = 0$) together with a number of peripherals (all other $x_{i,j}$'s with $i \neq 0$):

$$z_j = (\sum_{i=0}^{N_j} c_{i,j} x_{i,j}^{\beta_j})^{1/\beta_j} \tag{2.12}$$

where $c_{i,j}$ is decreasing in i for a given GPT j and the starting value $c_{0,j}$ is random. Equation (2.12) is similar to equation (2.5) in the QLGE case and implies once more that the peripherals are substitutes for each other, i.e. horizontal substitutability is present. Increasing variety models are always based on the idea that technological progress occurs as a result of new products which do not render the old products obsolete, which is also the case in this model - the cores and peripherals coexist with each one having its own market niche where it earns monopoly profits.

Both the core and peripherals make up the GPT itself, which is recognised as an ex post construct only. Basic R&D gives rise to the core of a potential new GPT. Applied R&D on this particular core then gives rise to peripheral (incremental) innovations, which increase the productivity of the core technology and allow for expansion of this core into a potentially successful GPT. It is the extent of use of the technology core and its scope for expansion that determine whether a potential GPT becomes an actual GPT. The characteristics of a particular core that determine factors such as its intrinsic profitability, its scope for expansion, and the R&D opportunities and efficiency of the corresponding applied R&D process are randomly distributed. The probabilistic nature of the innovation process is further depicted by the use of a Poisson process to describe the arrival of innovations.

The contribution of each new peripheral to a GPT is assumed to be decreasing in productivity terms with the number of components of a GPT so that additional components invented through applied R&D grow less and less promising from a profitability perspective over time. As the returns to variety within a GPT decrease over time the relative attractiveness of finding the core of the next GPT rather than continuing the expansion of the existing GPT increases. Applied R&D becomes less attractive relative to basic R&D and a reallocation of R&D effort towards basic R&D occurs. This in turn generates a higher probability that a new core will be found. Thus the expansion of a GPT will eventually lose momentum, while the incentive to search for a new core increases. This gives rise to cyclical growth patterns, implied by inherent technological limits rather than by the reallocations of resources from the final output sector and the R&D sector.

The decreasing contribution of each new peripheral is represented by $c_{i,j}$ in equation (2.12). This affects growth as follows: the more peripherals are invented, the lower is the value of $c_{i,j}$ and growth asymptotically approaches zero. Since $c_{i,j}$ has to be decreasing in j in order to model the asymmetries that are needed to represent the different components of GPTs, no increasing variety models with level effects exist.

Van Zon et al. also suggest that while the alternating phases of fast and slow growth to which the pattern of technology-core-discovery followed by peripheral-invention gives rise create long run growth with a Schumpeterian flavour, these "long waves" are not mechanistic in character. A large number of GPTs can coexist in the model, and the innovation of GPTs or peripherals is never so drastic that it drives out older GPTs completely. Innovations can, however be asymptotically drastic, in that the eventual demise of a GPT is certain in the long run because the possibilities for extension are limited; equally certain is that a new GPT will eventually arise.

The important aspect of the way in which these authors model the growth cycles is that these are partly driven by the arrival of new GPTs, but are also internally driven by the continuing development of GPTs and development races between active GPTs in the absence of the arrival of new ones. The model thus explains the cyclical pattern in output growth without having to resort to contractions of final output itself in response to favourable R&D prospects, since R&D workers need only switch between different forms of R&D, and do not need to switch between R&D and final output production. The main finding of the model is therefore to show that cyclical growth need not depend on the reallocation of homogenous labour between R&D and final output production, as is typical in the endogenous growth models of Romer (1990) and Aghion and Howitt (1992, 1998) and all the models discussed in this survey. According to Van Zon et al. (2003), this result better reflects the reality of the suitability of different types of labour to performing different tasks.

2.3.4 Knowledge-Driven Models with Level Effects (KDLE)

In knowledge driven GPT models growth is caused by the accumulation of knowledge capital and/or from the allocation of skilled labour in different sectors. Some models, such as Jacobs and Nahuis (2002), have one endogenous knowledge stock which can be influenced by allocating skilled labour to its production. Other models such as Nahuis (2004) and Carlaw and Lipsey (2006) have two endogenous knowledge stocks. In the case of Nahuis (2004) there is a firm-specific stock of productive knowledge and a stock of external knowledge capital. Carlaw and Lipsey (2006), who propose an alternative model, include a knowledge stock that increases the marginal productivity of inputs in final goods production and a knowledge stock produced by the GPT sector that increases the marginal productivity of applied R&D. All these models show level effects because the existing knowledge stocks are not obsolete after the arrival of a new GPT.

Jacobs and Nahuis (2002)

Jacobs and Nahuis (2002) build a model that captures "three key empirical facts during the 1980s and 1990s: an increasing skill premium, a fall in the real wages of unskilled workers and a slowing down of economic growth after the introduction of a GPT" (Jacobs and Nahuis, 2002, p. 243). Their model follows the tradition of the Uzawa-Lucas model as presented for example in Barro and Sala-i-Martin (2004). Economic growth is based on growing knowledge stocks and on the allocation decision of skilled workers.

The economy consists of a continuum of final goods producers j with a fixed mass 1. Each of them produces a final good X_j:

$$X_j = AF_j^{1-\alpha}K_j^{\alpha}((u_jH_j)^{\beta}L_j^{1-\beta})^{1-\alpha} \tag{2.13}$$

Where A is an exogenous technology parameter, K_j capital, H_j skilled labour, u_j is the fraction of skilled labour that works in the final goods sector and L_j unskilled labour. This equation is an extension of the simpler production function (2.10) in the IVGE case. F_j is firm-specific knowledge capital that is positively dependent on the amount of skilled labour employed in firm-specific knowledge production and on the productivity of research. The productivity of research is dependent on the GPT generation and is increasing in it.

Skilled and unskilled labour are fixed and not mobile between these two categories. The important decision governing the dynamics of the economy is where firms should employ skilled labour, i.e. determining the optimal value of u. The marginal productivity must be the same for both uses of skilled labour. A new GPT arriving exogenously increases the productivity of research B and results in skilled labour moving away from the production of final output and into knowledge production. This immediately leads to an economic slowdown before the economy reaches a new steady state with higher growth levels. The mechanics behind this are similar to those Schiess and Wehrli (2008a) show in their model before the arrival of a GPT. Again the higher productivity of research due to a new GPT leads to a higher steady state growth level since the growth-driving knowledge capital stock grows faster. Before this new steady state is reached, however, the economy shows transitional dynamics that hinder economic growth for a short time.[4]

Nahuis (2004)

Nahuis (2004) presents a model with two knowledge stocks and defines two research activities, innovation and learning. Innovation improves the productivity of the final good production through a so-called firm-specific stock of productive knowledge. Coming back to the simple framework of equation (2.1), this would correspond to the productivity parameter A. The firm-specific stock of productive knowledge can be increased by the allocation of skilled labour and by an increase in external knowledge capital which is accumulated through learning from competitors. The only input in

[4]The authors find explicit solutions for the steady states. The transitional dynamics are shown in phase diagrams and are caused by the adjustment of the predetermined technology-capital-stock ratio (F/K) to the jump variable u.

final good production $F(x)$ is unskilled labour.

Again, labour is not mobile between skilled and unskilled labour. However, skilled labour is also needed in the accumulation for the second knowledge stock, i.e. the stock of external knowledge capital. As a result, the firms have to decide over the allocation of skilled labour when maximising their profits. The second input in the accumulation of external knowledge capital is the learning potential of the specific firm, which depends on the available knowledge pool in the economy and on the size of the firm's own external knowledge stock. The lower the external knowledge stock is or the higher the available knowledge pool, the easier it is for a firm to learn. A new GPT which arrives exogenously leads to a higher knowledge pool, and therefore makes learning more productive.

The model is solved by a Hamiltonian maximisation for the producer which leads to the no-arbitrage conditions for investment in innovation and learning, each compared to the return on investing the same amount in the financial market. With a constant GPT technology, the economy is in a steady state where the economy and all the knowledge stocks grow at the same rate. The transitional dynamics after the arrival of a new GPT are numerically simulated and show a slowdown in growth and rising wages of skilled labour. This is caused by the reallocation of skilled labour from innovation to learning. Nahuis believes that this kind of reallocation as a reason for the economic slowdown is more consistent with empirical observations than the reallocation away from the production of final output as in Jacobs and Nahuis (2002).

Carlaw and Lipsey (2006)

Most of the models presented up to now (i.e. Aghion and Howitt (1998a), Helpman and Trajtenberg (1998a, 1998b), Petsas (2003), Schiess and Wehrli (2008a), Jacobs and Nahuis (2002), Nahuis (2004)) are concerned with the economy's behaviour over the lifetime of only one GPT or with the transition from an old GPT to a new one. Agents are assumed to be able to foresee the entire course of evolution of a GPT the moment it arrives. This allows for maximisation over the lifetime of the new technology and gives rise to a stationary equilibrium derived from the infinite horizon utility maximisation. While these are standard assumptions for conventional growth models, Carlaw and

Lipsey take issue with them, as we shall see in this Section.

In their 2006 paper, Carlaw and Lipsey argue that the GPT literature has not progressed significantly since the first generation GPT models discussed above, primarily because of the technical complexity of these early models, which makes them difficult to adjust in a way that increases their empirical relevance. According to the authors, this technical complexity arises from the assumptions of dynamically stationary equilibrium (all previous models produce either steady state or balanced growth) and perfect foresight by agents (i.e. agents maximize under conditions of certainty or risk) applied in the previous models. In order to address their criticism of the assumption of perfect foresight made explicitly or implicitly by other models, Lipsey and Carlaw propose a "second generation" model and attempt to introduce genuine uncertainty in their model in three ways. Firstly, the amount of new knowledge generated by resources devoted to basic research is uncertain; secondly, the time between arrivals of successive GPTs is uncertain; and finally, the effect of each GPT on productivity in the R&D sector is uncertain.

Agents maximise on expectations about the current marginal productivities of resources allocated to each of the economy's three sectors: consumption output, applied research (to develop applications of the GPTs to specific purposes) and basic research (looking for the next GPT), i.e. the resources are freely mobile between the different sectors and there is no distinction between skilled and unskilled labour. The agents cannot predict how these marginal productivities of resources in each sector will change over the lifetime of each GPT. Instead, they maximise in each period in a recursive fashion only considering the marginal productivities of the current period. This gives rise to a transitional competitive equilibrium that changes in each period.

The productivity of applied R&D is influenced by a fundamental knowledge stock produced in the GPT sector. Modelling the fundamental knowledge stock, Carlaw and Lipsey also assume that basic R&D and a new GPT increase the productivity of applied R&D and, additionally, take explicit account of technological spillovers from the knowledge in final good production.

The key behavioural characteristics of the Carlaw-Lipsey model can be described as follows: The productivity of the randomly-arriving GPTs is determined by the amount of basic research that has been endogenously generated since the previous GPT, plus a random component affecting the productivity of basic research. Growth is driven by a succession of endogenously generated GPTs with different productivity characteristics. This final assumption leads to the model's growth rates varying over the lifetime of one GPT and on average over the lifetimes of successive GPTs.

Carlaw and Lipsey cannot solve for a stationary equilibrium and transitional dynamics. Instead, they numerically simulate a maximisation problem in an iterative recursive fashion. They suggest that the resulting model is technically simpler than previous models, while reflecting more closely the observed empirical behaviour of GPTs. They do not, however, find decentralized solutions but rather arrive at a social planner solution since the maximisation problem involves the maximization of consumption with constraints from the basic and the applied research sector that show no imperfections.

In terms of developing a model that is comparable with empirically observed GPT behaviour, Carlaw and Lipsey suggest certain modifications to their own model. Firstly, they propose the introduction of a lag to ensure that GPTs do not have an instantaneous effect on raising the productivity of applied research. Secondly, they suggest that the model should allow for more than one GPT to exist in each time period. Thirdly, uncertainty should be introduced with respect to applied R&D. And finally, they argue for the introduction of a lag so that what is learned in applied R&D only affects the production function of consumption goods in a later period. This latter modification would allow for slowdowns after the introduction of some GPTs.

Lipsey et al. (1998) highlight the technical challenges of modelling the GPT phenomenon in a consistent manner and emphasise the limited usefulness of any theory of GPTs in predicting the impact of actual individual technologies on the economy as they arise. The authors still maintain, however, that empirically relevant theories can be developed, even if such theories do not reveal laws of motion that result in a unique stable equilibrium for a particular system, or in processes that are likely to be repeated with further simulations.

2.4 Discussion and Conclusions

A key finding of endogenous growth theory is that innovation is the main driver of steady state growth. This literature survey has covered growth models that look at the impact of a General Purpose Technology (GPT) on the economy and categorised them into a two dimensional framework. On the first dimension the proposed categories classify the models according to the various approaches in endogenous growth theory of quality ladder models (QL), increasing variety models (IV) and models with human capital/knowledge driven growth (KD). On the second dimension the different endogenous growth model approaches are distinguished according to the growth pattern of GDP, i.e. they are grouped into those models "with level effects" (LE) and those "with growth effects" (GE). The GE models need the arrival of a new GPT in order to sustain a positive long-term growth rate. In the LE case a new GPT only increases the long-term steady state growth rate which would in any case be positive, i.e. also without the arrival of a new GPT. In what follows we attempt to identify unifying points and open questions.

In the GPT models with growth effects (GE) presented in this article, long-term growth can only be sustained by the continuing arrival of new GPTs. In the QLGE models, e.g. the model of Aghion and Howitt (1998a), there would be no long-term growth without GPTs. The IVGE models also need new GPTs to sustain long-term growth because the marginal productivity of each new peripheral in final good production is decreasing in its number. Without a new GPT, which has a direct impact on the productivity in final good production and which leads to a higher marginal productivity of its peripherals compared to the peripherals of the old GPTs, growth would asymptotically approach zero. Typically, these type of models have horizontal substitutability, i.e. the different components of a GPT or the different intermediate goods belonging to one GPT generation are substitutes for each other. This horizontal substitutability does not replace the innovational complementarity that is characteristic for all GPT models, if complementarity is understood as it is described in the definition of a GPT in Bresnahan and Trajtenberg (1995) or Lipsey et al. (2005).

In models with level effects (LE) the economy shows steady-state growth without the arrival of a new GPT. The effect of a new GPT in these models is to increase the long-term steady state growth rate. For example, in the case of QLLE the economy shows a constant long-term growth rate without a new GPT since newly invented intermediate goods always have a higher quality level compared to older intermediate goods. This is because a new GPT only increases the quality jumps from one intermediate good to another. Contrastingly, in QLGE a new GPT increases the productivity of the sum of the components that are developed under that regime and this productivity parameter increases only after the arrival of a new GPT.

The increase in the growth rate due to the arrival of a new GPT is a drawback of the LE model design, because it implies that the economy grows exponentially. However, because these studies are trying to explain the transition to a new GPT and not long-term growth, this drawback does not negate the usefulness of these models to the theory.

Empirical studies find a delay in the economic impact of a new GPT. This delay is found in most of the models which concentrate on the time after the arrival of a new GPT. In all of the models that look at the phase after the arrival of a new GPT only in the IVGE case does the arrival of a new GPT lead to an immediate increase in GDP due to the so-called "love of variety effect". This effect stems from the representation of GPTs in an Ethier production function. Whenever the amount of capital is increased, the marginal productivity of labour in final good production increases immediately. But the same holds true for the arrival of new peripherals, so that they also cause economic growth. The marginal influence of each new peripheral decreases the larger is the number of peripherals belonging to a GPT. As a result, growth slows down during the lifetime of a GPT and the incentives are set to reallocate R&D in order to find a new GPT and once again promote economic growth.

There are different ways in which this delay is modelled. In the QLGE case innovators first have to build up a certain number of complementary components for the new GPT after its arrival. Only after a critical mass of such components has been developed, can the new GPT be applied in the final goods sector. Aghion and Howitt (1998a) even add a third stage to their model where the various sectors of the economy have to discover "templates" which are a prerequisite for building the critical number of components using the new GPT. In the QLLE case this delay is caused by the downward jump of consumption because of the higher productivity of research with the new GPT. This makes R&D more attractive and resources are withdrawn from final good production in order to invent new products. The same holds for the KDLE models which do not emphasize learning, i.e. for the models of Jacobs and Nahuis (2002) and Carlaw and Lipsey (2006).

In some models the delay is caused by learning. Greenwood and Yorukoglu (1997) found in general that the learning processes required to acquire the specific skills to put a new technology to productive use is important. In Nahuis' 2004 model the producers first have to learn about the opportunities offered by the new GPT and then have to experiment with it in order to discover ways in which the technology can be applied. The author models this by means of a knowledge gap that becomes larger after the arrival of a new GPT, which itself leads to a higher productivity of learning and therefore to a reallocation of workers to learning that is not directly productive.

The question of how one should model the mobility of labour is still open. Van Zon et al (2003) argue that it is more realistic to assume that cyclical growth is caused by the allocation decision of skilled R&D labour between different types of R&D, and that unskilled labour in final goods production cannot move to the R&D sector. Their paper directly criticises Aghion and Howitt (1992 and 1998) and Helpman and Trajtenberg (1998), i.e. the QLGE models in which labour is totally mobile. Similarly, Carlaw and Lipsey (2006) and Petsas (2003) also assume in their respective papers that the inputs are freely mobile between the sectors.

Jacobs and Nahuis (2002) and Nahuis (2004) take a position halfway between these two extreme positions since they assume that a part of the work force is unskilled and has to be employed in the final goods sector. The other part of the workforce consists of skilled labour and can be employed in research and in final goods production. In our opinion, the assumption of free mobility of skilled labour together with no mobility of unskilled labour is the most realistic, since the labour used in R&D is mostly highly specialised and requires a lot of human capital. An unskilled worker cannot acquire these skills in a short time period, as is for example shown by Theodossiou (1995) who finds that experienced or career workers are not interchangeable with other workers.

In most of the GPT models the arrival and the size of a new GPT is exogenous.

Bresnahan and Trajtenberg's model, for example, is concerned with the economy's behaviour over the lifetime of one GPT, and focuses on the relationships between an existing GPT and downstream sectors using that GPT, as well as on the relationships among these application sectors. Their partial equilibrium analysis shows that the evolution of a GPT gives rise to increasing returns-to-scale and that this plays an important role in determining the rate of technical advance in the cluster of associated sectors. The study does not, however, concern itself with the question of how and when GPTs themselves arise in the economy, nor does it explicitly look at the impact of GPTs on economic growth. Helpman and Trajtenberg's model of diffusion of a GPT is likely to result in a large number of alternative equilibriums since many different sequences of adoption by the various sectors are possible. Even more equilibrium trajectories would become feasible if expectations other than perfect foresight were allowed in the model. Helpman and Trajtenberg suggest that this is not necessarily a deficiency of the model itself, but rather a reflection of the complexity and inherent indeterminacy involved in the whole process of GPTs in the economy. Helpman and Trajtenberg acknowledge, however, that their basic model is limited by the fact that it ignores the endogenous nature of advances in the GPT itself and the associated feedback from user sectors to the GPT, which is considered to be an important part of the mechanism by means of which GPTs play their role of "prime movers" in the economy. The only model where the arrival of a new GPT is endogenised is the IVGE type where agents also take account of the effect a new GPT has in their maximisation problem and decide explicitly if they want to invest more in developing a new GPT generation.

We conclude that there are two possible approaches to endogenising the decision about the development of a GPT. The first approach is that of Van Zon et al. (2003) where it is a conscious decision following from the maximizing behaviour of the agents. In the second approach, GPTs are a by-product of research undertaken in order to develop new intermediates and/or final products. In the case of Schiess and Wehrli (2008a) it could for example be dependent on the aggregate quality index, i.e. the more applied R&D is performed, the higher is the chance of the arrival of a new GPT.

2.5 Appendix

2.5.1 Arbitrage Equations

In this appendix the arbitrage equations which govern the dynamics in the models are listed and explained. The details of these equations are of interest for those who wish to understand the technicalities behind the way in which resources are allocated among different sectors or shifted between different resource types. For comparison purpose, we first show the arbitrage equation of the standard quality ladder model used for example by Aghion and Howitt (1992).

Quality ladder models - A Schumpeterian approach

Innovations are assumed to arrive discretely with Poisson rate λn, where $\lambda > 0$ is an exogenous parameter and n is the current flow of labour services employed in research. The arbitrage equation that determines the allocation of labour between research and manufacturing is given by the following equation:

$$\omega = \lambda \frac{\gamma \tilde{\pi}(\omega)}{r + \lambda n} \tag{2.14}$$

where ω is the productivity adjusted wage rate w/A that a worker earns working in the manufacturing sector and the RHS of the equation is the expected reward from investing one unit flow of labour into research. In detail, $\tilde{\pi}$ indicates the flow of profits, γ the size of the productivity increase in final good production and r the interest rate.

In the steady state the allocation of labour between research and manufacturing remains constant over time. This allocation only changes when one of the exogenous factors on the RHS of equation (2.14) changes or during transition phases when, for example, people might anticipate that n will be higher in the future.

QLGE

In the QLGE context, the arbitrage equation states that the wage paid for research in phase 1 - when research has to be done in order to find appropriate intermediate goods for the new GPT (LHS of equation (2.15)) - must be equal to the expected intermediate monopolist's profit over the two phases due to the research undertaken in phase 1 (RHS of equation (2.15)).

$$\omega_1 = \frac{\lambda\gamma\left[\tilde{\pi}(\omega_2) + \mu\tilde{\pi}(\omega_1)/(r+\lambda n)\right]}{r+\mu} \tag{2.15}$$

where μ is the Poisson arrival rate of a new GPT, subindexes show the phase in which the economy is, r is the interest rate, λn it the probability of a success in innovation in intermediate goods and $\pi(\omega)$ is the flow of profits in the respective period. In contrast to equation (2.14), equation (2.15) considers that there are two phases with different expected values of profits. This equation is basically a nested equation that first considers the possibility of being driven to stage 1 where a new GPT is active and then considers the possibility of losing the monopoly because the economy has returned to state 2 where an intermediates producer using the new GPT has a monopoly.

QLLE

The arbitrage equation that guides the allocation of the resources looks somewhat different in the QLLE case from that used in the QLGE cases. In the QLLE case, households can save their income by buying stocks. As a result, their savings decision is made over the securities of a firm engaged in R&D and the level of R&D investments of a challenger.

$$\frac{V(\dot{\theta},t)}{V(\theta,t)}[1 - I(\theta,t)dt]dt + \frac{\pi(\theta,t)}{V(\theta,t)}dt - \frac{[V(\theta,t)-0]}{V(\theta,t)}I(\theta,t)dt = rdt \tag{2.16}$$

where $I(\theta,t)$ is the probability of a successful innovation of a higher quality good. On the RHS is the expected return of an alternative risk-less investment with a rate of return of r. The first term on the LHS considers the possible change in value $V(\theta,t)$ if there is no innovation, while the second term shows the dividend, i.e. the profit π of the firm, and the third term indicates the value of the firm in the event of successful innovation.

This leads to the following typical expression for the expected discounted profits of a successful monopolist:

$$V(\theta, t) = \frac{\pi(\theta, t)}{r(t) + I(\theta, t) - \frac{\dot{V(\theta,t)}}{V(\theta,t)}} \tag{2.17}$$

where r reflects the discounting of future profit, I the fact that a monopolist loses his position with a certain probability, and the last term in the denominator reflects the possible change in the value of the firm over time.

IVGE

The dynamics of the economy in the IVGE case are determined by a key arbitrage equation. The investment opportunities are provided by basic R&D or applied R&D activities where the former activity aims at inventing a new core while the latter focuses on inventing a new peripheral. The free mobility of R&D labour means that the marginal benefits of the different R&D activities must be equal in the optimum. This leads to the following optimum ratio of applied R&D R_j to basic R&D R_0:

$$R_j/R_0 = \left(\frac{PV\pi_{A_j+1,j}\mu_j\delta_j}{PV\pi_{0,A+1}\mu_0\delta_0}\right)^{1/(1-\beta)} \tag{2.18}$$

Where PV stands for the present values, μ is the arrival rate per unit of research input, δ is an exogenous productivity parameter and β follows from the CES function in equation (2.12). An increase in the expected profits leads to an increase in the corresponding R&D input.

Chapter 3

The Calm Before the Storm? - Anticipating the Arrival of General Purpose Technologies*

This paper presents a Schumpeterian quality-ladder model incorporating the impact of new General Purpose Technologies (GPTs). GPTs are breakthrough technologies with a wide range of applications, opening up new innovational complementarities. In contrast to most existing models which focus on the time *after* the arrival of a new GPT, the model developed in this paper focuses on the events *before* the arrival if R&D firms know the point of time and the technological impact of this drastic innovation. In this framework we can show that the economy goes through three main phases: First, the economy is in its old steady state. Second, there are transitional dynamics. These transitional dynamics are characterised by oscillating cycles: In the time immediately before the arrival of a new GPT there is an increase in R&D activities and growth going even beyond the old steady state levels. This is followed by a large slump in R&D activities using the old GPT. In a third phase, as the new GPT becomes active, the economy is in a new steady state with higher growth rates.

*This chapter represents joint work together with Daniel Schiess (ETH Zurich).

3.1 Introduction

Ever since the pioneering paper of Romer (1990), technological change as the driving force of economic growth has been in the focus of economic growth theory. Early endogenous growth models assumed that innovation follows a smooth path in the course of time. This implies that economic growth is driven by a constant stream of small innovations. However, a look back in economic history shows that, in any given era, economic development was driven by a small number of breakthrough technologies: The industrial revolution was facilitated by major improvements on the design of steam engines by James Watt. Later, electricity not only shaped the way how and where goods are produced, but also deeply altered the lifestyle of consumers. Finally, today's economic landscape has been transformed by the introduction of the computer and modern communication technologies such as the internet and e-mail.

Bresnahan and Trajtenberg (1995) pioneered the concept of "General Purpose Technologies" (GPTs), thus formalizing the idea that economic growth is driven by such breakthrough technologies. Lipsey, Bekar and Carlaw (1998) present the following definition: "A GPT is a technology that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many Hicksian and technological complementarities."[1]

We contribute to the GPT literature by analyzing the effect of a new GPT on R&D-activity and growth in a quality-ladder model based on the model on Schumpeterian growth by Barro and Sala-i-Martin (2004). Other examples where GPTs are considered within a quality-ladder framework are as follows: Petsas (2003) incorporates the idea of GPTs in the quality-ladder model of Dinopoulos and Segerstrom (1999) in order to model the diffusion of GPTs across industries. In an earlier paper, Cheng and Dinopoulos (1996), while not explicitly addressing GPTs, have built a quality-ladder model, where cycles arise due to a sequence of technological breakthroughs and subsequent incremental improvements. Smulders, Bretschger and Egli (2005) present how successive GPT generations within the quality-ladder framework of Grossman

[1] Both, the volume edited by Helpman (1998), especially the mentioned article by Lipsey, Carlaw and Bekar (1998), and the book by Lipsey, Carlaw and Bekar (2005) offer more background on the general concept of GPTs.

and Helpman (1991, chapter 4) can explain the long-term evolution of environmental quality.

In addition to incorporating the idea of GPTs in such a framework, we demonstrate that the mere anticipation of a new GPT induces cyclical behaviour in the economy: Initially, the economy using the old GPT is in a steady state with constant growth rates in output and R&D expenditures. As the arrival of a new GPT draws nearer these growth rates start to oscillate around the steady state levels. This is followed by an increase in R&D activities and growth going beyond the old steady state levels. Immediately before the arrival of the new GPT, there is a large slump in R&D activities resulting in lower growth.

3.1.1 Anticipating the Arrival of General Purpose Technologies

Both the main assumption of our model, the ability of firms to anticipate the arrival of new GPTs, and our result that this can influence R&D activities, can be observed in numerous instances in economic history. Again, the steam engine serves as a prime example:

- As described in Rosenberg and Trajtenberg (2004), as well as in Atack (1979), the United States adopted the steam engine as a source of power decades after it has been introduced in the United Kingdom.
- The invention of the Watt steam-engine was a technological milestone. Nevertheless only the invention of the high-pressure steam engine years later truly made steam-power a GPT (see Crafts, 2004).
- Furthermore, the steam engine was not a GPT from the beginning, but started off as a single purpose technology mainly used for pumping out water from mine shafts.

Likewise, the advent of the computer as a GPT did not come entirely unpredicted. As Lipsey, Carlaw and Bekar (1998) state: “For example, long before its full potential had been exploited (which is still in the future), it became apparent to many observers that electronic computers were on their way to becoming a pervasive GPT." Furthermore Eriksson and Lindh (2000) state that "... the idea of computers was thoroughly explored by researchers, like Alan Turing, already in the 1930s, although practical designs were far in the future." The information and communication technology revolution started in the United States before making its way to the rest of the world. Finally, the rise of the computer to a GPT was a process taking place over a considerable amount of time, as discussed by David (1990). Current examples for possible future GPTs are nanotechnology and nuclear fusion: While both technologies have been shown to work on a small scale with either limited applications or at relatively large costs, there exists a huge potential of future uses if a number of known technical problems can be solved.

Altogether the possibility of knowing about a future GPT before its actual arrival can stem from several sources: For instance a new GPT can be invented and widely used in a specific country before spreading across the world. Or the concept of a new GPT can be conceived in a theoretical context, but can only be used productively once technological advances allow the realisation of these ideas. Moreover, a number of GPTs started off as single purpose technologies before spreading throughout the economy.

Not only is it reasonable to believe that the arrival of a new GPT can be anticipated, it has also been observed that such expectations can have an influence on the extent of R&D activities: In the course of the 19th century, the replacement of water power as the main source of inanimate power by the steam engine seemed to be virtually inevitable. Nevertheless, some of the greatest leaps in efficiency of water power have been achieved during this time: Both the invention of the breastwheel and of the water turbine allowed a significantly larger amount of horsepower to be extracted from a given flow of water (see Lipsey, Carlaw and Bekar, 2005, chapter 6). Further examples for this type of development, as presented by Lipsey, Carlaw and Bekar (2005, chapter 6), are as follows: Initially, rail was not seen as a serious competition to canals for domestic cargo transportation in the United Kingdom, but rather as being complementary for short-distance transportation. As it became clear that railways would also be able to effectively compete in long-haul cargo transportation, the pressure to improve the canal system rose accordingly. As a final example, the impending spread of steam as a source of power for marine uses, sparked an increase in efficiency of sail (see for example Graham, 1956).

3.1.2 Previous Literature

Previous models of GPTs also focus on the effect of such breakthrough technologies on economic growth. The wave of models that followed the introduction of this concept by Bresnahan and Trajtenberg (1995) quickly showed that from a theoretical perspective GPTs are a double-edged sword: On one hand the idea that new GPTs provide a boost to long-term growth is generally agreed upon. In the model of Carlaw and Lipsey (2006), for example the arrival of new GPTs helps to sustain long-term growth, offsetting the loss of productivity due to the ongoing depreciation of applied knowledge. While this positive long-term effect ultimately prevails in all models, the introduction of a new GPT is usually considered to have a negative *short-term* impact on the economy.[2]

There exists a variety of explanations for such an initial slump in productivity and output following the introduction of a new GPT: Helpman and Trajtenberg (1998a) postulate that after the arrival of a new GPT, innovators first have to build up a critical mass of complementary components to this GPT (e.g. software for computers), before it can be usefully applied to produce final output. This causes an initial slump in growth, before it picks up a faster pace as soon as the new GPT becomes active in final output production. In their follow-up paper Helpman and Trajtenberg (1998b) model more precisely how a new GPT diffuses throughout the whole economy after its arrival. Building on the previous two models, Aghion and Howitt (1998a) present a model (based on Aghion and Howitt, 1998b) where the component-building phase is preceded by a stage where so-called “templates” for these components need to be discovered.

Greenwood and Yorukoglu (1997) offer another explanation for this phenomenon: They

[2] Our paper, as well as the subsequently presented papers, concentrate on theoretic modeling of the economic impact of GPTs. Nevertheless the notion that technological changes have contractionary effects in the short-run but positive long-term effects can also be found in empirical works, as for example in Basu, Fernald and Kimball (2006).

argue that new GPTs require the acquisition of specific skills before they can be put to a productive use. The related learning processes can take a considerable amount of time, as new GPTs are typically revolutionary and complex new technologies. This results once more in a productivity slowdown in the initial phase after the introduction of a new GPT. Similarly, Nahuis (2004) presents a model, where a new GPT sparks an initial phase of experimentation. He explains that when R&D workers are faced by such a revolutionary technology, they first have to explore the opportunities offered by it. Only afterwards the possibilities offered by the GPT can be usefully applied in a firm. Atkeson and Kehoe (2007) also postulate that the transition following a technological revolution is governed by "substantial and protracted" learning processes, thus delaying the positive impact on productivity of such a new technology. The fact that activities with a higher degree of complexity take a comparatively longer time to learn has also been demonstrated by Jovanovic and Nyarko (1995).

In business cycle theory, the effects of (changes in) expectations regarding the future behaviour of macroeconomic fundamentals, such as total factor productivity, have been thoroughly studied (see for example Beaudry & Portier, 2007 or Jaimovich & Rebelo, 2006). Meanwhile, the literature on GPTs is mainly concerned with effects taking place *after* the arrival of a new GPT. Nevertheless the idea that agents can have an advance knowledge about the arrival of a new GPT is not entirely new: Eriksson and Lindh (2000) present a model, building on Helpman and Trajtenberg (1998a), where the time of arrival of a new GPT is endogenised, inasmuch as the accumulation of social knowledge leads to invention of new GPTs.

By focussing on the time *before* the arrival of a new GPT, our model has a different focus than the models previously described. Despite this difference, it is not meant as a rival explanation for the dynamics arising due to new GPTs. It rather presents a channel that applies in addition to the ones described in those other models.

The remainder of this paper is organised as follows: In the following Section we introduce our model of GPTs in a quality-ladder framework. As a benchmark case, the analysis of the steady state behaviour is explored in Section 3, especially comparing steady states of two successive GPT generations. In Section 4 the transitional dynamics are shown, before we offer an outlook and some conclusions in Section 5.

3.2 GPTs in a Quality-Ladder Model

We present a quality-ladder model incorporating the arrival of new GPTs. In a quality-ladder model final goods are typically assembled of a number of intermediate goods, which in turn are produced in a fixed number of distinct varieties. The producers of these intermediate goods can invest in R&D to improve the quality of a specific intermediate good, thus moving it up the quality-ladder. We model the impact of new GPTs in terms of an increase in research efficiency in this sector. This approach is common in GPT-modeling. In the words of Jacobs and Nahuis (2002): "A GPT [...] affects the marginal productivity of research as it opens new opportunities for knowledge-creating activities throughout the economy." Accordingly they model the arrival of a new GPT (in their case the computer revolution) as an increase in research productivity. Bresnahan and Trajtenberg (1995) also stress the role of GPTs as "enabling technologies", which open up new opportunities instead of offering complete, final solutions. In their view, the productivity of R&D in downstream sectors increases through "innovational complementarities" arising from innovations in GPTs.

Our model of GPT-driven growth is based on the Schumpeterian model of quality ladders as described in chapter 7 of Barro and Sala-i-Martin (2004). The economy consists of three sectors: First, there is consumption. Second, there is an R&D sector where firms on one side produce a fixed variety of intermediate goods: These firms, called R&D firms in the remainder of this paper, may also perform in-house R&D in order to improve the quality of those intermediate goods. Third, the final goods sector demands and assembles these intermediate goods.

The crucial features of our GPT model are as follows: First, we introduce the concept of GPTs in this quality-ladder framework, by modeling the effect of a new GPT taking the form of an improvement in research efficiency as described in the first part of this Section. Second, we assume that the agents know about the arrival of the GPT. This leads to transitional dynamics before the arrival of a new GPT, during which the economy exhibits non-stationary growth rates.

If an R&D firm is successful in improving the quality of an intermediate good it can sell this good to the final goods producer at the monopoly price, since it holds the exclusive right to produce this intermediate good of the respective quality level. Final goods producers only use the leading-edge quality of each variety of goods.[3] Therefore the incumbent monopolist in a sector earns this monopoly profit in each period until another R&D firm succeeds in developing an even higher quality of this intermediate good. The probability of having a research success is determined by various factors: On one side the amount of R&D expenditures are endogenously chosen by the R&D firms. The efficiency of these expenditures in attaining a research success is determined by exogenous factors (such as the sector-specific difficulty of research and the current GPT level). The arrival of a new GPT increases, ceteris paribus, the probability of a research success.

3.2.1 Consumers and the Final Goods Sector

As in all quality-ladder models, quality improvements are the driving force of growth in our model, which of course take place in the R&D-sector. Nevertheless, we first present the final goods sector and the behaviour of consumers.

The representative consumer maximizes the overall utility U derived from consumption c as given by:

$$U = \int_0^\infty u(c(t))e^{-\rho t}dt \tag{3.1}$$

where ρ stands for the time preference rate. Consumers earn the interest rate r on assets and a wage w per unit of labour. Consumers spend their income on consumption and savings, therefore the accumulation of assets is given by:

$$\frac{d(assets)}{dt} = r(assets) + wL - C \tag{3.2}$$

Assuming a standard constant intertemporal elasticity of substitution (CIES) utility function and through a simple maximisation exercise the following Euler equation for consumption growth can be derived:

$$\frac{\dot{C}}{C} = (1/\theta)(r - \rho) \tag{3.3}$$

[3] The assumption that of each variety of intermediate goods only the highest quality grade is produced and used is also made in Barro and Sala-i-Martin, 2004. Additionally they show that the general nature of results is unchanged under an equilibrium with limit pricing.

with C as the aggregate consumption and θ as the elasticity of marginal utility, which is equivalent to the reciprocal of the elasticity of intertemporal substitution.

Apart from being consumed, the aggregate output Y is used in the production of aggregated intermediate goods X and total R&D investments Z. This is reflected by the following resource constraint for the economy:

$$Y = C + X + Z \tag{3.4}$$

The production function for a firm i in the final goods sector is given by:

$$Y_i = AL_i^{1-\alpha} \sum_{j=1}^{N} (\tilde{X}_{ij})^{\alpha} \tag{3.5}$$

where $0 < \alpha < 1$.

L_i is the labour input and $\tilde{X}_{ij}$ is the quality-adjusted amount of intermediate good j used in the production by firm i. N is the constant number of varieties of intermediate goods while A is an exogenous technology parameter.

The quality adjusted amount of an intermediate good $\tilde{X}_{ij}$ is determined by both the physical quantity of the respective intermediate X_{ij} and its current quality-level q^{κ_j}:

$$\tilde{X}_{ij} = q^{\kappa_j} X_{ij} \tag{3.6}$$

where $q > 1$ is a constant and a new invention raises κ_j by one. In accordance with the quality-ladder concept, a new invention takes the form of an improvement in the quality of an existing intermediate by a factor of q.

Final good firms maximize their profits, given that only goods of the highest available quality level in each sector are demanded. From this maximisation, the aggregate demand function for good j can be derived:

$$X_j = L(A\alpha q^{\alpha\kappa_j}/P_j)^{1/(1-\alpha)} \tag{3.7}$$

This expression represents the demand that firms in the R&D sector face. P_j is the price of the intermediate good j.

3.2.2 R&D Sector

R&D firms both produce and sell intermediate goods. Additionally, they can make R&D expenditures aiming at the invention of a higher quality good in a certain sector.

In order to maximize their profits they have to choose the optimal amount of R&D expenditures Z. For this maximisation they need to consider two phases: In a first phase they can perform research in order to attain a monopoly in the respective sector. The main trade-off here is that an increase in the probability of having a research success comes at the cost of an increase in research expenditures. In a second phase, after having made a successful invention, they start to hold the monopoly on the highest-quality good in this specific sector and decide on pricing and the amount produced: Accordingly they can derive a monopoly profit in each period until they are displaced by a competitor having the next research success in this sector. We assume free entry in the R&D sector and risk-neutral R&D firms.[4] Therefore the R&D firms equalise their R&D expenditures with the expected pay-off they receive from these investments, which is in turn subject to discounting and the future probability of being driven out of the market by a competitor.

The choice variable of R&D firms is the amount of inputs they use for research in each sector $Z(\kappa_j)$. This input influences the probability of having a research success in a certain sector, i.e. $p(\kappa_j)$ in the following fashion:

$$p(\kappa_j) = Z(\kappa_j)\phi(\kappa_j)B_m \tag{3.8}$$

where $\phi(\kappa_j)$ captures the difficulty of research in respect to the quality-ladder position of the sector. The current GPT of generation m, B_m, enters positively. In accordance to the idea that new GPTs lead to an enhancement in efficiency of R&D the arrival of a new GPT increases the value of B_m to $B_{m+1} > B_m$.

The monopoly profit flow a R&D firm that has had a research success receives from selling the corresponding intermediate good is characterised by the following equation:

$$\pi(\kappa_j) = (P_j - 1)X_j \quad \text{with} \quad P_j = \frac{1}{\alpha} \tag{3.9}$$

where the marginal cost of production equals 1 and X_j is given by equation (3.7). P_j is the usual optimal monopoly price, where the monopolist charges the markup $1/\alpha$ on the marginal costs. The following expression describes the monopoly profit flow of an

[4] Although risks in individual sectors are idiosyncratic, they are not on the aggregate level: Therefore R&D firms can also use a portfolio approach leading to results analogous to risk-neutrality.

innovator possessing the leading-edge technology:

$$\pi(\kappa_j) = \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} \tag{3.10}$$

where $\overline{\pi}$ is given by:

$$\overline{\pi} = \left(\frac{1-\alpha}{\alpha}\right) A^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} L \tag{3.11}$$

$\overline{\pi}$ is the basic profit flow, which is constant over time given that the size of the labour force L is fixed. Due to the higher demand for goods of a higher quality level, the profits of inventors $\pi(\kappa_j)$ increase with the quality level of intermediates κ_j.

In a sector with a given quality level κ_j investments in R&D are attractive if the R&D costs $Z(\kappa_j)$ are at least covered by the resulting return on these expenditures $p(\kappa_j)E[V(\kappa_{j+1})]$. $E[V(\kappa_{j+1})]$ is the expected present value of profit an intermediate goods producer obtains for his good of quality $\kappa_j + 1$. The size of $E[V(\kappa_{j+1})]$ depends on three major factors: The size of the profit flow the monopolist receives in each period $\pi(\kappa_{j+1})$, the probability that it is displaced by a future competitor inventing a good of an even higher quality given by $p(\kappa_{j+1})$ and the discount rate r.

Assuming that there is free entry, the expected return on R&D expenditures at any given time must be equal to the R&D expenditures:

$$Z(\kappa_j) = p(\kappa_j)E[V(\kappa_{j+1})] \tag{3.12}$$

By inserting $p(\kappa_j)$ from equation (3.8) and rearranging we can derive the following equation, which determines the optimal amount of research expenditures under free entry:

$$Z(\kappa_j)(\phi(\kappa_j)B_m E[V(\kappa_{j+1})] - 1) = 0 \tag{3.13}$$

As can be easily seen, the optimal amount of R&D expenditures $Z(\kappa_j)$ crucially depends on the size of $E[V(\kappa_{j+1})]$, which will therefore be more thoroughly explored in the next section.

3.3 Comparing Steady States

3.3.1 The General Case

The ultimate goal of our model is to investigate transitional dynamics caused by the anticipation of the arrival of a new GPT. Let us first, however, take a closer look at the effects of the introduction of a new GPT on steady states.

Consider a R&D firm that makes the κ_jth quality improvement at time t_{κ_j}: From then on it receives a flow of monopoly profit until it is displaced by a competitor inventing an even higher quality good in this sector. Therefore the firm that has invented technology κ_j earns the following expected present value of profit:

$$E[V(\kappa_j)] = \int_{t_{\kappa_j}}^{\infty} \left[\int_{t_{\kappa_j}}^{\tau} \pi(\kappa_j) e^{-\int_0^s r_u du} ds \right] g(\tau) d\tau \tag{3.14}$$

where $g(\tau)$ is the probability density function that the monopoly position ends at time τ due to a research success by a competitor. In the steady state, where $p(\kappa_j)$ and the duration of the monopoly are constant over time, $g(\tau)$ is given by:[5]

$$g(\tau) = p(\kappa_j) e^{-p(\kappa_j)\tau} \tag{3.15}$$

Since in the steady state not only $p(\kappa_j)$, but also the interest rate r are constant, the expression for the expected present value of profits as given by equation (3.14) simplifies to:

$$E[V(\kappa_j)] = \frac{\pi(\kappa_j)}{r + p(\kappa_j)} \tag{3.16}$$

By rewriting this equation we get the following no-arbitrage equation:

$$r = \frac{\pi(\kappa_j) - p(\kappa_j) E[V(\kappa_j)]}{E[V(\kappa_j)]} \tag{3.17}$$

The interpretation of this equation is straightforward: The rate of return on R&D must be equal to the interest rate r, representing an alternative investment. This equation does not only consider the profit flow at each point in time, but also the probability $p(\kappa_j)$ of being driven out of the market by a competitor. Accordingly the expected rate of return falls with the level of the probability of research success.

[5] For details on the derivation, see Barro and Sala-i-Martin, 2004, p. 345f.

R&D firms consider the free-entry condition (3.13) and the expected profit given by equation (3.16) in order to calculate their optimal amount of R&D expenditures, thereby determining their probability of research success. This probability crucially depends on the difficulty of research as given by $\phi(\kappa_j)$:

$$\phi(\kappa_j) = \left(\frac{\epsilon}{\zeta}\right) q^{-(\kappa_j+1)\alpha/(1-\alpha)} \tag{3.18}$$

This equation captures several effects: First, there is a constant parameter ζ, reflecting the costs of performing R&D. Second the difficulty of R&D rises with the quality of the good the R&D firm wants to improve. Finally, the term ϵ is later used to capture decreasing returns to current R&D, but is for now being held constant. Applying this $\phi(\kappa_j)$ to the free entry condition (3.13) and the general equation for the probability of having a research success (3.8) leads to the following expression for the probability of research success:

$$p = \frac{\epsilon\overline{\pi}B_m}{\zeta} - r \tag{3.19}$$

As only variables that are independent of the quality-level appear in this expression this probability is constant across all sectors. Furthermore the arrival of a new GPT, reflected by an increase of B_m to B_{m+1} leads to an increase in p. This increase is of course due to the fact that, triggered by the increase in the efficiency of R&D, the amount of resources devoted to R&D in sector j also rises so that the no-arbitrage equation (3.17) is again fulfilled. This can be seen in the following equation:

$$Z(\kappa_j) = \frac{q^{\frac{(\kappa_j+1)\alpha}{1-\alpha}}(\epsilon\overline{\pi}B_m - r\zeta)}{\epsilon B_m} \tag{3.20}$$

Additionally, the sectors on a higher quality level attract higher R&D expenditures.

By aggregation of the R&D expenditures of individual sectors as given by equation (3.20), the total amount of R&D expenditures in the economy can be derived as follows:

$$Z = \sum_{j=1}^{N} Z(\kappa_j) = \frac{q^{\frac{\alpha}{1-\alpha}}Q(\epsilon\overline{\pi}B_m - r\zeta)}{\epsilon B_m} \tag{3.21}$$

where

$$Q \equiv \sum_{j=1}^{N} q^{\kappa_j\alpha/(1-\alpha)} \tag{3.22}$$

is defined as the aggregate quality index, which captures the overall technological level of the economy. Clearly, Z is linearly dependent on Q and positively dependent on B_m.

The aggregate output of the final goods sector and the total intermediate demand can be derived analogously and are given by the following equations:

$$Y = A^{\frac{1}{1-\alpha}} \alpha^{\frac{2\alpha}{1-\alpha}} LQ \tag{3.23}$$

$$X = A^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} LQ \tag{3.24}$$

With a constant labour force, equations (3.23) and (3.24) imply that Y and X are linear functions of the aggregate quality index Q. Furthermore it follows from equation (3.21) that Z is a linear function of Q.

Just considering the steady state with a given GPT generation m, it follows from equation (3.4) that C is also a linear function of Q. This implies that the growth rates of all of these variables are equal to the growth rate γ of Q. To derive this growth rate, we need to know the expected change of Q per unit of time, which is given by:

$$E[\triangle Q] = \sum_{j=1}^{N} p(q^{\frac{(\kappa_j+1)\alpha}{1-\alpha}} - q^{\frac{\kappa_j \alpha}{1-\alpha}}) \tag{3.25}$$

which in turn leads to:

$$E\left[\frac{\triangle Q}{Q}\right] = p(q^{\frac{\alpha}{1-\alpha}} - 1) \tag{3.26}$$

Given a large number of sectors, the law of large numbers implies (despite the fact that technical progress in individual sector takes place in discrete steps) that the aggregated average growth rate of Q equals the expression on the right-hand side of equation (3.26). Inserting in equation (3.26) the expression for p in equation (3.19), we obtain the following growth rate for Q:

$$\gamma = \frac{\dot{Q}}{Q} = (\frac{\epsilon \overline{\pi} B_m}{\zeta} - r)(q^{\frac{\alpha}{1-\alpha}} - 1) \tag{3.27}$$

In order to derive the steady state, we need to equalise the growth equation (3.27) with the optimal growth rate of consumption as given by the Euler equation (3.3). Together these equations determine the steady state as plotted in Figure 3.1 for two consecutive GPT-generations, namely m and $m + 1$.

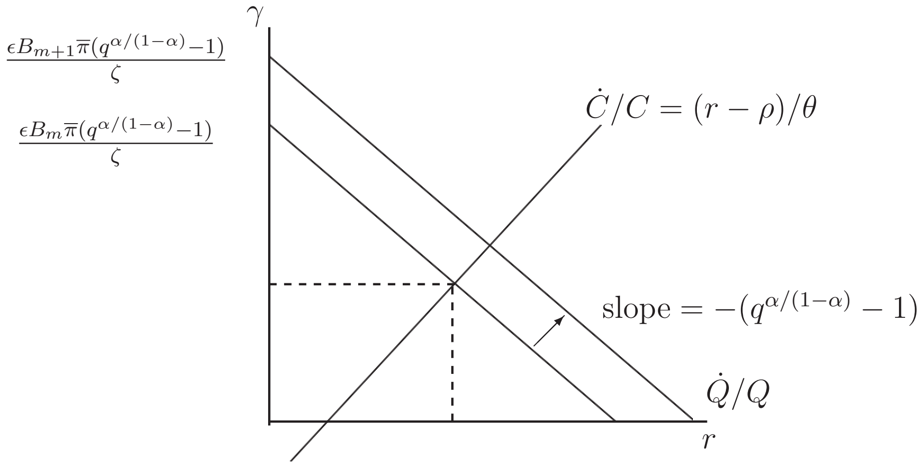

Figure 3.1: Determination of the Equilibrium Interest and Growth Rate

The arrival of a new GPT, as modeled by an increase in B, shifts the $\frac{\dot{Q}}{Q}$ line upwards. By utilizing the new GPT characterised by B_{m+1} the economy grows at a higher rate and has a higher interest rate than under the previous GPT generation: Remember that in the steady state with a constant GPT the growth rates of Y, X, Z and C all equal the growth rate of Q. Analytically, we can derive the following steady state values for the interest rate r and the growth rate γ, by equalizing the Euler equation (3.3) and equation (3.27):

$$r = \frac{\theta\epsilon B_m\overline{\pi}(q^{\frac{\alpha}{1-\alpha}}-1)+\rho\zeta}{\zeta(1+\theta(q^{\frac{\alpha}{1-\alpha}}-1))} \tag{3.28}$$

$$\gamma = \frac{(q^{\frac{\alpha}{1-\alpha}}-1)(\epsilon B_m\overline{\pi}-\rho\zeta)}{\zeta(1+\theta(q^{\frac{\alpha}{1-\alpha}}-1))} \tag{3.29}$$

To derive the probability of research success p, we can use (3.26) to get:

$$p = \frac{\gamma}{q^{\frac{\alpha}{1-\alpha}}-1} \tag{3.30}$$

From the above equations we can easily derive the following expression:

$$p = \frac{\epsilon B_m\overline{\pi}-\rho\zeta}{\zeta(1+\theta(q^{\frac{\alpha}{1-\alpha}}-1))} \tag{3.31}$$

These steady state values for p, r and γ imply that the arrival of a new GPT not only leads to an increase in both growth and interest rates, but also in the probability of a research success.

Altogether, considering only steady states, the impact of the arrival of a new GPT on the economy in our model is entirely consistent with the long-term effects observed in the majority of models in this field: First, the arrival of a new GPT makes investments in R&D more attractive, due to higher expected returns on research investments. Second, the new GPT generates a boost to the long-run growth rate of the economy.

3.3.2 Decreasing Returns to Current R&D

As has been described by Kortum (1993) and Stokey (1995) there are decreasing returns to current R&D efforts because of congestion externalities. This negative duplication externality is called "stepping on toes effect" by Jones and Williams (2000) and proposed to arise e.g. due to patent races. Applied to our model this implies that research does not only become more difficult the higher the quality of the good an R&D firms wants to improve upon, but also with rising R&D efforts at a point of time. We capture this effect in the following specification of $\phi(\kappa_j)$:

$$\phi(\kappa_j) = \left(\frac{1 - p(\kappa_j)}{\zeta}\right) q^{-(\kappa_j+1)\alpha/(1-\alpha)} \tag{3.32}$$

As in the general model presented in the previous section, research is more difficult the higher the new quality-ladder level of a new intermediate good is. In addition to this assumption, we model decreasing returns to current R&D by setting $\epsilon = 1 - p(\kappa_j)$. While any function where ϵ depends negatively on $p(\kappa_j)$ would result in similar qualitative results, we have chosen this specification for ease of computation of the transitional dynamics. Furthermore with this specification $0 \leq p(\kappa_j) \leq 1$ always holds as equation (3.8) and (3.32) imply

$$p(\kappa_j) = \frac{Z(\kappa_j) B_m q^{-(\kappa_j+1)\alpha/(1-\alpha)}}{\zeta + Z(\kappa_j) B_m q^{-(\kappa_j+1)\alpha/(1-\alpha)}} \leq 1 \tag{3.33}$$

Before the transition path using this specification is derived in the next Section, the implications of this specification of $\phi(\kappa_j)$ on steady state values are shown. The probability of research success is now given by equation (3.34) and the total amount of R&D expenditures by equation (3.35):

$$p = \frac{\overline{\pi} B_m - r\zeta}{\zeta + \overline{\pi} B_m} \tag{3.34}$$

$$Z = \frac{q^{\frac{\alpha}{1-\alpha}} Q(\overline{\pi} B_m - r\zeta)}{1+r} \tag{3.35}$$

The steady state values of the interest rate, growth rate and the probability of research success are now given by the following three equations:

$$r = \frac{\theta \overline{\pi} B_m (q^{\frac{\alpha}{1-\alpha}} - 1) + \rho(\zeta + \overline{\pi} B_m)}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi} B_m} \tag{3.36}$$

$$\gamma = \frac{(q^{\frac{\alpha}{1-\alpha}} - 1)(\overline{\pi} B_m - \rho\zeta)}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi} B_m} \tag{3.37}$$

$$p = \frac{\overline{\pi} B_m - \rho\zeta}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi} B_m} \tag{3.38}$$

These steady state values for p, r and γ imply that the arrival of a new GPT under this specification of $\phi(\kappa_j)$ leads qualitatively to the same implications as in the general case, i.e. to an increase in both growth rates and interest rates.

3.4 The Calm Before the Storm – Transition Paths

If researchers do not know about the arrival and the future course of a new GPT, but only know about the current marginal return on R&D expenditures (as in Carlaw and Lipsey, 2006), the economy would simply jump from one steady state to another upon the arrival of a new GPT.

However, the arrival of a new GPT might very well be foreseen, in which case the arrival of a new GPT *does* give rise to transitional dynamics. Let us therefore assume that the time of arrival of the next GPT t^* is known in advance. Due to this information, R&D firms using the GPT of generation m adjust their R&D decisions in the time before the arrival of the GPT of generation $m+1$. In the example of the United States of the late 19th century, it is obvious that firms could predict the rise of steam as a power source. However, the subsequent replacement of steam by electricity decades later could hardly have been taken into account. We therefore make the additional assumption that R&D firms are only concerned with the current and the next GPT generation. This seems reasonable because (apart from the fact that technological breakthroughs in the far future are virtually impossible to predict) the intervals between the arrival of new GPTs are typically very large compared to the lifetime of a single invention. In our model this leads to the simplification that the interest rate and the probability of research success will jump to the new steady state values at the time of arrival of the new GPT and will remain there forever.

3.4.1 Derivation of R&D Expenditures in the Transition Phase

Before simulating the transition path, we describe the derivation of the model equations for this phase, still assuming the specification $\phi(\kappa_j)$ with decreasing returns to R&D given by equation (3.32). Basically the same equations as before for the consumers and the R&D firms hold. However, one important change has to be taken into account: Due to the possible fluctuation of the probability of research success and the interest rate in the transition phase, the results regarding the expected payoff on R&D expenditures used in the previous Section (e.g. equations (3.16) and (3.17)) do not apply directly during the transition phase. The expected future profits of the incumbent monopolist are still discounted by the interest rate and by the probability of losing the monopoly. We define ω_t according to equation (3.39) as the overall multiplier of the profit flow in case of a successful invention that encompasses both the varying interest rates and the probabilities of being displaced as a monopolist:

$$\omega_{t+1} = \int_{t_{\kappa_j}}^{\infty} \int_{t_{\kappa_j}}^{\tau} e^{-\int_0^s r_u du} g(\tau) ds d\tau \tag{3.39}$$

Rewriting equation (3.14) by inserting both (3.10) and (3.39) we get the following expression for the expected payoff in case of a research success during the transition phase:[6]

$$E_t[V(\kappa_j + 1)] = \omega_{t+1} \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} \tag{3.40}$$

Using the specification of $\phi(\kappa_j)$ in equation (3.32) the expression for p_t is now found by inserting equation (3.40) into the free-entry condition (3.13):

$$p_t = 1 - \frac{\zeta}{B_m \omega_{t+1} \overline{\pi}} \tag{3.41}$$

[6] In the steady state case ω_{t+1} reduces to $\omega_{t+1} = \frac{1}{r + p(\kappa_j)}$ leading to equation (3.16).

The amount of resources devoted to R&D in sector j and the aggregate amount of resources devoted to R&D can be calculated in the same manner as in the steady state and are given by:

$$Z_t(\kappa_j) = \frac{q^{\frac{(\kappa_j+1)\alpha}{1-\alpha}}(B_m\omega_{t+1}\overline{\pi} - \zeta)}{B_m} \tag{3.42}$$

and

$$Z_t = \sum_{j=1}^{N} Z(\kappa_j) = \frac{q^{\frac{\alpha}{1-\alpha}}Q_t(B_m\omega_{t+1}\overline{\pi} - \zeta)}{B_m} \tag{3.43}$$

Again, the higher the aggregate quality index is, the more research is performed. R&D input is also positively dependent on the current GPT level. Furthermore, the higher the future interest rate or the probability of research success, the smaller is the R&D investment. This is captured by the fact that Z_t is positively dependent on ω_{t+1}.

The general expression for the expected change in quality, equation (3.26), remains valid. By inserting equation (3.41) we derive the following growth rate for Q:

$$\frac{\dot{Q}_t}{Q_t} = \frac{B_m\omega_{t+1}\overline{\pi} - \zeta}{B_m\omega_{t+1}\overline{\pi}}(q^{\frac{\alpha}{1-\alpha}} - 1) \tag{3.44}$$

As can be easily seen in equation (3.43), the aggregate research expenditures Z_t are again linearly dependent on the quality index Q. Due to the fact that only the R&D sector is directly affected by changes in the current GPT, the optimisation problems for the final goods sector and for the consumer remain the same as in the steady state. This means that the same equations (3.23) and (3.24) apply for X and Y in the transition phase, both of which are linearly dependent on Q. Again it follows that C is linearly dependent on Q as well. Hence, we can take the same steps as before for the derivation of the steady state in order to calculate r_t, γ_t and p_t during the transition phase. This results in the following equations:

$$\gamma_t = (1 - \frac{\zeta}{B_m\omega_{t+1}\overline{\pi}})(q^{\frac{\alpha}{1-\alpha}} - 1) \tag{3.45}$$

$$p_t = 1 - \frac{\zeta}{B_m\omega_{t+1}\overline{\pi}} \tag{3.46}$$

$$r_t = \theta(1 - \frac{\zeta}{B_m\omega_{t+1}\overline{\pi}})(q^{\frac{\alpha}{1-\alpha}} - 1) + \rho \tag{3.47}$$

As in the steady state case, the growth rate is positively dependent on the current GPT level and q. B_m enters positively in the probability of research success p_t and the interest rate r_t.

3.4.2 Simulation Results

The time-frame for which R&D firms have to choose a time-path with varying research expenditures is restricted to the time before the arrival of a new GPT. This is due to the assumptions that the time of arrival of the next GPT t^* is known in advance and that afterwards the steady state values for p_t and r_t will apply from time until eternity. This allows us to solve the optimisation problem of R&D firms and solve the transition path numerically using backward induction.

In our specific case, the intuition of this procedure is as follows: At the time of arrival t^* of the new GPT of generation B_{m+1}, the economy immediately jumps to the new steady state as described in the previous Section and remains there forever. Firms that take the decision on how much to invest in R&D in the last period before the arrival of the GPT of generation B_{m+1}, i.e. in the period $t^* - 1$, face the following problem: The payoff on their R&D expenditures is still governed by the old GPT which is less efficient than the next GPT generation. On the other hand, the rate by which their potential invention will be displaced in the future will be determined by the new, more efficient GPT. In other words, they have the disadvantage that they produce in a period where the expected probability of research success is ceteris paribus smaller than in all subsequent periods. This of course leads to a reduction in research expenditures in this period. In period $t^* - 2$, the outcome of period $t^* - 1$ and all subsequent periods is known to all firms and the maximisation problem is solved conditional to these future constraints. We continue with this procedure until the level of the old steady state is approximately reached, i.e. when the time until the arrival of the next GPT is large enough that the impact on current R&D of this future development is negligible.

As in the previous Sections we are interested in the overall behavior of the economy, not of single firms or sectors. Therefore only aggregate values for the whole economy are taken. Accordingly we do not follow the profits of each R&D firm individually, since it is reasonable to assume that due to the law of large numbers a fraction $p(\kappa_j)$ of R&D firms is actually successfully innovating and offers an intermediate product of a higher quality.[7] Again the growth rate of the aggregate quality index determines aggregate growth.

[7] See Appendix 3.6.1 for further details on the aggregation of the profit flow.

The results of our simulation are shown in the subsequent figures, whereby a new GPT is supposed to arrive at time $t^* = 0$.[8] From that time on, the economy remains in the new steady state. The dashed line in Figure 3.2 represents the expected present value of profits after a successful innovation $E_t[V]$, which of course rises at a constant rate in the new steady state. Immediately before the arrival of the new GPT in t^* though, there is a sharp reduction in these expected profits. This is the logical result of the fact that in the time immediately before the arrival of the new GPT R&D firms are most affected by the acceleration in R&D in the future due to the more efficient GPT of the next generation.

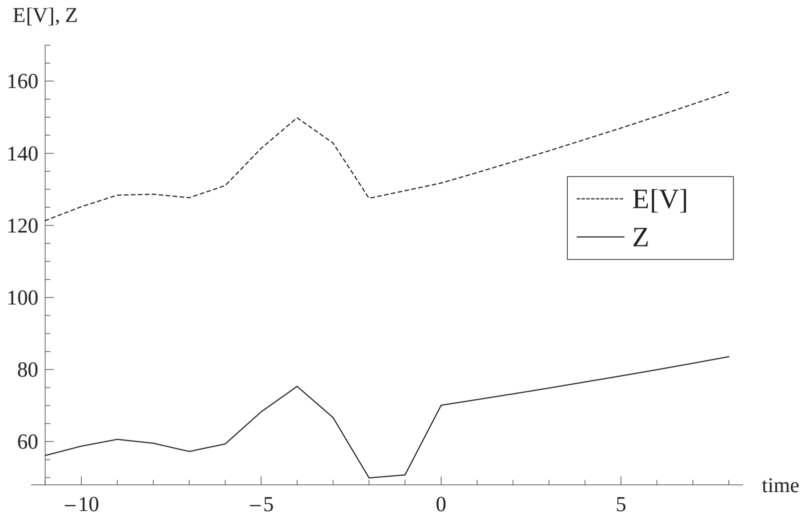

Figure 3.2: Expected Present Value of Profits after a Successful Innovation $E[V]$ and R&D Investment Z

The probability of research success is dependent on the amount of R&D expenditures and therefore exhibits the same behaviour as the research expenditures.[9] Since the expected profit falls at the end of the lifetime of the old GPT, R&D investments (see Figure 3.2) become less attractive and therefore decrease. What happens *before*

[8] Please note that the simulation is performed in discrete time steps. Furthermore, we have calibrated our simulation to fit yearly data. This can be seen in Appendix 3.6.2, where the parameters chosen for the numerical solution are presented.

[9] See Appendix 3.6.3 for a plot of the time path of p and of the expected present value of profit before the research success $p_t * E_t[V]$, i.e. the expected profit a firm faces making his research decision, not knowing if it is successful.

the slump in R&D expenditures and the related probability is more intriguing: The research activity in the economy rises even beyond the old steady state levels. This is due to the fact that R&D firms know about the slump in research activities during the last periods of the transition phase. As this leads to a lower chance of being displaced as a monopolist in this phase, research becomes relatively more attractive in the phases before the slump. Initially, R&D investment is departing from the steady state by minimal oscillation around the old steady state values. The amplitude of this oscillation is becoming bigger the nearer the arrival of the new GPT is.

The dynamics described above during the transition path can also be seen in the time path of the growth rate and the interest rate depicted in Figure 3.3. After leaving the old steady state the economy is characterised by cycles. The growth rate and the interest rate start to oscillate around the old steady state values. Four periods before the arrival of the new GPT the maximum values of this path are reached. In the periods ultimately before the arrival of the new GPT the growth rate and the interest rate fall. Altogether there is only a short time where the economy suffers from lower growth compared to the old steady state.

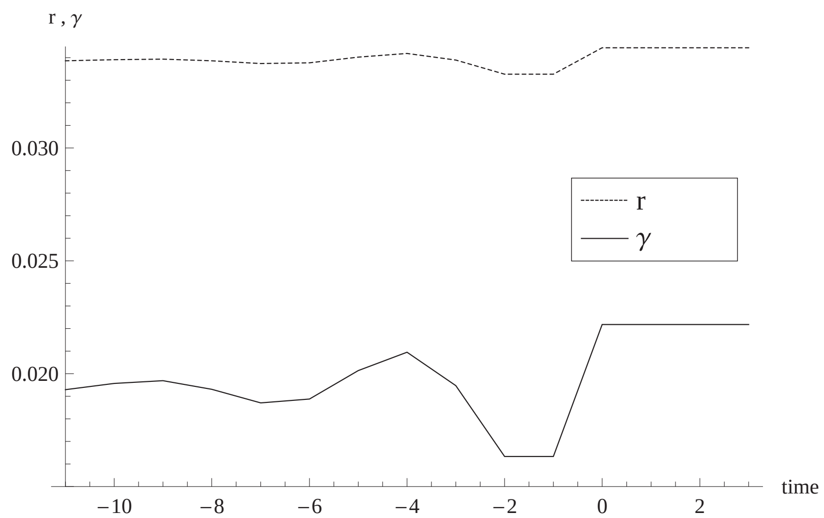

Figure 3.3: Interest Rate and Growth

Altogether, the dynamics in our model can be divided in three phases: First the economy is in the steady state using the old GPT. Because firms anticipate the arrival of the GPT of the next generation, a phase of transitional cycles is characterised by oscillation. Shortly before the arrival of a new GPT, R&D activity and growth rates increase beyond the old steady state levels before there is a slump. Finally, in a third phase, the economy is in the new steady state using the new GPT resulting in higher growth rates and interest rate levels. As has been shown in Section 1 the result of our model that the introduction of a new GPT is preceded by a surge in R&D activities using the old GPT before its ultimate demise also has several examples in history.

3.5 Conclusions

In order to investigate the cyclical effects caused by GPTs we introduce the notion of GPTs in the quality-ladder model on Schumpeterian growth by Barro and Sala-i-Martin (2004). In our model the arrival of a new GPT results an increase in R&D productivity: This increase in research efficiency makes investments in R&D more attractive. Regarding steady states, this leads to higher growth and interest rates.

Contrary to previous models on cycles induced by changes in GPTs, our analysis concentrates on the time *before* a new GPT arrives. In doing so, we can show within our model framework that a slowdown in output growth can also occur in the time immediately before the arrival of a new GPT. This slump is preceded by a period of increased R&D activity and oscillatory cycles.

While a surge in research activities in anticipation of a future rival technology has many examples in history, reality is of course more complex in many respects: For instance the time of arrival of a new GPT is usually not clear-cut. Furthermore, a number of GPTs can be active simultaneously. Both of these obvious limitations are shared with most existing models dealing with GPTs. Nevertheless, our model presents a channel that applies in addition to the ones described in other GPT models. While the vast majority of theories on GPTs explain an initial slump in productivity after the arrival of a new GPT, we present a channel on how a new GPT can induce cycles even before its arrival. This automatically opens possibilities for future research, as these two approaches could be combined in a single model: Such a model could incorporate both the cycles in research activities in anticipation of a new GPT *and* processes taking place after the new GPT has arrived, as described in other models.

3.6 Appendix

3.6.1 Derivation of the Aggregate Profit

The profit flow per unit of time for an individual successful R&D firm is given by equation (3.10):

$$\pi(\kappa_j) = \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} \tag{3.48}$$

By aggregating the profits, we get:

$$\pi = \int_{j=0}^{N} \pi(\kappa_j) = N\overline{\pi}Q \tag{3.49}$$

By taking a continuum of firms going from 0 to 1, setting the limits on the integral accordingly and by using equation (3.11), we obtain the profit flow per unit of time for the aggregate of R&D firms:

$$\pi(\kappa_j) = (\frac{1-\alpha}{\alpha}) A^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} LQ \tag{3.50}$$

3.6.2 Parameters used for Numerical Solution of the Transition Path and the Resulting Steady State Values

Parameter	GPT B_m	GPT B_{m+1}
B	1.3	1.69
α	0.3	0.3
θ	0.2	0.2
ρ	0.03	0.03
ζ	10	10
A	15	15
L	2	2
Q		10
q	1.1	1.1

Table 3.1: Parameters used for Numerical Solution of the Transition Path

The parametrisation of our model is shown in Table 3.1. While the parameters are chosen to both fulfill basic assumptions and to yield sensible results for growth and interest rates, the resulting dynamics are robust across a wide range of parameters, as shown in Appendix 3.6.4. Note that only the explicit value for Q at the point of time when the GPT of generation $m+1$ arrives is listed. The reason is that while the growth rates of the aggregate quality level Q are endogenous in our model, we had to define the explicit value of Q at a point of time in order to calculate the remaining values.

The evolution of the GPT parameter B_m is modeled to move along a quality-ladder which is similar to the dynamics in the R&D sector:

$$B_m = d^m \tag{3.51}$$

where $d > 1$. The increase in R&D efficiency due to the arrival of a new GPT is therefore modeled through an increase of B_m by the factor d. Our simulation starts with generation 0 where $m = 1$ and we assume that $d = 1.3$. The steady state values resulting from our simulation are listed in Table 3.2.

Parameter	GPT B_m	GPT $B_m + 1$
r	3.39%	3.44%
p	46.5%	53.2%
γ	1.94%	2.22%

Table 3.2: Steady State Values of the Numerical Solution

3.6.3 Additional Figures of the Transition Path

The slump of the present value of expected profits before the arrival of the new GPT as described in the main text in Figure 3.2 can also be seen in Figure 3.4 where the expected payoff to R&D expenditures Z, $p_t * E_t[V]$ (i.e. the expected present value of profits a firm faces making its research decision, since it gets the expected profit only with probability p_t) is depicted. The same applies to Figure 3.5 where the probability of research success is plotted.

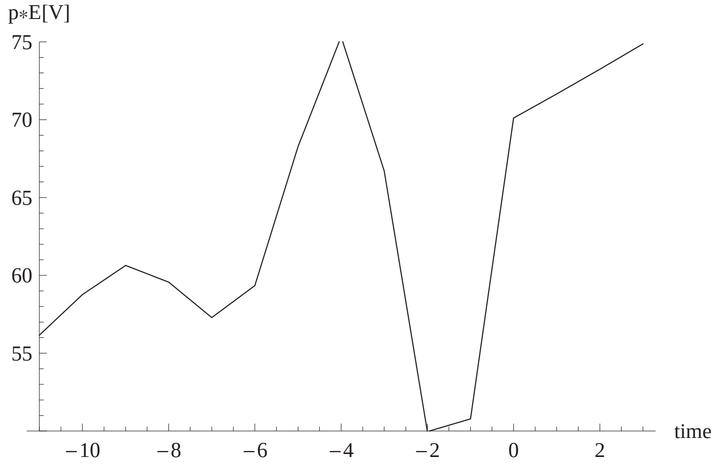

Figure 3.4: Expected Return on R&D Expenditures $p_t * E_t[V]$

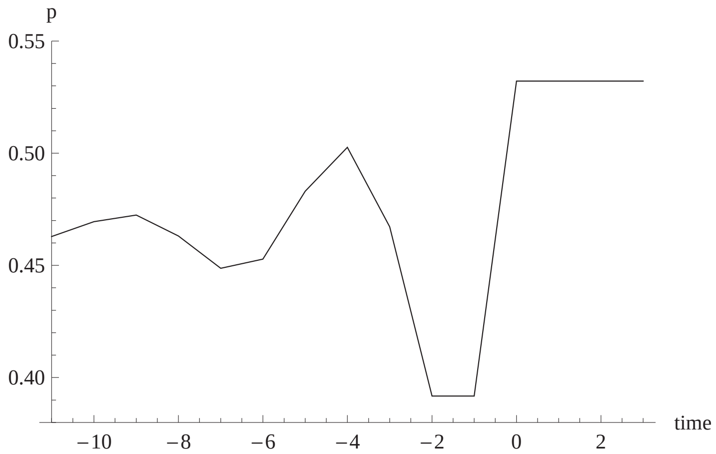

Figure 3.5: Probability of Research Success p_t

3.6.4 Sensitivity Analysis

The qualitative results of the numerical simulation of the transition path presented in the main part of this paper are very robust to changes in the exogenous parameters (presented in Appendix 3.6.2). This of course includes the cyclical behaviour of the transition path. Meanwhile, in Table 3.3 the impact of a ceteris paribus change of a single exogenous parameter on the resulting variables, namely r, p and γ, is described.

As can be easily seen, an increase in the parameters which have a positive influence on the demand of intermediate goods, i.e. A, L and α have a positive impact on all

Parameter	r	p	γ
α	$\Uparrow$	$\Uparrow$	$\Uparrow$
A	$\Uparrow$	$\Uparrow$	$\Uparrow$
L	$\Uparrow$	$\Uparrow$	$\Uparrow$
ζ	$\Downarrow$	$\Downarrow$	$\Downarrow$
θ	$\Uparrow$	$\Downarrow$	$\Downarrow$
ρ	$\Uparrow$	$\Downarrow$	$\Downarrow$
Q	-	-	-
q	$\Uparrow$	$\Downarrow$	$\Uparrow$

Table 3.3: Sensitivity Analysis with Respect to a Ceteris Paribus Increase of a Parameter

endogenously determined variables. Furthermore a change in demand parameters does not influence the size of the oscillation during the transition phase.

Conversely an increase in the costs of performing R&D ζ lowers the exogenous variables lowers p, r and γ but the expected profit $E[V]$ rises. Furthermore Z is lower in the new steady state, since the effect of the lower p dominates the effect of the higher $E[V]$. Additionally Z oscillates more during the transition phase, leading to temporarily higher levels than in the benchmark case previously presented. The lower steady state value of the R&D input Z is straightforward since ζ reflects the costs of R&D. Output is higher before, the same in the first period of the new steady state and then smaller.

Raising the preference parameters ρ and θ has a positive impact on the interest rate r, but also lowers p, $E[V]$ and Z which in turn leads to a lower growth rate γ. Output is only affected through the lower growth rate: It is higher during the transition phase, the same in the first period of the new steady state compared to the specification described in the main text, and then smaller due to the smaller growth rate in the new steady state.

The size of Q in the first period of the new steady state determines the level of output, Z and $E[V]$ but has no impact on p, r and γ.

If q is increased, both r and γ increase, whereas p decreases and $E[V]$, Z and output are higher in the new steady state but smaller before.

Chapter 4

Long-Term Growth Driven by a Sequence of General Purpose Technologies*

We present a Schumpeterian model of endogenous growth with General Purpose Technologies (GPTs) that captures two important historical stylized facts: First, from the beginning of mankind until today GPTs are arriving at an increasing frequency and, second, all GPTs are heavily depended on previous technologies. In our model, the arrival of GPTs arises stochastically depending on the currently available applied knowledge stock. This way of modelling leads to an increasing frequency of arrivals and allows for a model which is more in tune with the historical reality than the existing GPT models.

*This chapter represents joint work together with Daniel Schiess (ETH Zurich).

4.1 GPTs and Long-Term Growth

A small number of ground-breaking inventions arriving in ever decreasing time intervals can be identified as important driving forces of long-term economic growth: In early human history millennia passed between transforming innovations such as the domestication of plants and animals or the Bronze Age and the Iron Age. Later, in the course of a single century, the era of the industrial revolution witnessed the rise of the steam engine and production in large-scale factories, followed by the birth of railways and the steam ship. Finally, it took only a few decades to transform the economic landscape through the introduction of personal computers and the rapid spread of the Internet.

The view that such breakthrough technologies, which are called "General Purpose Technologies" (GPTs), are true "engines of growth" has been shaped by Bresnahan and Trajtenberg (1995): They regard GPTs as being radical innovations in the sense that they are " ... characterised by the potential for pervasive use in a wide range of sectors and by their technological dynamism. As a GPT evolves and advances it spreads throughout the economy, bringing about and fostering generalised productivity gains." They also emphasise that GPTs are "enabling technologies", which give rise to new opportunities instead of offering complete, final solutions.

In this paper we present a model where long-run growth is driven by GPTs. Specifically, the probability that a new GPT arrives depends on the amount of previously accumulated applied knowledge. This allows us to model long-term growth as driven by a sequence of GPTs, which, due to the rising stock of applied knowledge, arrive at ever shorter time intervals. Furthermore, we model economic cycles within the lifetime of a single GPT, assuming that the economic impact of such a new technology decreases over time.

By modeling the arrival of new GPTs as being dependent on the stock of available applied knowledge and the resulting increase in the frequency of arrivals of new GPTs, our model captures two stylized facts on the evolution of GPTs in history: First, the time interval between the arrival of new GPTs has become ever shorter. Second, new GPTs are usually based on previously invented technologies and existing knowledge.

Taking the Internet as an example, its invention would not have been possible without a multitude of previous inventions ranging from the computer to electricity.

4.1.1 Stylized Fact 1: Ever Decreasing Time Intervals between GPTs

The fact that GPTs arrive at an ever faster pace becomes obvious when looking back at economic history. Taking the list of historical GPTs compiled by Carlaw and Lipsey (2006), as shown in Table 4.1, as a reference point, it becomes clear that the interval between the arrival of individual GPTs has steadily decreased over time. This general trend is described by Carlaw and Lipsey (2006, p. 131-133) as follows:

> “Although others might expand or contract our list by a few items it illustrates several important points. First, the current ICT revolution is not unique; there have been (GPT-driven) ’new economies’ in the past. Second, GPTs have not been common in human experience, averaging between two and three per millennium over the last 10,000 years. Third, the rate of innovation of GPTs had been accelerating over the whole period. We start with millennia between GPTs, then centuries. In the eighteenth century there are two important GPTs, four in the nineteenth century, and seven in the twentieth.”

Despite this empirical pattern of an acceleration in the arrival rate of new GPTs, none of the previous models on GPT considers this fact: On one hand, a majority of the literature on GPTs is concerned with the lifetime of a single GPT, focussing on the impact of new GPTs on economic cycles. Examples for such models are Helpman and Trajtenberg (1998a and b), Aghion and Howitt (1998a), and Jacobs and Nahuis (2002).

On the other hand, previous models on long-term growth driven by GPTs either assume fixed time intervals between the arrival of new GPTs or a stochastic pattern with no long-term trend in either direction: Aghion and Howitt (1998b) present a Schumpeterian model in which long-term growth is driven by a sequence of innovations with an arrival rate which is proportional to the amount of labor devoted to research. Carlaw and Lipsey (2006) developed a model in which GPTs arrive one after the other, with

No.	GPT	Date
1	Domestication of plants	9000 - 8000 BC
2	Domestication of animals	8500 - 7500 BC
3	Smelting of ore	8000 - 7000 BC
4	Wheel	4000 - 3000 BC
5	Writing	3400 - 3200 BC
6	Bronze	2800 BC
7	Iron	1200 BC
8	Waterwheel	Early medieval period
9	Three-masted sailing ship	15th century
10	Printing	16th century
11	Steam engine	Late 18th to early 19th century
12	Factory system	Late 18th to early 19th century
13	Railway	Mid 19th century
14	Iron steamship	Mid 19th century
15	Internal combustion engine	Late 19th century
16	Electricity	Late 19th century
17	Motor vehicle	20th century
18	Airplane	20th century
19	Mass production, continuous process, factory	20th century
20	Computer	20th century
21	Lean production	20th century
22	Internet	20th century
23	Biotechnology	20th century
24	Nanotechnology	Sometime in the 21st century

Table 4.1: Historical GPTs as listed in Lipsey et al. (2005, p. 132)

only one GPT being active in any given period. In their model the arrival of a new GPT is governed by a constant random variable, thus the expected time interval between two GPTs remains always the same. Finally, the models by Van Zon and Kronenberg (2003 and 2006) allow for different GPTs being active simultaneously. But again the expected time interval between the arrivals of new GPTs does not reflect our stylized fact 1.

4.1.2 Stylized Fact 2: GPTs Based on Current Stock of Applied Knowledge

Isaac Newton is frequently quoted (e.g. by Scotchmer, 1991), to illustrate that even the greatest minds in history depend on already existent knowledge: "If I have seen far, it is by standing on the shoulders of giants." Just as non-radical inventions more often than not build on previously existing knowledge, all GPTs had its origins to a certain extent in already present technologies.

Even a cursory glance at some of the GPTs in the past shows this very clearly: The invention of moveable type printing by Johannes Gutenberg in the second half of the 15th century dramatically changed the way how both secular and religious knowledge was disseminated: Without this invention neither the spread of Protestant Revolution nor the diffusion of scientific knowledge beyond the walls of monasteries and early universities would have been possible at the pace observed in history. Gutenberg made the huge step away from previous methods of reproduction of written information (such as woodblock printing and the production of manuscripts on parchment) by combining a multitude of existing technologies, instead of starting from scratch (Day, 1990): The moveable types were derived from stamps used by jewelers to mark their products, while the printing press itself was modeled on the wine press. Paper already existed in his time and while not suited very well for handwritten volumes, turned out to be ideal for this new application. Furthermore ink similar to the one used for handwriting, instead of the ink used for woodblock printing was applied by Gutenberg. Altogether, despite the fact that this achievement took a great extent of ingenuity and inventive spirit, the invention of modern book printing relied heavily on previously existent applied knowledge from various sectors of the economy.

The same reasoning holds true for the steam engine, which was invented by James Watt towards the end of the 18th century. Previously steam has already been used to drive atmospheric engines, such as the Newcomen engine. Again a large part of James Watt's genius laid in combining a number of already existent technologies (Sommerscales, 1990): His steam engine still maintained the basic principle of using steam to move a piston within a cylinder, but while previous engines used atmospheric pressure to drive the power stroke, his engine used steam for this vital step. Another major improvement was that, while in earlier machines steam was condensed inside the cylinder, he added a separate condenser to cool down the steam exhausted from the piston. These two modifications to previous steam engines allowed the Watt engine to extract much larger horsepower from a machine of a given size with a significantly larger fuel efficiency. Not only did this invention heavily build on previously existing technologies, it also facilitated the birth of subsequent GPTs such as the iron steam ship, railways and ultimately the internal combustion engine and the automobile.

As a final example, the invention of the computer would have been impossible without another GPT, electricity, being already in existence. It also relied on previous practical inventions: These date back as far as the idea of storing information on punched cards, as pioneered in the form of the Jacquard loom, and ideas from the theoretical foundations on computing laid out by Alan Turing in the 1930s. Similar musings could, to various degrees, be done for all GPTs in history.

Models considering the fact that the arrival of new GPTs depends on existing knowledge are scarce: In the model of Eriksson and Lindh (2000), which is based on Helpman and Trajtenberg (1998a), a new GPT arrives as soon as the number of components under the current GPT passes a certain threshold. In Carlaw and Lipsey (2006) the size of an endogenously created pool of basic knowledge, while not affecting the arrival rate of new GPTs, influences the size of the impact of a new GPT.

The remainder of this paper is structured as follows: In Section 2 we present our theoretical model of GPT-driven endogenous growth. The main implications of our model and the results of our simulations are shown in Section 3, while we conclude and offer some outlook in Section 4.

4.2 Long-Term Growth Driven by a Sequence of GPTs

We present a Schumpeterian model of long-term growth in a quality-ladder framework, which is a discrete-time version of the model presented in Schiess and Wehrli (2008a). Whereas the original model studies the transition from an old to a new GPT and focuses on the time frame immediately before the arrival of a new GPT, the present model focuses on the long-term evolution of the economy over the lifetime of several GPTs.

The impact of a current GPT on the productivity of quality-improving R&D is subject to obsolescence. In other words, the productivity of R&D decreases over time and only the arrival of a new GPT gives a boost to the efficiency of R&D and eventually to economic growth. Hence, in our model long-term growth is sustained by the arrival of successive GPTs. The arrival of new GPTs is not exogenous, but determined by the currently available stock of applied knowledge. As a result, we can account for the fact that the time interval between the arrival of new GPTs has constantly decreased over the course of history. Together, these characteristics of our model allow for a more realistic representation of the previously mentioned stylized facts of the historical development of GPTs than the existing GPT models.

There are three sectors present in our model: The final goods sector, the intermediate goods sector and consumption. Being a quality ladder model there is a fixed number of varieties of intermediate goods, each with a corresponding current quality level. As the final good is assembled using these intermediate goods, growth in this model is driven by improvements in the quality level of intermediate goods. The aggregate amount of final goods can be used either for consumption C, as an input Z needed to perform R&D, or for intermediate goods X. In Section 4.2.1 the crucial decision of intermediate firms over the amount of R&D expenditures is explained in detail. Section 4.2.2 explains the final goods sector and consumption. Finally, the model equilibrium is presented in Section 4.2.3.

4.2.1 Determinants of R&D Expenditures

An intermediate goods firm can make R&D expenditures $Z(\kappa_j, t)$ in an intermediate goods sector j with the current quality level κ_j in order to attempt to invent a good with an even higher quality $\kappa_j + 1$. If such an intermediate goods firm succeeds in inventing a new quality in this sector, it will displace the previous monopolist and henceforth hold the monopoly on this variety of intermediate good. In a Schumpeterian fashion, it will hold this monopoly (therefore reaping monopoly profits by selling this variety of intermediate good to the final goods sector according to the demand function in each period) until it is displaced by yet another successful intermediate goods firm. This process of continuous innovations leads to an increase in the quality of available goods, thereby driving economic growth.

To find the optimal amount of $Z(\kappa_j, t)$ an individual intermediate goods firm has to take into account two main determinants: First it needs to consider the probability of having a research success in relation to its R&D expenditures. Second, it needs to build expectations on its payoff in case of having a research success.

Probability of a Research Success

The probability of a research success $p(\kappa_j, t)$ is given by the following equation:

$$p(\kappa_j, t) = Z(\kappa_j, t)\phi(\kappa_j)B(t) \tag{4.1}$$

The currently active GPT $B(t)$ positively influences the probability of a research success. This is modeled according to the notion that GPTs do not directly influence the efficiency of final goods production, but rather allow for an increase in R&D efficiency (see for example Jacobs and Nahuis, 2002). The evolution of $B(t)$ over the course of a single GPT, which is subject to obsolescence, and over a succession of GPTs will be presented in detail in Section 4.2.1.

Furthermore, equation (4.1) captures the effect that a higher amount of R&D expenditures $Z(\kappa_j, t)$ increases the probability of a research success. Finally $\phi(\kappa_j)$ is a parameter, which captures the difficulty of doing R&D especially in relation of the quality the R&D firm wants to improve upon. This difficulty parameter $\phi(\kappa_j)$ is given by:

$$\phi(\kappa_j) = \left(\frac{1 - p(\kappa_j)}{\zeta}\right) q^{-(\kappa_j+1)\alpha/(1-\alpha)} \tag{4.2}$$

The difficulty of performing R&D in a sector with the current quality level κ_j is therefore determined by three factors: First, there is a constant cost parameter ζ. Second, there is an increase of difficulty of R&D, which rises with the quality of the variety of the intermediate good it wants to improve upon. This is given by the expression $q^{-(\kappa_j+1)\alpha/(1-\alpha)}$. Third $\phi(\kappa_j)$ contains decreasing returns to current R&D, e.g. due to duplication, captured by the negative effect of $p(\kappa_j)$.

Arrival of new GPTs

In order to capture some of the stylized facts on the course of individual GPTs and the arrival of new GPTs in history, we model $B(t)$ as follows: At the moment when a new GPT arrives, $B(t)$ starts off with a level of $\overline{B}$ and subsequently depreciates with a rate d in every period. This process continues until a new GPT arrives, so that $B(t)$ jumps back to $\overline{B}$. The arrival of a new GPT is governed by a poisson process. Accordingly, the current $B(t)$ is given by the following set of equations:

$$B(t) = \begin{cases} (1-d)B(t-1) & if \quad a(t-1) = 0 \\ \overline{B} & if \quad a(t-1) \geq 1 \end{cases} \tag{4.3}$$

where $a(t)$ is drawn according to a Poisson process with the mean $\lambda(t)$ of the Poisson distribution given by:

$$\lambda(t) = \frac{\varphi Q(t-1)}{B(t-1)} \tag{4.4}$$

where $0 < \varphi < 1$.

This specification of the Poisson distribution captures several stylized facts on the long-term evolution of GPTs. The fact that the arrival of new GPTs is facilitated by the amount of currently available applied knowledge is accounted for by the inclusion of the aggregate quality index Q in this equation: A larger amount of applied knowledge as measured by Q increases the probability of a new GPT arriving. Contrarily, the fact that $B(t-1)$ negatively affects the probability of arrival of a new GPT leads to an initial drop in λ upon the arrival of a new GPT. Afterwards, as $B(t)$ is constantly decreasing, λ rises again. This behaviour is consistent with features of other GPT models, where the arrival of a new GPT initially binds significant R&D resources for exploring the possibilities offered by the new GPT. In the example in Carlaw and Lipsey (2006), the arrival of a new GPT leads to a drop in basic research which in their model is vital for new GPTs. Afterwards the amount of basic research increases again over the lifetime of the GPT.

While of course both Q and B constantly change, the behaviour of λ over time can be nicely illustrated by deriving the expected time until the arrival of a new GPT. This is given by the waiting time distribution of the above defined Poisson process with rate λ. The expected time T one must wait until the next GPT arrives is given by the following cumulative distribution:[1]

$$F(t) = P(T \leq t) = 1 - e^{-\lambda t} \tag{4.5}$$

By differentiating equation (4.5) we derive a density function with mean:

$$E(T) = \frac{1}{\lambda} \tag{4.6}$$

[1] This equation can be derived by using the fact that $P(T > t) = e^{-\lambda t}$ following from the Poisson distribution and the use of the complement rule.

And finally together with equation (4.4):

$$E(T) = \frac{B(t-1)}{\varphi Q(t-1)} \tag{4.7}$$

As can be seen in equation (4.7) the higher the quality index Q, the shorter is the expected waiting time for a new GPT. Additionally, there is also a cyclical component during the lifetime of an individual GPT: While initially, there is an increase in the expected waiting time, it gets gradually lower in the course of a GPT, as the current $B(t)$ gradually drops from the initial $\overline{B}$.

Expected Profits

Another main determinant of the amount of R&D performed is the expected profit in case of a research success $E[V(\kappa_{j+1})]$. In determining the amount of information the R&D firms have, we basically follow the line of reasoning of Carlaw and Lipsey (2006): They argue that it is impossible for agents to predict either the development of a single GPT or the exact time of arrival of a new GPT. Due to this uncertainty, the assumption of perfect foresight taken in the majority of growth models cannot be sustained. Carlaw and Lipsey therefore propose two possible ways how agents maximise their utility in each period recursively: One approach would be that agents are not forward looking at all, therefore only considering the marginal products of the current period and maximizing solely their current profit. Another possibility is that, while agents are forward looking, they simply assume that marginal products across all sectors remain constant at the level currently observed and maximise accordingly in every period over an infinite time horizon.

While Carlaw and Lipsey (2006) chose the first approach for their own model, we use the second approach: Applied to our model this basically means that R&D firms expect that the current equilibrium levels of the interest rate r and of the probability of a research success p apply for the whole future.[2] The profit flow per period of an innovator possessing the leading-edge technology is given by:

$$\pi(\kappa_j) = \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} \tag{4.8}$$

[2]Therefore they implicitly also assume that no new GPT arrives over the whole lifetime of their products, i.e. that $a(t)$ is always 0.

where $\overline{\pi}$ is the basic profit flow, which is constant over time due to the fact that A and L in final goods production are constant:

$$\overline{\pi} = \left(\frac{1-\alpha}{\alpha}\right) A^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} L \tag{4.9}$$

The profits of inventors $\pi(\kappa_j)$ increase with the quality level κ_j of the variety of an intermediate good due to the higher demand for intermediate goods of a higher quality level from the final goods sector, as we will see in the demand function, which will be derived in Section 4.2.2.

The incumbent monopolist can reap the monopoly profit $\pi(\kappa_j)$ in every period until it is displaced by an intermediate goods firm inventing an even higher quality. The current probability that the monopolist with a good of quality κ_j remains in the market is therefore given by $1 - p(\kappa_j)$. Additionally, future profits are discounted according to the current interest rate r. As intermediate goods firms assume that both the interest rate and the probability of a research success remain constant over time, the expected profit of a monopolist is given by:

$$\overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} + \left(\frac{1-p(\kappa_j)}{1+r}\right) \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} + \left(\frac{1-p(\kappa_j)}{1+r}\right)^2 \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} + ... + \left(\frac{1-p(\kappa_j)}{1+r}\right)^n \overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}} \tag{4.10}$$

Since this is a geometric series, by taking the limit n $\to \infty$ this simplifies to:

$$E[V(\kappa_j)] = \frac{\overline{\pi} q^{\frac{\kappa_j \alpha}{1-\alpha}}}{r + p(\kappa_j)} \tag{4.11}$$

The interpretation of this expression is straightforward: The expected profit from a successful innovation rises with its quality level due to the higher demand for higher quality intermediate goods. Contrarily, both a higher discount rate and a higher probability of being displaced by a future competitor lower the expected profit.

4.2.2 Final Goods Sector and Consumers

In the final goods sector an amount of Y_i of a final good i is produced using a constant technology A and labor L_i according to the following production function:[3]

$$Y_i = A L_i^{1-\alpha} \sum_{j=1}^{N} (\tilde{X}_{ij})^{\alpha} \tag{4.12}$$

[3]The derivation of the equation in this section follows closely the approach in Schiess and Wehrli (2008a).

where $0 < \alpha < 1$.

The number of varieties of intermediate goods is given by the fixed number N. The fact that each of these varieties of intermediate goods has a specific quality level is reflected in the following equation:

$$\tilde{X}_{ij} = q^{\kappa_j} X_{ij} \tag{4.13}$$

X_{ij} is the physical amount of an intermediate good, while $q^{\kappa_j} > 1$ is the highest quality in which this intermediate good is currently available.

The final goods firms, operating under perfect competition, only demand the highest quality available in each sector, as in Barro and Sala-i-Martin (2004).[4] This leads to the following aggregate demand equation:

$$X_j = L(A\alpha q^{\alpha\kappa_j}/P_j)^{1/(1-\alpha)} \tag{4.14}$$

Intermediate goods firms hold a monopoly on their goods, selling them to the final goods sector with a monopoly markup. They set the price as $P_j = \frac{1}{\alpha}$. Faced with the aggregate demand function (4.14), intermediate goods firms provide the following amount of an intermediate good X_j:

$$X_j = LA^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} q^{\kappa_j \frac{\alpha}{1-\alpha}} \tag{4.15}$$

Aggregating across all final goods firms and assuming a fixed aggregate amount of labor L we get the following aggregate amount of intermediate goods X and of final goods Y:

$$X = A^{\frac{1}{1-\alpha}} \alpha^{\frac{2}{1-\alpha}} LQ \tag{4.16}$$

$$Y = A^{\frac{1}{1-\alpha}} \alpha^{\frac{2\alpha}{1-\alpha}} LQ \tag{4.17}$$

The aggregate quality index Q is given by the following equation:

$$Q \equiv \sum_{j=1}^{N} q^{\kappa_j \alpha/(1-\alpha)} \tag{4.18}$$

[4]Barro and Sala-i-Martin (2004) show in the appendix of chapter 7 that even if the implicit assumptions that back the result of only the highest quality available being demanded are not satisfied, the general nature of the results remain the same.

By the summation of the highest available quality in each intermediate goods sector, the quality index Q gives an accurate representation of the current technological level of the economy. For this reason Q is used as an indicator of the currently available applied knowledge stock.

Consumers, representing the third sector of our model, derive utility from consumption as given by:

$$U = \int_0^\infty u(c(t))e^{-\rho t} dt \tag{4.19}$$

and optimise their consumption path as determined by the following Euler-equation:

$$\frac{\dot{C}}{C} = (1/\theta)(r - \rho) \tag{4.20}$$

Ultimately the consumption sector is used to close the model, once equilibrium production and R&D expenditures are determined.

4.2.3 Model Equilibrium

Assuming free entry in the intermediate goods sector we can now find the optimal amount of R&D expenditures $Z(\kappa_j, t)$, by equalizing the expected payoff of such an investment with the according probability of having a research success $p(\kappa_j, t)$ multiplied by the expected monopoly profit associated with inventing an intermediate good of higher quality, $E[V(\kappa_{j+1}, t)] * p(\kappa_j, t)$. Therefore the free entry condition is given by:

$$Z(\kappa_j, t)(\phi(\kappa_j)B(t)E[V(\kappa_{j+1}, t)] - 1) = 0 \tag{4.21}$$

In order to find the equilibrium aggregate research expenditures we insert the expected profit from having a research success given by equation (4.11) together with the difficulty of performing R&D (4.2) into this free entry condition. This allows us to solve for the probability of having a research success, which is given by:

$$p(t) = \frac{\overline{\pi}B(t) - r(t)\zeta}{\zeta + \overline{\pi}B(t)} \tag{4.22}$$

As this equation is independent of the quality level in a specific sector, research expenditures are uniformly distributed among all intermediate goods sectors. By inserting this equation into the probability of having a research success as given by equation

(4.1) we can derive the R&D expenditures in a specific sector j and then aggregate across all intermediate goods sectors. This results in the following amount of aggregate R&D expenditures:

$$Z(t) = \sum_{j=1}^{N} Z(\kappa_j, t) = \frac{q^{\frac{\alpha}{1-\alpha}} Q(t)(\overline{\pi}B(t) - r(t)\zeta)}{1 + r(t)} \tag{4.23}$$

As elaborated in our baseline quality-ladder model (Schiess and Wehrli, 2008a) output growth is proportional to the expected proportional change of the quality index Q. Therefore we can use equation (4.22) together with the Euler equation (4.20) to derive the equilibrium growth rate $\gamma(t)$ and the interest rate $r(t)$ at a moment in time:

$$\gamma(t) = \frac{(q^{\frac{\alpha}{1-\alpha}} - 1)(\overline{\pi}B(t) - \rho\zeta)}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi}B(t)} \tag{4.24}$$

$$r(t) = \frac{\theta\overline{\pi}B(t)(q^{\frac{\alpha}{1-\alpha}} - 1) + \rho(\zeta + \overline{\pi}B(t))}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi}B(t)} \tag{4.25}$$

Finally, by inserting equation (4.25) into equation (4.22) the following expression for $p(t)$ can be derived:

$$p(t) = \frac{\overline{\pi}B(t) - \rho\zeta}{\theta\zeta(q^{\frac{\alpha}{1-\alpha}} - 1) + \zeta + \overline{\pi}B(t)} \tag{4.26}$$

While these equations allow us to determine γ, r and p at a point of time, long-term economic dynamics are driven by a sequence of GPTs, the arrival of which is stochastic, despite the fact that the probability of such an event is endogenous to the model. These long-term dynamics are described in the next Section.

4.3 Model Behaviour and Numerical Simulations

The qualitative dynamics of our model arising from the previous equations are as follows: In the short-term, GPTs cause a cyclical behaviour of the economy. This is characterised by an increase in the growth rate immediately after the arrival of a new GPT and a subsequent decrease over the lifetime of a single GPT. The initial increase is caused by the rise of the efficiency of R&D due to the new GPT. This leads to an increase in R&D activities in the intermediate goods sector, which in turn leads to a larger growth rate. Due to the decrease of R&D efficiency in every period without the arrival of a new GPT, characterised by the decrease in $B(t)$, R&D becomes gradually less attractive between the arrivals of two GPTs. This contributes to a decrease in growth rates in the economy over the lifetime of a single GPT. Therefore, from a long-term perspective, growth is only sustained by the continuing arrival of new GPTs, which revive the growth process by leading to another increase in R&D activities.

Our second stylized fact, that the arrival of new GPTs depends on the available pool of applied knowledge, is modeled through the dependence of the poisson process determining the arrival of new GPTs on the available knowledge stock in equation (4.4). This leads to the result that, as the available amount of applied knowledge measured by the aggregate quality index Q increases, the frequency of arrivals of new GPTs increases as well. Hence, by only considering the second stylized fact we obtain, as a result, the first stylized fact of an ever increasing frequency.

To illustrate this behaviour, we now simulate our model numerically and define one period as being equivalent to one year. Simulations are also used by van Zon et al. (2003 and 2006) and Carlaw and Lipsey (2006) to show the long-term economic development driven by a sequence of GPTs. Unlike in our model, they cannot account for the observed increase in the frequency at which new GPTs arrive. Carlaw and Lipsey (2006) calibrate their model to a constant expected time interval of 30 years between GPTs, while Van Zon et al. (2003 and 2006) take arbitrary parameter values for their numerical simulations. In Van Zon et al. (2003) 14 GPTs arrive during a period of 300 years, whereas already six GPTs are invented after the first 50 years. In Van Zon et al. (2006), 14 GPTs are found after 200 years, which is closer to the historical reality. However, after 40 years, there are already six GPTs active.

We calibrate our model to cover the historical arrival of new GPTs over the past two centuries, i.e. the years from 1809 until 2008 AD. We again refer to the list of GPTs by Lipsey et al. (2005) shown in Table 4.1. According to their list in the 19th century four GPTs appeared (in the order of their appearance: railway; iron steamship; internal combustion engine; electricity) while in the 20th century seven GPTs arose (in the order of their appearance: motor vehicle; airplane; mass production, continuous process, factory; computer; lean production; internet; biotechnology). Therefore the targeted number of GPTs arriving during the 200 years covered by our simulation is taken as approximately 11. The targeted growth rate in the final period of our simulation corresponds to the average growth rate of the OECD economy in 2008, which is at 2.9% (OECD, 2008).

α	0.3
θ	0.2
ρ	0.03
ζ	5
d	0.05
A	15
L	2
$B(1)$	1.3
$\overline{B}$	2
$Q(1)$	1
q	1.1

Table 4.2: Parameters used for Numerical Solution

The parameter values used in our simulations are shown in Table 4.2. The initial value of Q, i.e. $Q(1)$, is set to 1. The values for α, θ and ϕ are chosen to be within the value range usually found in the literature. Furthermore $B(1)$ is assumed to be 1.3 with a $\overline{B}$ of 2. The other parameters are used to calibrate the model in order to achieve the previously stated properties. To do so we have chosen the values so that in the average of one thousand simulation runs the desired growth rate and arrival rate of GPTs is achieved. We thereby follow an approach which is widely used in the simulation of business cycle models, for example in Jaimovich and Rebelo (2006).

The number of GPT generations arriving over a time period of 200 years resulting from a total of 1000 simulation runs, are shown in Figure 4.1. The thin lines show the results of individual simulation runs, while the bold line represents the average vintage of GPTs taken over all simulations. It becomes obvious that our model can be calibrated in a way that can realistically depict both the absolute number of GPTs invented in the past 200 years and their approximate arrival rate. The acceleration of the arrival of new GPTs is also mirrored by our model. Interestingly, while we can chose the parameters so that in terms of expected values, the historical development of the various GPTs can be approximated, there is a wide spread of other scenarios using the very same values. The number of GPTs invented during the time frame of

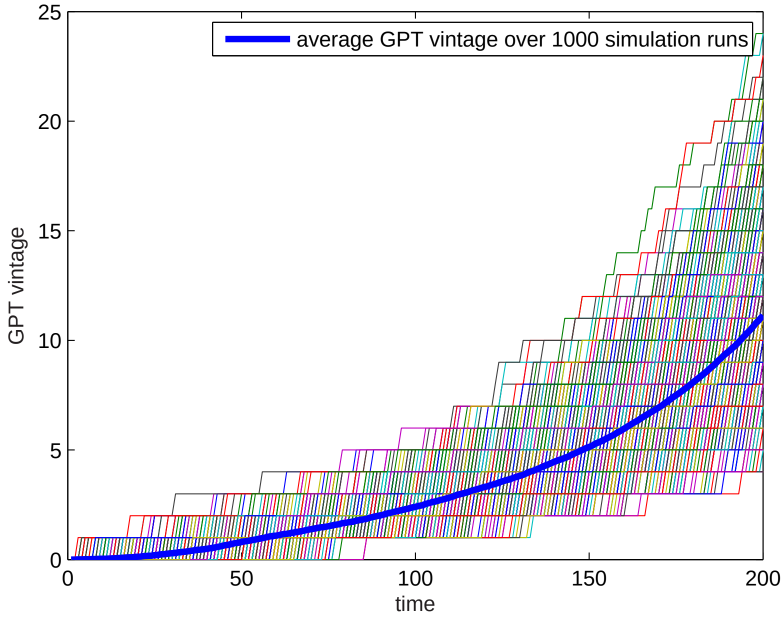

Figure 4.1: GPT Vintage in the 1000 Simulation Runs

our simulation ranges from 4 to 24. This illustrates that, given that long-term growth is driven by the arrival of subsequent GPTs, the outcome is still highly stochastic.

Growth cycles triggered by the repeated arrival of new GPTs are shown in Figure 4.2 for five different simulation runs. The Figure shows two typical patterns: First, the arrival of a new GPT gives a boost to growth, as it mitigates the decreasing returns of R&D over time within a single GPT generation. Therefore, the arrival of a new GPT can be seen in Figure 4.2 as a jump of the growth rate that is followed by decreasing growth rates. Second, the amplitude of the cycles is decreasing due to the ever shorter time intervals between the arrival of two subsequent GPTs. At the start of the period, growth reached very low levels such as 0.5%, whereas at the end of the simulated period growth stops to fall earlier.

The development of R&D expenditures is equally interesting: Just as economic growth, R&D shows a cyclical behaviour which is subject to the arrival of new GPTs. More R&D is undertaken directly after the arrival of a new GPT since a new GPT increases the marginal productivity of R&D and makes it therefore attractive for firms to use their resources for R&D. Furthermore an increase of R&D expenditures can be observed

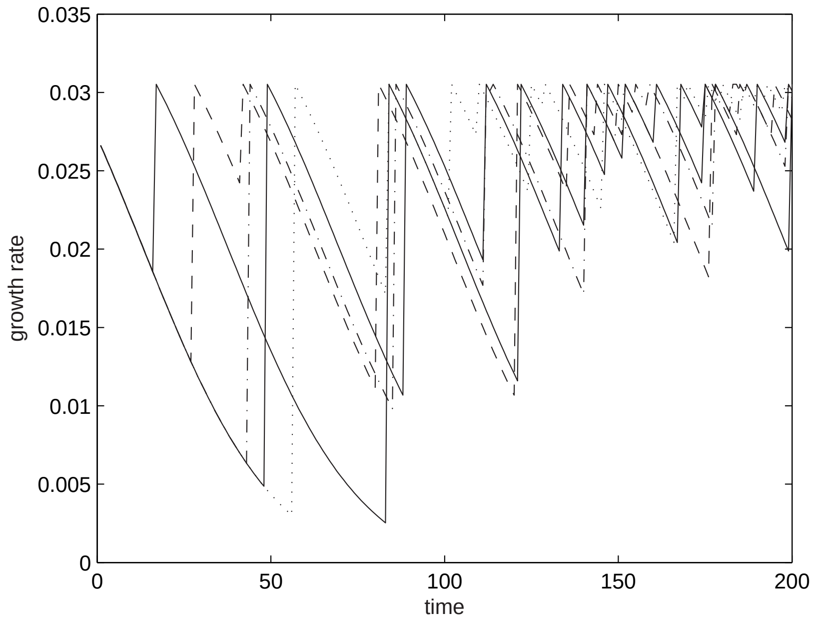

Figure 4.2: Growth Rate

as general trend over time.

4.4 Conclusions and Outlook

We have presented a quality ladder model of endogenous Schumpeterian growth in which GPTs increase the efficiency of R&D in the intermediate goods sector. This model allows for a more realistic description of the historical facts surrounding the emergence of new GPTs and the frequency of their arrival, which state that new GPTs arise in an ever higher frequency. The stochastic arrival of new GPTs depends positively on the currently available amount of applied knowledge. This way of modeling the arrival of new GPTs mirrors another historical stylized fact: All GPTs heavily depended on previous technologies and on existing knowledge.

The representation of the two mentioned stylized facts drawn from economic history in a model of long-term economic development is unique in the existing GPT literature. However, there are of course several possibilities for future extensions. One way to enrich our model would be to introduce a basic research sector, which unlike the R&D

in the intermediate goods sector would be explicitly devoted to research aiming at the invention of new GPTs. This would furthermore allow for a role of government funded R&D, as private firms have a low incentive to perform such basic R&D due to the fact that returns on new GPTs are hard to appropriate. Finally, a future model could consider that an ever increasing number of GPTs arriving could compete for scarce R&D resources, thereby partially offsetting the beneficial effects of these “engines of growth”.

Chapter 5

General Purpose Technologies and R&D Expenditures: An Empirical Study

This study uses single equation estimations and a system of simultaneous equations using three-stage least squares with a panel of 19 OECD countries over the time period 1981 - 2004 to test hypotheses on the behaviour of different types of R&D expenditures during the diffusion of a General Purpose Technology (GPT). We find that per capita R&D expenditures increase and the share of basic R&D expenditures decreases during the diffusion process. This indicates that basic R&D is the basis for applied R&D on a new GPT to be productive.

5.1 Introduction

The personal computer (PC) and the internet are large breakthrough technologies that have changed our daily life and the working process dramatically and have increased the productivity. Gruber (2001) shows that information technology (IT) intensity and business R&D intensity are correlated in Europe and that IT firms are the main R&D spenders together with the pharmaceutical industry. A close look at the R&D expenditures over time reveals that R&D expenditures have been rapidly increasing after the introduction of the PC by IBM in 1981, with the share of basic R&D expenditures being rather volatile. This study tests if these increases are really due to the diffusion of new breakthrough technologies which qualify as General Purpose Technologies (GPTs) and examines the causes of the volatility of the share of basic R&D expenditures.

GPTs are characterised by an inherent capacity for technological improvement, giving rise to many complementarities which bring about increasing returns to scale (Bresnahan and Trajtenberg, 1995). The first models with GPTs were developed by Bresnahan and Trajtenberg (1995) and Helpman and Trajtenberg (1998a and 1998b). In their models and most subsequent ones, productivity normally slows down immediately after an arrival of a new GPT, before the economy continues to grow on a higher scale, because users and producers first have to adapt to the new technology. This adaption is mostly done by reallocating resources to the R&D sector, which leads to increases in R&D expenditures after the arrival of a new GPT and decreases once the new technology can be fully applied in the economy, i.e. once the diffusion process has stopped. Although this pattern is quite intuitive, it has not yet been confirmed by larger empirical studies.

Jovanovic and Rousseau (2005) present the broadest empirical study on GPTs. They discuss the identifying points of a GPT and test them empirically for electricity and information technology (IT). They conclude that both qualify as GPTs and that computers are clearly the most revolutionary GPT. However, they do not study the impact of a GPT on research and development.

Beyond explaining the increase in R&D expenditures the question arises why R&D expenditures are so volatile. Normally, the distinction between basic and applied R&D

is not made in endogenous growth theory and there are only a few models that consider it.[1] In Evenson and Kislev (1976) and Malla and Gray (2005), basic R&D increases or maintains the productivity of applied R&D, whereas in the model of Carlaw and Lipsey (2006) the purpose of basic R&D is to find a new GPT. In the latter model, the productivity of applied R&D relative to basic R&D increases after the arrival of a new GPT and therefore the share of basic R&D falls straight after the arrival of a new GPT. Over time the productivity of applied R&D decreases because the largest possible complementary innovations are found, and the share of basic R&D increases again until a new GPT arrives.

To answer the questions posed above, this study checks three main hypotheses: First, it is tested if per capita R&D expenditures increase after the arrival and during the first part of the diffusion process of a new GPT. Second, we examine the behaviour of the share of basic R&D expenditures. The effect of the diffusion of a GPT is from a theoretical point of view not clear: The share is expected to decrease during the diffusion of a GPT if basic R&D is needed as basis for applied R&D, because after the arrival of a new GPT a new fundamental knowledge base has to be accumulated in order to make applied R&D on the new GPT more productive. The share of basic R&D is expected to increase if the purpose of basic R&D is to find new GPTs, as in the model of Carlaw and Lipsey (2006). Third, higher R&D expenditures, GDP per capita, human capital, and greater openness of the economy are expected to enhance the diffusion of a GPT.

PCs and the internet are chosen as the GPTs to be studied in this empirical estimation over the time period 1981 - 2004 because Jovanovic and Rousseau (2005) show that computer technology is the most prevalent technology for which data is widely available.

Thanks to the estimations related to the first two hypotheses, we gain some new insights concerning the reaction of different types of R&D during the diffusion of a new GPT that can be employed in future theoretical modeling. We find that per capita R&D expenditures increase during the diffusion process of a GPT, and that the share of basic R&D expenditures decreases, which is a unique result that has not been found before.

[1]See for example Schneller (2008) for an overview of models that explicitly consider basic R&D.

We are also adding some new insights to the empirical literature on technology diffusion by testing the third hypothesis with data on the diffusion of PCs and the internet. In contrast to Chinn and Fairlie (2004) who present estimations for the very short period from 1999 - 2001, Vicente and Lopez (2006) who only had data for 2002, and Kiiski and Pohjola (2002) with data from 1995 - 2000, we are looking at a much longer time horizon in our estimations. The only study of the diffusion of computer technology that also considers a long time horizon is the paper of Caselli and Coleman (2001). Additionally to their study, we are adding to the literature by including R&D expenditures and using a system of simultaneous equations.

The remainder of the paper is structured as follows: In Section 5.2 the main hypotheses for the estimations are presented. The data is described in Section 5.3. The estimations and results are shown in Section 5.4. We are fist estimating single equation estimations on per capita R&D expenditures, the share of basic R&D expenditures and the diffusion of a GPT in order to test separately the different hypotheses in Section 5.4.1. Second, the main results of three-stage least square estimations that take the endogeneity of some variables and the inherent multicollinearity into account are presented in Section 5.4.2. Section 5.5 concludes.

5.2 Hypotheses

Several hypotheses are tested with different empirical methods. The three main hypotheses and an additional hypothesis on human capital are presented in this Section.

5.2.1 R&D Expenditures

With the advent of a new GPT, the economy has to adapt to the new technology and firms therefore increase their R&D expenditures. In the model of Helpman and Trajtenberg (1998a) innovators in the R&D sector have to first find a certain amount of complementary components to the new GPT so that it can be used to produce final output. Aghion and Howitt (1998a) have a similar mechanism: Firms have to acquire so-called "templates" through the innovation process in order to build new intermediate goods based on the new GPT. Jacobs and Nahuis (2002) state that "a GPT [...] affects the marginal productivity of research as it opens new opportunities for knowledge-creating activities throughout the economy." Therefore, research expenditures increase due to their higher profitability after the arrival of a GPT. R&D expenditures show the same behaviour after the arrival of a GPT in the model of Schiess and Wehrli (2008a). The focus in their paper lies on the period before the new GPT arrives. They find that once people anticipate the arrival of a new GPT, R&D expenditures fall a short time before the arrival. But before this slump, R&D expenditures rise over the level of the old steady state. In this paper we are concentrating on the time after the arrival of a GPT because we do not have sufficient data to test any hypothesis about the behaviour of R&D expenditures before the arrival. Our hypothesis following from the literature discussed above is that R&D expenditures should rise after the arrival of a GPT.[2]

Hypothesis 1: Per capita R&D expenditures increase after the arrival and during the first period of the diffusion process of a new GPT.

R&D expenditures increased over time for most of the countries included in the sample at hand, as can be seen from Figure 5.1, where five countries with the highest R&D expenditures (France, Italy, Japan, Korea and the United States) are shown, and from Figure 5.2 for the other countries in our panel. Interestingly, the countries with decreasing R&D expenditures are all from Eastern Europe: in the Czech Republic, the R&D expenditures decrease from 2455 million $ in 1991 to 2159 million $ in 2004, in Hungary from 2001 million $ in 1990 to 1660 million $ in 2001 and in the Slovak Republic from 204 million $ in 1994 to very low 118 million $ in 2004, i.e. they had a decrease of 58% over 10 years! These decreases are due to the economic transition and reorientation after the collapse of the Soviet Union. Poland is the only Eastern European exception that shows increasing R&D expenditures during that time period.

The first micro computer was "MITS/Altair", which was introduced by big success and drove out competing alternatives (Langlois, 2002). In the time directly after 1981, R&D expenditures increased and in some countries, as for example in the United States in Figure 5.1, even increased faster. The rise of the internet as the dominant network

[2] See Wehrli and Saxby (2008) for a more detailed literature review.

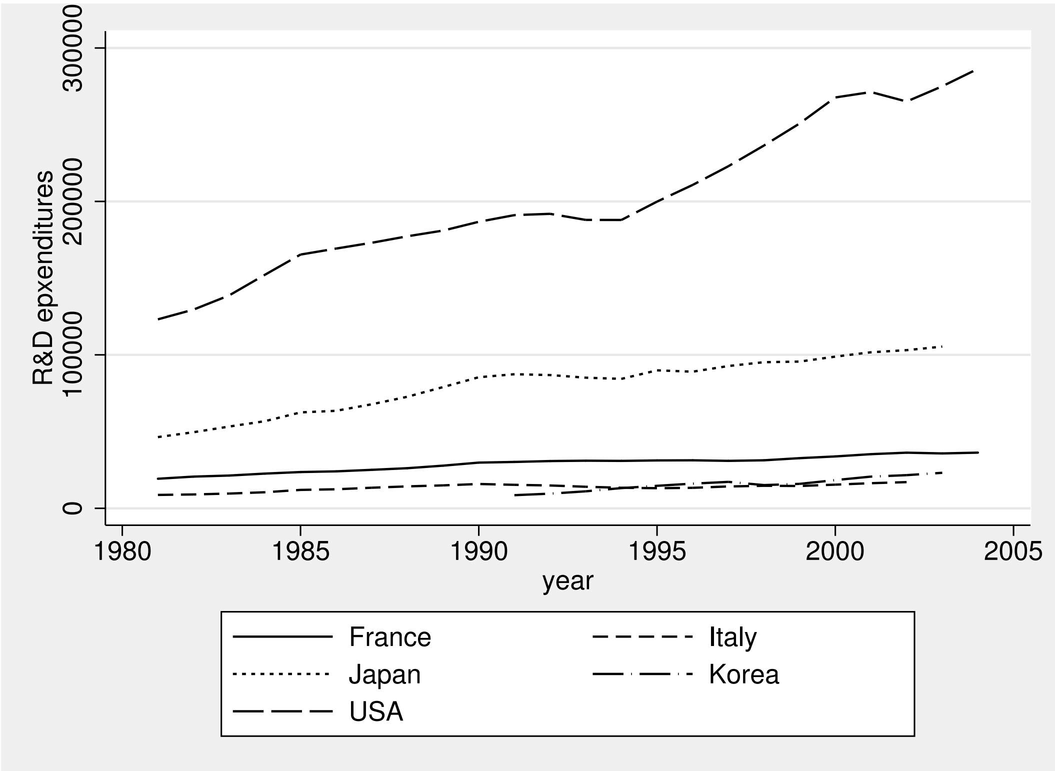

Figure 5.1: R&D Expenditures

started after the invention of the World Wide Web (WWW) with the diffusion of the first graphics-capable webbrowser “Mosaic” in 1993. If we look again at the United States, which were the first to adopt the internet, in Figure 5.1, we see that R&D expenditures increase faster than before 1993. The same is found for most of the western countries in Figure 5.1 and 5.2.

Guellec and Ioannidis (1997) examine possible causes of R&D expenditure fluctuations empirically. They use a panel of 12 OECD countries over the time period 1972 - 1996 and find that GDP plays the most significant role in explaining R&D expenditures in both the long and the short run. The higher the GDP the higher are the R&D expenditures. Government funding of research is found to have a positive effect. This view has been refined in Guellec and Van Pottelsberghe de la Potterie (2003). Fiscal incentives and direct funding of R&D stimulate business-funded R&D, but research done by the governmental sector has a negative effect, and research performed by the high education sector has no impact. The negative impact of government-performed research is mainly caused by the negative impact of its defence component. In this

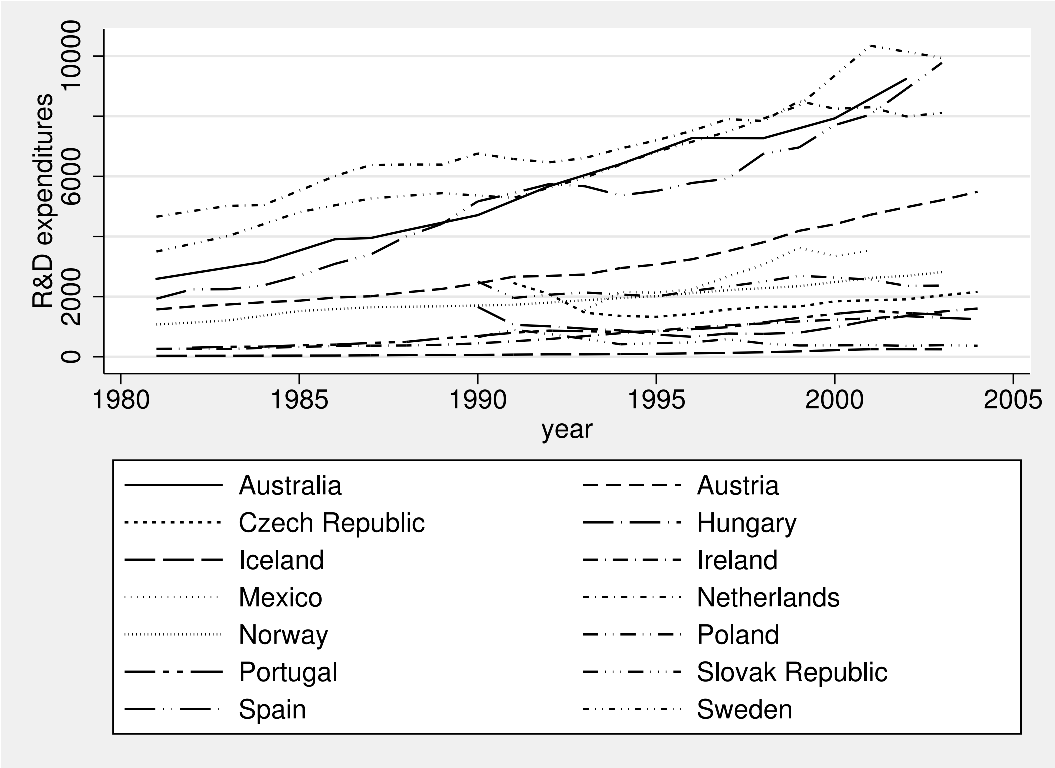

Figure 5.2: R&D Expenditures

paper we are only testing Guellec and Ioannidis' first main result on GDP, because our variable of interest is total R&D expenditures and not only business or public R&D expenditures.

5.2.2 The Share of Basic R&D Expenditures

Basic and applied R&D expenditures are distinguished according to the following definitions in the Frascati Manual (OECD, 1993): "Basic research is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any particular application or use in view. Applied research is original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific practical aim or objective." They differ also in the time horizon. The potential rewards of basic research are more in the long term, whereas the rewards of applied research are mostly realized in the short term. Since there is no particular application in view, the outcome of basic R&D expenditures is more uncertain. It can normally only be seen at a late stage of a basic R&D project if its results are useful. Moreover, basic R&D is often a prerequisite for maintaining or increasing the profitability of applied research (Malla and Gray, 2005). The return of basic research is therefore often hard to measure or can only be recognized after applied R&D has been undertaken, and after some time has passed.

Most endogenous growth models do not distinguish between basic and applied research, and there is only a small literature on the influence of the arrival and/or diffusion of a new GPT on the different types of R&D. There are good reasons to expect the share of basic R&D to increase during the diffusion process, as well as for it to decrease.

Evenson and Kislev (1976) were among the first to build a theoretical model that distinguishes between basic and applied research. Applied research is viewed as a search in a given distribution and basic research shifts this distribution. The applied scientists perform tests and each trial results in an observation which is drawn from a random given distribution. The parameters of the distribution are not affected by the work of the applied scientist, but by basic researchers who discover new technologies represented by the opening up of new exponential distributions for the search of the applied scientists. It follows from this model that we expect lagged basic R&D expenditures to positively influence applied R&D expenditures since "technological research is filling a gap between basic knowledge and the level of technology in practice" (Evenson and Kislev, 1976, p. 272). Evenson and Kislev's finding is supported by Malla and Gray (2005) who build a related model. They test their hypothesis empirically with data from the agricultural biotech industry in Canada and find that there are "diminishing returns to the experimental search process. [...] This implies that basic research is required to maintain the profitability of applied research" (Malla and Gray, 2005. p. 435). Guellec and Van Pottelsberghe de la Potterie (2001, 2004) find the same results empirically by taking public R&D in their 2004 paper as a proxy for basic R&D, and Griliches (1995), Mansfield (1980) and Link (1981) all find a significant premium on basic research.

In the model of Evenson and Kislev (1976), basic R&D has a similar impact as a GPT in theoretical models on GPTs, as for example in Jacobs and Nahuis (2002) or Schiess and

Wehrli (2008a). In these models with only one homogenous type of R&D, a GPT opens new opportunities for R&D due to the higher probability of research success caused by the new GPT generation. Therefore, the arrival of a GPT increases the productivity of R&D. If the only purpose of basic R&D is to increase the productivity of applied R&D, one could expect that there will be less basic R&D after the arrival of a new GPT because the GPT itself brings an increase in the productivity of applied research. So there is not an immediate need to raise the productivity of applied R&D through basic R&D after the arrival of a new GPT. Applied R&D becomes less productive some time after the arrival because the most obvious inventions with the new GPT have been found, and basic R&D expenditures might rise again. Our expectation following from this strand of literature is therefore that the share of basic R&D expenditures should rise during the diffusion of a GPT.

This hypothesis is strengthened by the GPT-model of Carlaw and Lipsey (2006). In their model, the agents allocate resources between three sectors (consumption, applied and basic research) by maximizing the expectations about the current marginal productivities of consumption output, applied research (i.e. developing applications of the GPTs to specific purposes), and basic research (i.e. searching for the next GPT). The arrival of a new GPT increases the productivity of applied R&D relative to basic R&D. This leads to an increase in applied R&D expenditures and a decrease in basic R&D expenditures. Applied R&D expenditures cannot increase without crowding out basic R&D expenditures because the R&D budget is limited and cannot be expanded on a large scale, since most R&D is financed through cash-flow and not through debt. Rafferty (2003) calls this the cash-flow effect.

The definitions of R&D expenditures as presented above are close to the definitions of inputs for GPTs and its complements from Bresnahan and Trajtenberg (1995), where the single, perpetual GPT is owned by a monopolist, who optimally chooses how fast to improve its general productivity, while users of the GPT in the application sectors choose how fast to improve their own specific application of that GPT. In this context, one could interpret basic R&D as expenditures undertaken in order to find new GPTs, and applied R&D as expenditures to implement a GPT, i.e. to find or improve an application of an existing GPT, so that the hypothesis of an increasing share of basic R&D is supported. We are sceptical about this interpretation and also about the names of the different R&D types in the model of Carlaw and Lipsey (2006), because these definitions do not necessarily coincide with the definitions from OECD (1993), since basic research is not only done to find new GPTs, but also to gain new knowledge for technologies that are far more limited and will never turn into a GPT.

The crucial question is if basic R&D is needed to establish a GPT-specific foundation for applied R&D to be productive, or if the GPT establishes this foundation by itself without requiring inputs from basic R&D. If basic R&D is needed to exploit the potential productivity gains in research and/or production from the new GPT, then the share of basic R&D expenditures should increase immediately after the arrival of a GPT, and decrease thereafter during the diffusion process.

Hypothesis 2: The share of basic R&D expenditures is expected to decrease during the diffusion of a GPT if it is needed to set the basis for applied R&D expenditures, and to increase if it is needed to develop the next GPT.

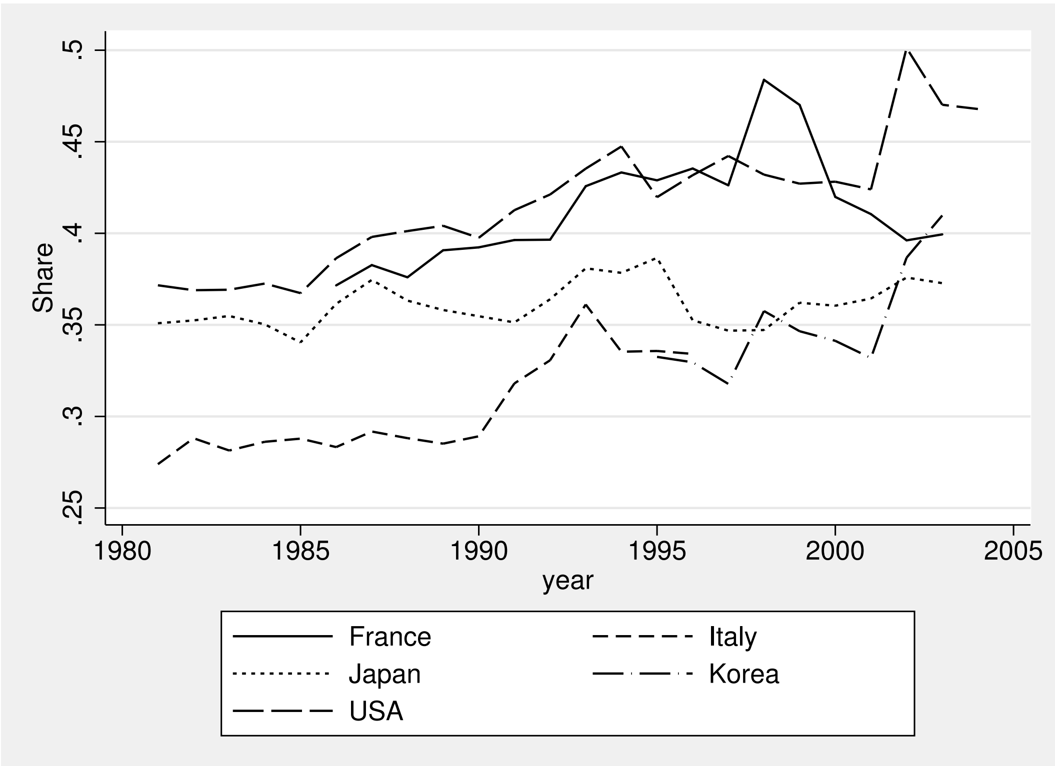

Figure 5.3: Share of Basic R&D Expenditures

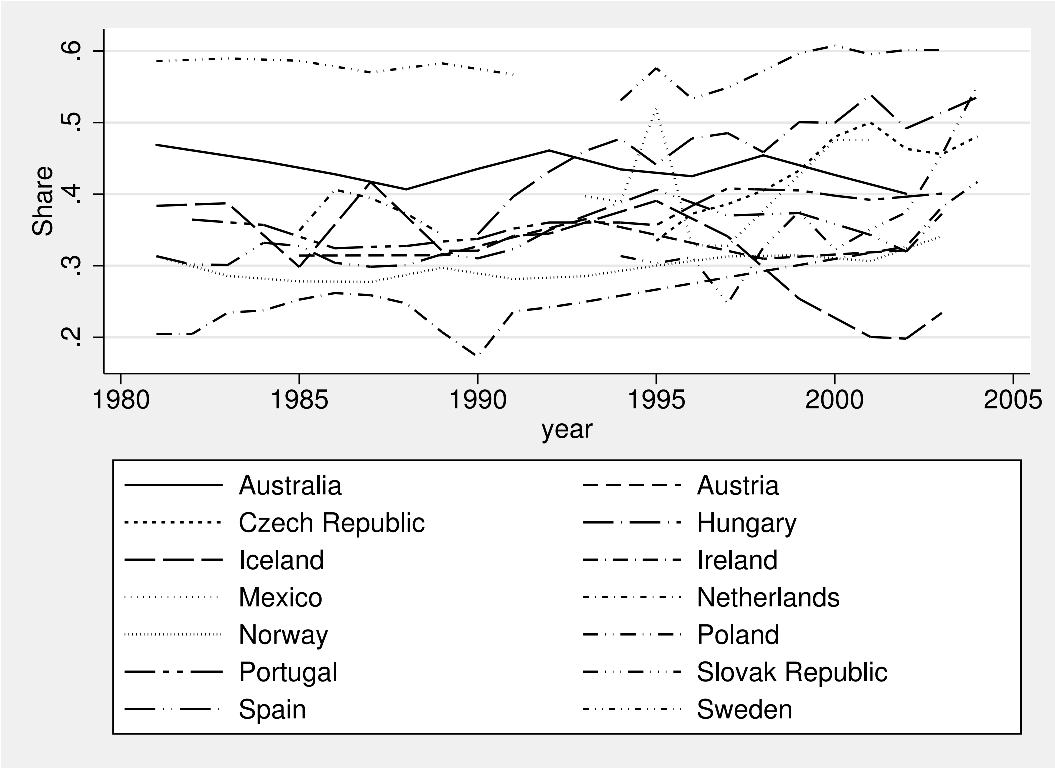

Figure 5.4: Share of Basic R&D Expenditures

Similar to total R&D expenditures, the share of basic R&D expenditures also shows a positive time trend over the last decades. This can be seen in Figure 5.3, which shows the share of basic R&D expenditures over time for five countries with the highest R&D expenditures and in Figure 5.4 for the other countries. A few countries have a decreasing share, as for example Australia and Iceland. In general, the share of basic R&D expenditures is much more volatile than overall R&D expenditures because basic R&D expenditures behave counter-cyclically (Rafferty, 2003). Another possible explanation is that the arrival and the diffusion of a new GPT has a larger impact on the decision on the type of R&D (i.e. in our case the decision between basic and applied R&D expenditures). Therefore, it is important that we not only focus on the influence of GPT diffusion on overall R&D expenditures, but also consider if and how the composition of R&D expenditures changes during the diffusion process.

Regarding the empirical drivers of the different types of R&D expenditures, Rafferty (2003) shows that the determinants of basic R&D expenditures differ from the determinants of applied R&D expenditures. He especially focuses on the influence of business cycles on the composition of firm-financed R&D expenditures. He uses data from the National Science Foundation (NSF) over the time period 1953 - 1996. There are three different types of R&D expenditures in the NSF data: basic, applied, and development R&D. Rafferty sums the first two to the so-called "frontier R&D" because they show the same cyclical behaviour. Frontier R&D is defined as building new scientific knowledge, whereas development R&D tries to develop a product that can be sold on the market. If these definitions are compared to the definitions of basic and applied R&D in the Frascati Manual (OECD, 1993), it can be clearly seen that Rafferty's definition of frontier R&D corresponds to basic R&D in the OECD dataset, and development R&D to applied R&D.

According to Rafferty (2003), firms are expected to do less research during recessions due to the cash-flow effect, which takes account of the fact that private firms finance most of their R&D internally. The opportunity cost effect works in the opposite direction: during recessions the opportunity cost of doing research is smaller due to the smaller return to productive activity. As a proxy for the opportunity cost effect, which should capture the counter-cyclical behaviour of R&D expenditures, Rafferty (2003) takes the variable *final sales*. Using three-stage least squares, he finds that firms increase the amount of basic R&D expenditures and reduce the amount of applied R&D during recessions, i.e. "more basic R&D expenditures are counter-cyclical, whereas development R&D expenditures are pro-cyclical." This means that the cash-flow effect is stronger than the opportunity cost effect when a firm decides about applied R&D expenditures, and vice versa for basic R&D. This result contrasts with Waelde and Woitek (2004), who find that aggregate R&D expenditures are pro-cyclical, but cannot find a significant effect on basic and applied R&D. In general, there is no clear empirical consensus on the cyclical behaviour (Waelde and Woitek, 2004). Following these findings, we are going to test for the cyclical behaviour of the share of basic R&D expenditures. In contrast to Rafferty (2003), we are capturing the cyclical effects through the unemployment rate.[3]

[3] The variable capturing cyclical effects is explained in detail in Section 5.3.

5.2.3 The Diffusion of a GPT: PC and Internet

There are almost no theoretical models that explicitly treat the diffusion of GPTs. A rare exception is the model of Helpman and Trajtenberg (1998b), where the 1998a model with only one final good sector is modified to represent multiple final goods sectors, which allows tracing the dynamic trajectory of the economy as consecutive sectors adopt the new GPT. The inherent features of GPTs provide a mechanism by means of which they function as "engines of growth" in the economy. Each GPT leads to the development of compatible components, which can be any kind of inputs or complementary investment. As the next better GPT becomes available, it is adopted by an increasing number of sectors and fosters complementary advances that raise the attractiveness of its adoption. That is, advances in other areas resulting from the new GPT make the adoption of this particular GPT more favourable. As a result, demand for the new GPT rises, which induces further technical progress in the GPT, which again leads to a new round of advances downstream, and so on. In this way the use of the GPT spreads throughout the economy, and its effects become significant at the aggregate level and affect overall growth. Each sector generates a cycle similar in nature to the economy-wide cycle described above, whereby real income is initially depressed and then pushed up as the sector adopts the new GPT in manufacturing, realising its benefits in the form of enhanced productivity. As all sectors adopt the GPT, they each begin to engage once more in R&D, immediately realising the benefits of complementary investments (since they are all already using the GPT) and bringing about sustained and widespread growth. It follows from this model that R&D expenditures should stimulate the diffusion of a GPT and should therefore be considered in the estimations on the diffusion of a GPT.

Most of the GPT models look at what happens after the exogenous arrival of a GPT and do not explicitly consider the exact diffusion path of a GPT and its determinants. In these models, such as for example Helpman and Trajtenberg (1998a) and Aghion and Howitt (1998a), new intermediate goods that belong to the specific new GPT have to be invented before the new GPT shows its effects on productivity, or specific knowledge stocks have to be built up in models such as Nahuis (2004) and Jacobs and Nahuis (2002). Some models, as for example Petsas (2003) do model the diffusion process. But they assume an epidemic model for the diffusion of a new GPT which is represented by a differential equation with only exogenous variables. In the sectors that have already adopted the new GPT, the R&D efficiency increases, which leads to higher R&D expenditures. Although all these models do not answer questions about the exact diffusion process of a GPT, they still indicate that it is accompanied by an increase of R&D which again allows and stimulates the economy-wide diffusion.

However, a more detailed theoretical understanding of the diffusion of a GPT is of interest because it is by means of this process that complementary investments and technological change in the user sectors are fostered, and that sustained and pervasive productivity gains are brought about in the economy as a whole.

There is a large empirical literature on the diffusion of technologies, and specifically on the diffusion of information and communication technology. Keller (2004) observes that a country needs a certain absorptive capacity to be able to adopt a new technology and that human capital and R&D expenditures are important factors for this absorptive capacity.

In a broad study, Comin and Hobijn (2004) look at cross-country technology adoption using panel data analysis. They cover 25 major technologies - not only GPTs - over the last two centuries and find evidence for trickle-down diffusion, i.e. the economically leading countries invent and adopt new technologies first. The most important determinants are human capital, type of government, degree of openness to trade, and adoption of predecessor technology, which all have a positive influence on the speed of the adoption. They also estimate some specifications with a proxy for a GPT, for which they choose electricity production as an independent variable. It turns significantly positive in some specifications but is not robust to changes in independent variables and in included countries.

Caselli and Coleman (2001) present one of the first studies that looks explicitly at the diffusion of ICT. They use computer investment per worker as a measure of technology adoption, which they consider a good proxy since computer technology is an embodied technology. Computer investment per worker is measured in some estimations by imports of computer equipment, and alternatively in other estimations by production data using the formula that adoption equals production plus imports minus exports.

They find "new confirmatory evidence that recent technological developments have had a skill-biased component" because high levels of educational attainment influence PC adoption positively (Caselli and Coleman, 2001, p. 331). Other robust results are that computer investment responds positively to a country's openness to manufacturing imports from OECD countries, and positively to high overall investment rates. They also find some impacts of the structure of the economy, i.e. a large share of agriculture in GDP is associated with lower adoption of computers. However, they find mixed evidence on the manufacturing share in GDP. There is no significance in their full-sample result, which they see as "consistent with the view that computers are a general-purpose technology, with a broad scope of applicability" (Caselli and Coleman, 2001, p. 333). This interpretation seems rather narrow, though, since the definition of a GPT does not rule out that its diffusion may be faster in some sectors.

Chinn and Fairlie (2004) concentrate in their empirical estimation on the diffusion of personal computers and Internet over the very short period of 1999 - 2001 for a panel of 161 countries. They use *personal computers per 100 persons* and *internet users per 100 persons* to measure technological diffusion. They find that the big international differences in ICT diffusion is mainly caused by differences in income. They also find that public investment in human capital stimulates the diffusion of both technologies. Furthermore, they find that telephone line density is important.

Kiiski and Pohjola (2002) estimate the diffusion of internet across OECD countries for the time period 1995 - 2000. They run cross-section and panel estimations and find GDP per capita and Internet access costs as the most important determinants. For the OECD sample, education is insignificant, but for a larger sample including developing countries with more than 1 million inhabitants and more than 50 internet hosts, it turns statistically significant if measured with attendance in university education. Because of multicollinearity issues, they propose a three-stage least square estimation with one equation for the diffusion, one for the infrastructure (where GDP per capita is the dependent variable), and one for the access costs. Using this simultaneous equation approach, their main findings are strengthened.

Finally, Vicente and Lopez (2006) offer a different approach to investigating the determinants of the patterns of ICT diffusion (Internet, computer and mobile phone use) through individual decisions for the EU-15 using a survey of 10'306 interviews done in 2002. They run logit estimations, where the dependent variable is the individual's decision whether to use the technology. They find that the level of an individual's income and education have a positive impact. For example, people with a university education have a 5.1 times higher probability of using the internet than people with only a primary school degree. Moreover, younger people and men are more likely to use ICT. In a second estimation, they introduce supplementary country-specific variables for the equation estimating the adoption of the internet and they find that GDP, openness and R&D expenditures increase the probability of using the technology.

In a nutshell, there is evidence for the positive influence of human capital on the diffusion of GPTs. But it is not clear from the literature which one of the large number of human capital-related variables is the correct one that leads to the best and most accurate results. Secondary enrollment rates give best results for the period before 1970 in Comin and Hobijn (2004), because there is much more variation than in primary enrollment rates and because the skills that are needed for technology adoption are mostly learned after primary school. They find the attainment rate for tertiary education to be the best variable for the period after 1970, because modern technologies require college-level skills. In general, education is most significant in their estimations for the adoption of electricity, mass communication and personal computers. Chinn and Fairlie (2004) take public investment in human capital as a proxy for human capital, which is significantly positive for computer use but insignificant for internet use. They also use the illiteracy rate, which is insignificant. This is not surprising because the use of ICT technologies needs more sophisticated skills than reading.

In the single equation approach in Kiiski and Pohjola (2002), the variable *average years of schooling* and *percentage of higher education* are insignificant for the OECD sample. For a larger sample including developing countries, these variables turn statistically significant thanks to greater variation in the education variables. In their last estimations using three-stage least square, *percentage of higher education* is still significantly positive but *average years of schooling* is again insignificant.

In general, we expect education to be significant and to stimulate the diffusion of a new GPT. But we do not clearly favor one of the possible variables. It should not be a variable that considers only primary schooling because the skills required for ICT adoption are more complex than the basic ones taught at primary school. We choose *education expenditures* because it covers the longest time horizon and offers the most observations.

Trade is also expected to be an important determinant of technology diffusion. It affects technology adoption in a country through a push and a pull effect (Comin and Hobijn, 2004). The first effect means that countries that import more from technologically advanced countries are more exposed to new technologies and are therefore adopting it faster than countries importing less. The latter effect describes how incumbent firms have to be more innovative when they are exposed to foreign competition in order to keep up with their foreign competitors. Hence the more open a country, i.e. the more it exports and imports, the earlier it is expected to adopt a new technology.

According to Keller (2004) human capital and R&D expenditures are often proposed as the most important determinants of successful technology diffusion. A lot of studies confirm the role of human capital, as has been shown in this section. Most of the studies discussed above neglect R&D expenditures, even though Gruber (2001) finds IT intensity to be closely related with R&D intensity. Most of the studies that consider R&D expenditures have total factor productivity or productivity growth as regressors. We are not aware of a lot of studies that estimate the influence of R&D expenditures on direct technology diffusion measures. For comparison with other studies, we omit R&D expenditures in some specifications. This also allows us to gauge their importance in explaining GPT diffusion.

Hypothesis 3: R&D expenditures, GDP per capita, human capital and the openness of the economy are important positive determinants of the diffusion of a GPT.

The diffusion of personal computers over time is plotted for some selected countries of our sample in Figure 5.5.[4] The United States is the leading country in PC adoption.

[4]The figures on the diffusion of the PC and the Internet do not start at 0 units because data on the diffusion of a new technology is in general not available for its very first phase since the importance of a technology can only be seen after its introductory phase. Therefore, statistics about the diffusion of a technology are only collected and available after they are judged to be important (Comin and Hobijn, 2004).

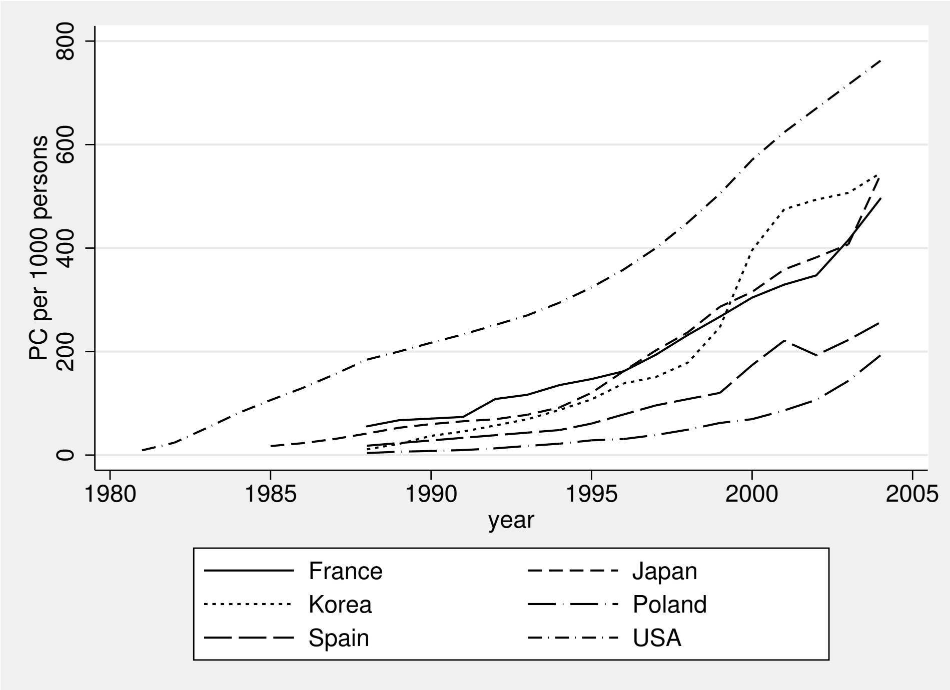

Figure 5.5: PCs per 1000 Persons over Time

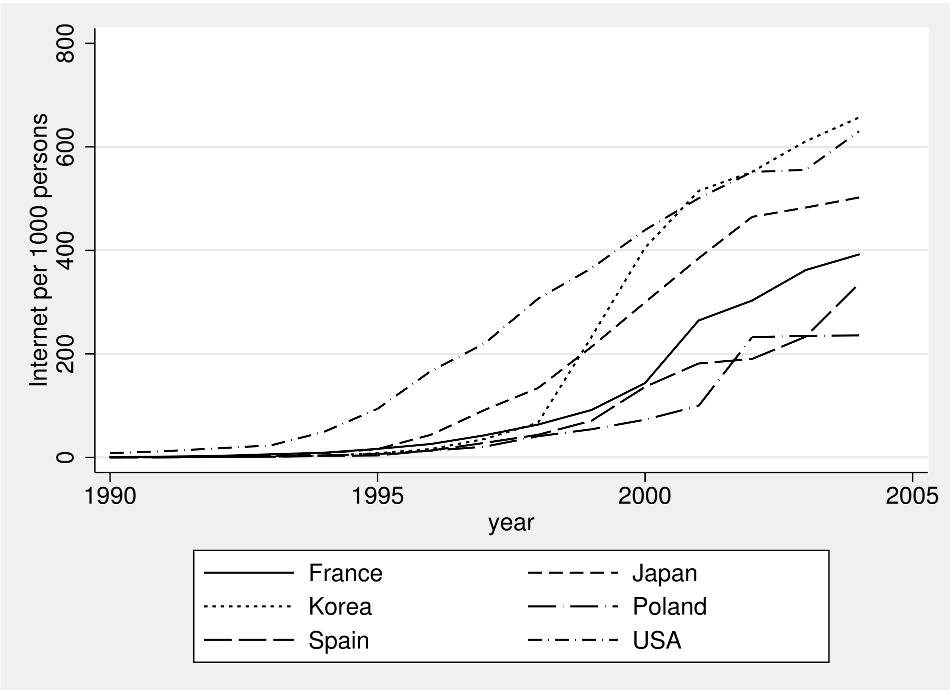

Figure 5.6: Internet Users per 1000 Persons over Time

Over the observed time period, the number of PCs rises for most countries. The number of people using the internet is also constantly rising, as can be seen in Figure 5.6. However, the diffusion of the internet starts later. In most countries internet use took off after 1995. Its start is in most countries characterized by a large increase in the number of users. This can for example be seen for Poland after 2001 and for Korea around 1998.

5.2.4 Human Capital

As we saw above, human capital is a main input factor in the research sector and plays a major role for the ability of an economy to adapt to a new technology. Therefore, the last hypothesis looks at the impact of human capital not only on the diffusion of a GPT but also on the amount of overall per capita R&D and on the share of basic R&D.

Hypothesis 4: A country with higher human capital adapts a new GPT faster and is more productive in research, particularly basic research, and therefore allocates more resources to research.

In the seminal paper on endogenous growth theory of Romer (1990), labour is divided into qualified and unqualified labour, where only qualified workers can perform research. He finds among other things that the higher the share of qualified labour in an economy, the higher is the steady state growth rate. Human capital therefore plays an important role for the productivity of the research sector, and we expect higher human capital to lead to higher R&D expenditures. This expectation is confirmed by the panel analysis of Griffith et al. (2004), who find that human capital stimulates innovation and the absorptive capacity of an economy.

5.3 Data

In the panel used for the empirical estimations in this paper, 19 OECD countries are included for the time period 1981 - 2004.[5] The independent variables are based on the

[5]The countries in the panel are: Australia, Austria, Czech Republic, France, Hungary, Iceland, Ireland, Italy, Japan, Korea (Rep.), Mexico, Netherlands, Norway, Poland, Portugal, Slovak Republic,

existing empirical literature on the determinants of R&D expenditures on a macroeconomic level (e.g. Guellec and Ioannidis, 1997) and on the empirical literature on the diffusion of technologies (e.g. Caselli and Coleman, 2001, and Chinn and Fairlie, 2004). An overview over all variables is given in Table 5.1. Data for our dependent variables on R&D expenditures is taken from the SourceOECD database (OECD 2007).[6] R&D expenditures are listed according to the categories basic, applied and experimental R&D in the SourceOECD database. The mean of applied R&D is 7408.11 million $ and higher than the mean of basic R&D. But basic R&D is more volatile than applied R&D, as indicated by the standard deviations in the last column. The share of basic R&D expenditures *SHARE* is built from the available data on basic and applied R&D expenditures by dividing *BASIC* through the sum of *BASIC* and *APPLIED*.

In our estimations on the diffusion of PCs and the internet, we employ *PC per 1000 persons* and *internet users per 1000 persons* as dependent variables, following Chinn and Fairlie (2004). The data is taken from the World Development Indicators (2006). Comin and Hobijn (2004) state that using data on the adoption of a specific technology in contrast to using other proxies such as imports (used by Caselli and Coleman, 2001) reduces the risk of having heterogeneity in the measures of technology. Moreover, by using a "micro" measure of technology as dependent variable, "we are inclined to interpret the identified correlations with aggregate explanatory variables as 'causal' relations" (Comin and Hobijn, 2004, p. 40), because the simultaneity bias is not a large problem for regression results with "micro" dependent variables and overall macroeconomic variables as independent variables.

Human capital (*EDU*) is proxied by education expenditures as percentage of GNI and is taken from the WDI online database (World Development Indicators, 2006). Northern European countries spend the most on education. Sweden has the highest mean of all countries in the sample (7.42%) and in 2004 Iceland spent 7.44% of GNI for education which is the highest percentage for 2004 in the sample. Iceland is followed by Sweden and Norway. Spain has the weakest mean (3.63%). However, Spain caught up and can be found in the mid-field in 2004. Several countries show remarkable increases in their

Spain, Sweden and USA.

[6]Table 3 from the Science and Technology Database (Current domestic expenditure on Research - Development by sector of performance and type of Research - Development, Vol 2004 release 02).

Variable		N	Mean	S.D.
Endogenous variables				
RND	R&D expenditures [Million constant $ 2000 prices and PPPs]	348	24592.11	53879.26
RNDCAP	R&D expenditures per capita [Million constant $ 2000 prices and PPPs]	348	0.338	0.246
BASIC	Basic R&D expenditures [Million constant $ 2000 prices and PPPs]	258	4897.77	616.85
APPLIED	Applied R&D expenditures [Million constant $ 2000 prices and PPPs]	251	7408.11	844.32
SHARE	Share of basic R&D in total R&D expenditures	251	0.38	0.09
PC	PCs per 1000 persons	322	188.72	9.58
INT	Internet users per 1000 persons	280	155.97	11.40
EDU	Adjusted savings: education expenditures as percentage of GNI	434	4.89	1.18
SCHOOL	Percentage of population over 25 with completed post-secondary education	294	9.12	0.30
Independent variables				
rgdpch	Real GDP per capita [$ in 2000 constant prices]	441	17767.37	339.76
pop	Population [in 1000s]	456	42353.98	2874.25
trade	Trade to GDP	416	66.88	1.69
kg	Government share of real GDP	441	19.16	0.26
ki	Investment share of real GDP	441	22.29	0.24
agrishare	Value added of the agricultural sector in % of GDP	439	5.482856	3.666128
cycle	Business cylce [1-unemployment rate]	405	0.93	0.002
lifeexp	Life expectancy	425	75.50638	3.089316

Table 5.1: Descriptive Statistics

education expenditures over time: Iceland only spent 4.15% in 1990 and in Norway education expenditures rise from 5.38% in 1981 to 7.34% in 1995 and still spends 7.05% in 2004.

We take the percentage of the population over 25 that has successfully completed a post-secondary education (*SCHOOL*) from Barro and Lee (2000) as an alternative measure of human capital in order to check the robustness of our results. Their widely used data is only available in five year intervals. The observations in between were gained by interpolation following Griffith et al. (2004). The United States, as the leader, has a mean of 26.82%, whereas Portugal has the lowest value (4.08%). Traditionally another variable, i.e. *Years of schooling* from Barro and Lee (2000), is also taken as a proxy for human capital in growth econometrics. We decided in favor of the variables *EDU* and *SCHOOL* because we are interested in the quality of human capital in OECD countries where schooling levels are high but differences in the education structures may introduce a bias for certain countries where secondary and tertiary school is longer or may take various forms.[7] Comin and Hobijn (2004) found that "there is much less variation in primary enrollment rates than in secondary enrollment rates. Furthermore, skills required for the use of most of the technologies in our sample go beyond the basic ones acquired in primary school" (Comin and Hobijn, 2004, p. 73). The variable *SCHOOL* still has some shortcomings as mentioned in Barro and Lee (2000, p.12): "First, the measure of educational attainment does not take account of the skills and experience gained by individuals after their formal education. Second, the measure does not directly measure the human skills obtained at schools and, specifically, does not take account of differences in the quality of schooling across countries." Therefore we prefer to use *EDU* in our main estimations. Moreover, the data are available for a longer time horizon than the data for *SCHOOL*, and they have a larger standard deviation.

Most of the independent variables are taken from the Penn World Tables (Heston et al., 2006), i.e. population (*pop*), real GDP per capita (Constant Prices: Chain series) (*rgdpch*), investment share of real GDP (*ki*) and government share of real GDP (*kg*). The values are in constant 2000 USD and PPP. Our measure for openness, i.e. Trade to GDP (*trade*), comes from OECD (2007), and life expectancy (*lifeexp*) and the value added of the agricultural sector (*agrishare*) from the World Development Indicators (2006). We do not include any institutional variables because they seem to be relatively unimportant for the technology adoption in a sample of OECD countries after World War II (Comin and Hobijn, 2004), and because Chinn and Fairlie (2004) find policy variables to be statistically insignificant or economically unimportant in estimations on technology diffusion.

We use annual data, which is common in the literature on the effects of R&D expen-

[7] In Switzerland, for example, most people leave school after nine years. But education does not stop by leaving school, since the educational system relies strongly and successfully on vocational studies.

ditures on productivity (see for example Bassanini and Scarpetta, 2001, Malla and Gray, 2005, Guellec and Van Pottelsberghe de la Potterie, 2001, and Guellec and Ioannidis, 1997). The use of annual data differs from the more standard use of five-year averages in growth econometrics, which are constructed in order to eliminate cyclical effects (Durlauf et al., 2005). Bassanini and Scarpetta (2001) have a sceptical view on using five-year averages. They think that "the lack of synchronization in country business cycles does not purge five-year averages from cyclical influences" (Bassanini and Scarpetta, 2001, p.43). Frantzen (2000) compares in his paper estimations with annual data and five year averages. He concentrates more on the results from annual data because the loss of information by averaging the data is too high. Due to this information problem, we also favour annual data. Nevertheless, we have to control for cyclical effects since we are only interested in long-term development and trends. For this purpose the variable *cycle* - defined as *1 minus the unemployment rate* (see e.g. Guellec and Van Pottelsberghe de la Potterie, 2001 and 2004) - is used. A popular alternative indicator of cyclical effects is *capacity utilization*. Guellec and Van Pottelsberghe de la Potterie (2001 and 2004) however argue that *capacity utilization* applies only to manufacturing industries, which account only for about 20 percent of GDP in OECD countries.[8] Country dummies are included in all equations in order to control for country-specific fixed effects. A time variable that takes account of time-specific effects is also included in all estimations.[9]

5.4 Empirical Estimations

The estimations in this paper are done in two steps. The first step involves the estimation of a single equation approach with fixed effects to test the four main hypotheses in section 5.4.1. In the second step, taking the endogeneity of some variables and the inherent multicollinearity into account, a system of simultaneous equations using three-stage least squares is estimated in section 5.4.2. The system consists of equations for the endogenous variables per capita R&D expenditures ($RNDCAP$), share of basic

[8]Alternatively, Bassanini and Scarpetta (2001) include first differences of the steady-state determinants in order to control for year-to year variations in output due to cyclical effects.

[9]Hausman tests and Wald tests have been used in order to test for the appropriate dummy structure.

R&D expenditures (*SHARE*), human capital (*EDU*) and one of the proxies for the diffusion of a GPT (*PC* or *INT*).

5.4.1 Single Equation Approach

Hypothesis 1 concerning per capita R&D expenditures derived in section 5.2.1 is tested and the determinants of per capita R&D expenditures are estimated in the first part of this Section. This is followed by estimations for the share of basic R&D expenditures (Hypothesis 2 in section 5.2.2) and for the diffusion of a new GPT (Hypothesis 3 in section 5.2.3). Aspects of hypothesis 4 about the influence of human capital are tested in all the estimations below.

R&D Expenditures

In order to verify hypothesis 1, i.e. if per capita R&D expenditures increase during the diffusion process, fixed effects estimations are used with R&D per capita as dependent variable. The independent variables follow from the existing theoretical and empirical literature and are lagged by one period. The estimations are done for both proxies for the diffusion of a GPT, i.e. for *PC* and *INT*. The fixed effects specification is suggested by a Hausman test, which rejects at the one percent level that there are no individual effects in our sample.

We find that per capita R&D expenditures increase as more firms and households are equipped with PCs. Per capita R&D expenditures increase by 6'380 USD when PC users per 1000 persons increases by 100 users. This result is very robust as can be seen from Table 5.2, which shows some selected estimations. Column 1 shows a specification without a time variable. We prefer the other specifications because *time* is always significant. The diffusion of the GPT (*PC*) is always positively significant confirming the findings from the theoretical literature. The more the PC diffuses through the economy of a country, the higher the per capita R&D expenditures. Education expenditures (*EDU*) influence per capita R&D expenditures positively as expected. The more people are educated, the more productive are R&D expenditures and therefore the more is invested in R&D. GDP per capita (*rgdpch*) is in all the relevant specifi-

COEFFICIENT	(1) RNDCAP	(2) RNDCAP	(3) RNDCAP	(4) RNDCAP	(5) RNDCAP
PC	0.000638***	0.000759***	0.000753***	0.000761***	0.000752***
	(10.2)	(11.0)	(11.0)	(11.2)	(11.1)
rgdpch	0.00000345	0.0000105***	0.0000102***	0.0000103***	0.00000960**
	(1.02)	(2.78)	(2.72)	(2.75)	(2.58)
pop	-0.000000994	-0.000000440	-0.000000592		
	(-1.22)	(-0.55)	(-0.76)		
trade	-0.000861**	-0.000316	-0.000488		
	(-2.07)	(-0.73)	(-1.33)		
EDU	0.0250***	0.0277***	0.0282***	0.0282***	0.0297***
	(4.25)	(4.81)	(4.95)	(5.01)	(5.37)
kg	-0.000273	0.00306		0.00458	
	(-0.069)	(0.77)		(1.36)	
ki	0.00415***	0.00585***	0.00540***	0.00591***	0.00505***
	(2.63)	(3.66)	(3.63)	(3.71)	(3.45)
cycle	0.0276	-0.317*	-0.309*	-0.326*	-0.322*
	(0.17)	(-1.71)	(-1.67)	(-1.78)	(-1.75)
time		-0.00783***	-0.00747***	-0.00837***	-0.00821***
		(-3.76)	(-3.68)	(-4.28)	(-4.20)
Constant	0.0748	0.248	0.324**	0.195	0.302**
	(0.40)	(1.33)	(2.05)	(1.14)	(1.98)
Observations	253	253	253	253	253
Number of countries	19	19	19	19	19
R^2	0.73	0.75	0.75	0.75	0.74

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.2: Fixed Effects Estimation of Per Capita R&D Expenditures with PC

cations positive and significant so that the first main result of Guellec and Ioannidis (1997) is confirmed. The investment share (*ki*) has a positive impact. The cyclical effects are negative, but only at a 10% significance level. After taking account of the different independent variables, there is even a negative time trend.

The results shown in table 5.2 with *PC* as a proxy for the diffusion of a GPT are, in general, robust to changes in the independent variables included in the estimation, and also quite robust to a change in the proxy for diffusion. The results with the variable *INT* are shown in table 5.8 in the appendix. The only difference is that the investment share (*ki*) is only significant at a lower confidence interval when we drop the share of government expenditures (*kg*), and *kg* enters now significantly negative if we drop *ki* from the estimations. This is caused by multicollinearity, since the correlation between *ki* and *kg* is -0.44.[10]

The Share of Basic R&D Expenditures

We expect the share of basic R&D expenditures to react due to the diffusion of a new GPT. But the theoretical models do not lead to a clear-cut hypothesis about the behaviour of the different types of R&D expenditures and about the factors that influence the decision in which type of R&D to invest, as we have seen in section 5.2.2. In the estimations below, the same independent variables as in the estimations for the overall R&D expenditures are chosen. *PC*, the proxy for the diffusion of a GPT, is significantly negative in some specifications in Table 5.3. This indicates that the share of basic R&D decreases during the diffusion of a GPT. Basic R&D seems to be more important at the beginning of the diffusion, and applied R&D more important in later stages. Basic R&D might not be the type of R&D that aims especially at inventing new GPTs, since the expenditures devoted to it do not increase during the diffusion process as one would expect from the model of Carlaw and Lipsey (2006). Basic R&D may not be the most appropriate name in the model of Carlaw and Lipsey (2006). It could be called GPT-R&D or one could model the arrival of a GPT as a by-product

[10] We did not mention this problem of multicollinearity in connection with the estimation with *PC* because in that case *ki* is always significant and *kg* is also insignificant when we exclude *ki* from the estimation.

COEFFICIENT	(1) SHARE	(2) SHARE	(3) SHARE	(4) SHARE	(5) SHARE	(6) SHARE	(7) SHARE
PC	-0.000268***	-0.000249***	-0.00000110	0.00000940			
	(-3.93)	(-3.71)	(-0.014)	(0.14)			
RNDCAP			-0.388***	-0.394***	-0.359***	-0.355***	-0.355***
			(-6.30)	(-6.73)	(-8.02)	(-7.94)	(-7.95)
rgdpch	0.0000125***	0.0000131***	0.0000172***	0.0000175***	0.0000148***	0.0000150***	0.0000146***
	(3.49)	(3.80)	(5.04)	(5.38)	(5.18)	(5.24)	(5.23)
pop	0.000000781		0.0000000862		0.000000585		
	(1.13)		(0.13)		(1.25)		
trade	0.00102***	0.000969***	0.000519	0.000531*	0.000696**	0.000570**	0.000571**
	(2.69)	(3.29)	(1.41)	(1.93)	(2.52)	(2.22)	(2.22)
EDU	-0.00544	-0.00753	-0.0000618	-0.000415	-0.00290	-0.00422	-0.00406
	(-1.10)	(-1.58)	(-0.013)	(-0.091)	(-0.74)	(-1.11)	(-1.07)
kg	-0.00208		-0.000900		0.00239	0.00178	0.00172
	(-0.56)		(-0.26)		(1.01)	(0.77)	(0.75)
ki	-0.00272*	-0.00224*	-0.000354		0.000467	0.000624	
	(-1.95)	(-1.71)	(-0.26)		(0.49)	(0.65)	
cycle	-0.507***	-0.506***	-0.576***	-0.587***	-0.509***	-0.515***	-0.472***
	(-2.77)	(-2.77)	(-3.39)	(-3.74)	(-3.54)	(-3.58)	(-3.69)
time	0.00234	0.00228	0.000839	0.000604	0.000605	0.000902	0.00116
	(1.16)	(1.24)	(0.45)	(0.37)	(0.42)	(0.64)	(0.86)
Constant	0.630***	0.627***	0.711***	0.703***	0.563***	0.617***	0.594***
	(3.57)	(4.34)	(4.24)	(5.54)	(4.39)	(5.09)	(5.13)
Observations	184	184	168	168	206	206	206
Number of countries	19	19	17	17	18	18	18
R^2	0.37	0.36	0.51	0.51	0.52	0.52	0.52

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3: Fixed Effects Estimation for Share of Basic R&D Expenditures with PC

of R&D as done in Schiess and Wehrli (2008b) where the probability of the arrival of a new GPT rises the higher the aggregate quality level is, i.e. the more successful research aiming at inventing new intermediate goods is. The negative sign for *PC* in Table 5.3 gives some evidence that basic R&D might be needed to set the basis for applied research to exploit the productivity gains thanks to the new GPT.

Per capita R&D expenditures are found to robustly influence the share of basic R&D. The higher the per capita R&D expenditures, the lower is the share of basic R&D. The effect of an increase in per capita R&D expenditures by 1000 USD is to decrease the share by 0.36% - 0.39%. This indicates that basic R&D sets the basis for applied R&D. Countries with smaller R&D budgets also have to do a certain amount of basic R&D in order to keep applied R&D productive as for example in the model of Evenson and Kislev (1976).

When *RNDCAP* is included as independent variable, *PC* is not significant anymore. The correlation between them is 0.66. This leads to multicollinearity and *PC* is only significant due to the omitted variable bias. Therefore we think that the more relevant estimations in Table 5.3 are estimations (3) - (7) with insignificant *PC*, and that basic R&D as defined here does definitely not coincide with basic R&D as defined in the model of Carlaw and Lipsey (2006).

The share of basic R&D expenditures increases with per capita GDP (*rgdpch*) and with the openness of the economy (*trade*). Surprisingly, education is insignificant. Despite the fact that basic research is the most complex of all types of R&D and human capital was therefore expected to be especially important. The investment share does not have a robust impact, being significant only in estimations (1) and (2).

The share of basic R&D is clearly counter-cyclical so that the opportunity cost effect prevails. In sum, the results show that the richer and more open economies are, the higher the share of basic R&D expenditures, especially during recessions.

The results for GDP per capita and the cyclical behaviour are very robust and significant at the one percent level across all possible specifications. The results concerning the openness of an economy are also robust. If *INT* is used instead of *PC*, as shown in the appendix in Table 5.9, the above-mentioned results are the same, and again the correlation between the proxy for the GPT (in this case *INT*) and *RNDCAP* is 0.56, which is still quite high.

The Diffusion of PCs and the Internet

Again the estimations are done with a fixed effects estimator supported by the results of the Hausman tests. The independent variables are again all lagged by one period. The results of different estimations for the diffusion of PCs are shown in Table 5.4. Per capita R&D expenditures (*RNDCAP*) positively and robustly influence the diffusion of PC. The share of basic R&D expenditures (*SHARE*) is insignificant, except when we exclude per capita R&D expenditures. We conclude that *SHARE* should not to be included in the estimations with *RNDCAP*, and that estimation (3) shows the preferred specification, while specifications (2) and (7) allow us to compare our results with those of other studies that use *RNDCAP*.

Education expenditures (*EDU*) are mostly insignificant. It may be that the variation in the data is too low since we are only considering OECD countries with a high level of education expenditures. Kiiski and Pohjola (2002) have the same problem and can solve it by introducing non-OECD countries, for which we do not have any data. We tried the estimations with other proxies for human capital without success. *EDU* only turns significant when neither *RNDCAP* nor *SHARE* are included. In that case, education expenditures stimulate the adoption of PCs.

Trade is significantly positive, as we expected from Caselli and Coleman (2001) and Comin and Hobijn (2004). But we cannot identify if it is due to a push or a pull effect. This result contrasts with that of Chinn and Fairlie (2004), who show that the openness of an economy is not important to explain the diffusion of the PC. They find a similar result for the diffusion of the internet, where openness is either insignificant or significantly negative. They explain their counter-intuitive results by stating that their measure for openness reflects the effects of large closed economies in the data set like, for example the United States.

The investment share (*ki*) has a negative influence. It seems that adopting PCs is a substitute for investment. Adopting PCs can also be understood as investment in future higher rewards, which are uncertain. Surprisingly, the agricultural share (*agrishare*) enters with a positive coefficient. This result is quite similar to Chinn and Fairlie

COEFFICIENT	(1) PC	(2) PC	(3) PC	(4) PC	(5) PC	(6) PC	(7) PC
RNDCAP	222.1***		392.1***		222.7***	233.1***	
	(3.01)		(8.16)		(3.05)	(3.19)	
SHARE	-186.7			-390.9***	-185.5	-139.3	
	(-1.55)			(-3.82)	(-1.55)	(-1.19)	
EDU	3.516	12.61**	-0.249	7.104	3.554	2.808	12.52**
	(0.61)	(2.39)	(-0.046)	(1.22)	(0.62)	(0.49)	(2.37)
rgdpch	0.0234***	0.0318***	0.0161***	0.0297***	0.0233***	0.0245***	0.0327***
	(5.49)	(9.79)	(4.36)	(7.83)	(5.84)	(6.21)	(10.4)
ki	-7.124***	-8.917***	-9.161***	-7.370***	-7.144***	-6.600***	-8.202***
	(-4.51)	(-6.27)	(-6.89)	(-4.56)	(-4.62)	(-4.33)	(-6.13)
agrishare	19.15***	29.41***	22.15***	19.40***	19.15***	21.99***	29.27***
	(4.68)	(8.03)	(5.99)	(4.64)	(4.70)	(5.86)	(8.21)
kg	0.267	-6.583*	-4.028	1.758			
	(0.068)	(-1.83)	(-1.20)	(0.44)			
pop	0.00130*	-0.00116	0.0000579	0.00159**	0.00129*		
	(1.66)	(-1.57)	(0.080)	(1.98)	(1.74)		
trade	1.095**	0.295	0.818**	1.167***	1.079***	0.905**	0.794**
	(2.50)	(0.73)	(2.12)	(2.61)	(2.95)	(2.56)	(2.38)
cycle	-457.4**	-340.7**	-56.95	-593.4***	-456.1**	-464.9**	-368.2**
	(-2.27)	(-2.06)	(-0.36)	(-2.95)	(-2.28)	(-2.31)	(-2.22)
time	13.30***	17.63***	16.31***	14.03***	13.36***	14.04***	16.53***
	(6.77)	(10.9)	(10.5)	(7.03)	(7.48)	(8.01)	(10.8)
Constant	-252.3	-344.4**	-465.5***	-168.5	-246.1	-230.2	-539.7***
	(-1.27)	(-2.02)	(-2.88)	(-0.84)	(-1.39)	(-1.30)	(-3.81)
Observations	200	305	271	200	200	200	305
Number of countries	19	19	19	19	19	19	19
R^2	0.91	0.89	0.91	0.90	0.91	0.91	0.89

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.4: Fixed Effects Estimation for the Diffusion of PC

(2004), where urban population enters significantly negative, for which they offer no clear explanation. Population (*pop*) is positive in some specifications, but mostly only at the 10% level. The share of government expenditures (*kg*) does not matter, and there is evidence for anti-cyclical behaviour of PC diffusion.

The same estimations are done with *INT* instead of *PC* in Table 5.5. The additional estimations (8) - (10) are done because *trade* is always insignificant and can therefore be excluded. Our interpretations are therefore mainly based on these estimations.

The evidence about per capita R&D expenditures and the share of basic R&D expenditures is strongly confirmed for the diffusion of the internet. *EDU* even enters significantly negatively (when *RNDCAP* is included) or insignificant (when *RNDCAP* is not included). Comparing the result of insignificance with the existing literature, our results are not confirmed. Dasgupta et al. (2005) for example state that the use of PCs needs a high level of education, but for the use of the internet and telephones only very little education is needed. This was also found by Chinn and Fairlie (2004) using years of schooling as proxy which is not significant in their estimation. Gruber (2001) argues that other variables should be used because education is still important for the adoption of any kind of ICT, and that the important factors are whether the students are already taught computer literacy at primary school levels and whether the teachers are well trained.

Trade is always insignificant. But *pop* turns significant. Its significance is especially high when we exclude *trade* and *kg*. Therefore we may conclude that for the adoption of the internet it is more important that you have a big network with which you can communicate and which exhibits network externalities than that your country is open.

The same results for *ki* and *rgdpch* are obtained as in the estimations for the diffusion of PCs. However, *rgdpch* becomes insignificant when we exclude *trade*. The puzzling result for *agrishare* remains in the equations (1)-(7) in Table 5.5, but in estimations (8)-(10) *agrishare* is insignificant.

Looking at equations (8)-(10), we find that internet diffusion is strongly influenced by per capita R&D expenditures and population size has a positive influence. Investment and surprisingly education affect internet diffusion negatively, whereas per capita GDP has no impact. As was discussed in section 5.2.3, economists commonly agree on the

COEFFICIENT	(1) INT	(2) INT	(3) INT	(4) INT	(5) INT	(6) INT	(7) INT	(8) INT	(9) INT	(10) INT
RNDCAP	831.7***		774.4***		827.7***	872.5***		842.2***	834.9***	827.6***
	(6.82)		(9.81)		(6.85)	(7.10)		(6.94)	(6.90)	(6.90)
SHARE	-220.0			-979.2***	-227.4	-87.06		-180.9	-183.2	-226.8
	(-1.10)			(-5.15)	(-1.15)	(-0.44)		(-0.93)	(-0.94)	(-1.28)
EDU	-23.05**	10.40	-12.74	-2.106	-23.33**	-23.62**	9.947	-25.16**	-27.33**	-28.95***
	(-2.04)	(1.03)	(-1.29)	(-0.17)	(-2.08)	(-2.06)	(0.98)	(-2.28)	(-2.54)	(-2.80)
rgdpch	-0.00151	0.0242***	0.000827	0.0185***	-0.000828	0.00234	0.0259***	-0.00300	-0.00161	-0.00243
	(-0.23)	(4.30)	(0.14)	(2.73)	(-0.13)	(0.37)	(4.79)	(-0.47)	(-0.26)	(-0.40)
ki	-7.412***	-7.533***	-7.484***	-8.492***	-7.228***	-4.954**	-6.539***	-7.353***	-6.706***	-7.164***
	(-2.82)	(-3.04)	(-3.45)	(-2.82)	(-2.83)	(-1.98)	(-2.85)	(-2.80)	(-2.65)	(-3.01)
agrishare	6.606	38.68***	21.95***	0.146	6.432	16.81**	39.68***	5.830	4.802	
	(0.75)	(4.95)	(2.97)	(0.015)	(0.73)	(2.04)	(5.16)	(0.66)	(0.55)	
kg	-2.117	-7.297	-3.199	2.617				-5.239		
	(-0.32)	(-1.11)	(-0.55)	(0.34)				(-0.91)		
pop	0.00470***	-0.000239	0.00292*	0.00649***	0.00486***			0.00418**	0.00441***	0.00481***
	(2.70)	(-0.14)	(1.85)	(3.29)	(2.93)			(2.54)	(2.71)	(3.33)
trade	0.698	-0.214	0.267	1.179	0.820	0.412	0.180			
	(0.92)	(-0.29)	(0.41)	(1.37)	(1.26)	(0.63)	(0.28)			
cycle	-259.6	138.8	313.1	-661.7*	-267.5	-373.2	109.0	-220.5	-224.2	-212.9
	(-0.79)	(0.48)	(1.22)	(-1.79)	(-0.82)	(-1.12)	(0.38)	(-0.68)	(-0.69)	(-0.66)
time	24.98***	33.31***	28.82***	26.66***	24.56***	26.74***	32.68***	26.42***	25.83***	25.34***
	(7.34)	(10.9)	(10.7)	(6.85)	(7.87)	(8.61)	(11.3)	(8.73)	(8.74)	(9.01)
Constant	-440.3	-1159***	-1115***	-171.5	-490.7	-374.3	-1350***	-355.8	-475.0	-421.5
	(-1.28)	(-3.75)	(-4.13)	(-0.44)	(-1.61)	(-1.20)	(-5.40)	(-1.07)	(-1.55)	(-1.46)
Observations	174	271	241	174	174	174	271	174	174	174
Number of countries	19	19	19	19	19	19	19	19	19	19
R^2	0.87	0.81	0.87	0.83	0.87	0.86	0.81	0.87	0.87	0.87

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.5: Fixed Effects Estimation for the Diffusion of the Internet

fact that technology adoption is driven by income and human capital, although the evidence on human capital is not very clear. We are puzzled that we only find little evidence concerning income and human capital, which is inconsistent with the previous empirical literature. Hence, we think that this question needs further investigations in the next Section, where a more sophisticated estimation method is used.

5.4.2 System of Simultaneous Equations

In the estimations in this Section three-stage least square estimations are used in order to tackle possible endogeneity and multicollinearity problems that may have caused some of the puzzling results in the previous sections. The assumption of the classical regression model that the observations on the independent variables are fixed in repeated samples is violated due to the independent variables in the R&D expenditure equation that are endogenous. Therefore, the estimation method has to consider that a system of simultaneous equations is being estimated. Durlauf et al. (2005) state that one could model as many as possible of the variables that are endogenous in growth econometrics. They cite the paper of Tavares and Wacziarg (2001) as a leading example estimating the influence of democracy on development through a system of simultaneous equations for the different possible channels.

First, the empirical model is explained before presenting the main results of this study.

Empirical Model

The main interest lies in the question whether the diffusion of a GPT influences overall R&D expenditures and the share of basic R&D expenditures once we have considered the other possible macro determinants of R&D. Therefore equations with per capita R&D expenditures and the share of basic R&D expenditures as dependent variables, and several independent variables that follow from the hypotheses in the theoretical literature and from the results found in the single equation estimations discussed above are estimated.

The single equation estimations have shown that the diffusion of a GPT influences per capita R&D expenditures but does not affect the share of basic R&D expenditures.

Furthermore, it has been shown that the share of basic R&D expenditures is strongly influenced by per capita R&D expenditures, which should therefore be considered as endogenous. Following the results of the single equation estimations, the following first two equations of the system of simultaneous equations are proposed:

$$RNDCAP = \alpha_1 + \alpha_2 GPT + \alpha_4 EDU + \alpha_5 X + \epsilon_A \tag{5.1}$$

$$SHARE = \beta_1 + \beta_3 RNDCAP + \beta_4 EDU + \beta_5 X + \epsilon_B \tag{5.2}$$

where GPT stands for the measure of the diffusion of a GPT, i.e. either PC or INT, and X for a vector of independent variables. The diffusion of a GPT has a direct impact on per capita R&D expenditures, but only an indirect one on the share of basic R&D expenditures through the variable $RNDCAP$. The diffusion of a GPT is influenced by several independent variables that also influence the decision on per capita R&D expenditures; e.g. countries with higher human capital EDU are expected to do more research and are also expected to adopt a new GPT faster. Therefore, the diffusion of a GPT is treated as an endogenous variable since it might have the same determinants as R&D expenditures. The same holds for education expenditures. Moreover, we would like to verify the results derived in section 5.2.3 where we found that R&D expenditures reinforce the diffusion process. Hence, we use a system of simultaneous equations that estimates the determinants of the diffusion of a GPT (equation (5.3)) and of investment in human capital (equation (5.4)) besides the two R&D equations (5.1) and (5.2):

$$GPT = \delta_1 + \delta_3 RNDCAP + \delta_4 EDU + \delta_5 X + \epsilon_G \tag{5.3}$$

$$EDU = \gamma_1 + \gamma_5 X + \epsilon_E \tag{5.4}$$

Equation (5.3) captures the determinants of the diffusion of a GPT and is specified as the estimations in section 5.4.1. The variables for equation (5.4) follow mainly from the estimation in Bretschger (2007). He estimates the different channels through which energy prices affect growth. To estimate the human capital channel, he uses the same endogenous variable and *energy use per capita, initial years of average schooling, GDP, government share, openness, life expectancy* and *population growth* as independent variables. *Energy per capita* is found to have a significant negative influence and *initial years of average schooling* and *GDP* a significant positive effect. In all equations, X

includes a full set of country dummies, a time variable, and a variable capturing cyclical effects.

Three-stage least squares (3SLS) is used to estimate the model. This system equation method has a smaller asymptotic variance-covariance matrix and brings efficiency gains, because it estimates all equations simultaneously and utilizes knowledge of all the zero restrictions in the entire system (Kennedy, 2003). We use 3SLS instead of 2SLS because it is reasonable to assume that the disturbances in the different equations are correlated due to non-included institutional parameters such as for example property rights.[11]

Estimation Results

Table 5.6 shows the results from the estimation of the system of simultaneous equations. The different equations are shown in columns (2) - (5). The second column presents the coefficients of the independent variables of the first equation with per capita R&D expenditures (*RNDCAP*) as endogenous variable, the third column with the share of basic R&D expenditures (*SHARE*), the fourth with *PC* and the fifth column presents the equation with education expenditures (*EDU*). The independent variables that are included in one or more equations are listed in the first column.

As main result, *PC* is found to increase per capita R&D expenditures and, additionally, it indirectly decreases the share of basic R&D expenditures because *RNDCAP* enters significantly negative in equation (2) in Table 5.6. The effect of *PC* on *SHARE* is -0.000612, i.e. if 100 additional persons of 1000 persons are using a PC the share of basic R&D expenditures decreases by 0.06. The hypothesis that basic R&D is especially needed as a basis for applied research to be productive on a new GPT generation in the sense of the model of Evenson and Kislev (1976) is confirmed. In their model, basic R&D increases the productivity of applied R&D by increasing its expected outcome. Therefore, the interpretation of our result is that basic R&D is required in a first period of the adoption of a new GPT, in order to supply basic GPT-specific knowledge that applied R&D needs to be productive.

There is no direct effect of *PC* on *SHARE* since *PC* is always insignificant when

[11] See Tavares and Wacziarg (2001) and Wacziarg (2001) for a more detailed description of three-stage least squares.

COEFFICIENT	(1) RNDCAP	(2) SHARE	(3) PC	(4) EDU
PC	0.000612**			
	(2.30)			
RNDCAP		-0.989***		
		(-4.85)		
EDU	0.0728***	0.0368***	33.06	
	(2.93)	(3.19)	(0.96)	
rgdpch	0.0000144**	0.0000304***	0.0338***	-0.0000799*
	(2.20)	(5.50)	(4.97)	(-1.72)
trade	-0.00127**	-0.0000397	0.0654	
	(-2.55)	(-0.098)	(0.12)	
ki	0.00694***		-3.399*	-0.00664
	(2.60)		(-1.80)	(-0.31)
kg				0.100***
				(2.61)
pop	-0.000000637			
	(-0.83)			
lifeexp				0.429***
				(3.94)
agrishare			26.87**	
			(2.46)	
cycle	-0.230	-0.765***	-547.5**	3.346
	(-0.92)	(-4.78)	(-2.25)	(1.31)
time	-0.00495	0.00385**	12.96***	-0.0654*
	(-1.01)	(1.99)	(6.02)	(-1.82)
Constant	-0.0714	0.542***	-283.8	-30.05***
	(-0.33)	(3.96)	(-1.16)	(-3.70)
Observations	190	190	190	190
R^2	0.96	0.75	0.94	0.70

z statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.6: Main Estimation Results with Three-Stage Least Square

RNDCAP is included in equation (2). The preliminary results from the fixed effects estimations in section 5.4.1 that basic R&D is not the type of R&D that leads especially to new GPTs - as in Carlaw and Lipsey (2006) - is confirmed.

Looking more closely at the *RNDCAP* equation (1) in Table 5.6, the major results from the single equation approach in section 5.4.1 are strongly confirmed. Education, per capita GDP and the investment share are all significantly positive. Trade is again negative and is in contrast to the single equation approach robust. This runs against the expectation that a country that is more open should also be more innovative because it is more exposed to foreign competition. On the other hand, a country that is more open can also import new technologies, does not have to invent everything on its own, and therefore has lower R&D expenditures.

Concerning the influence of per capita R&D expenditures on the share of basic R&D expenditures, the previous result is confirmed. The results for the *SHARE* equation (2) change a bit compared to the results in Table 5.3. Countries with a higher per capita income still have a higher share of basic R&D, and the share is still countercyclical. However, education expenditures now have a positive sign, which is in line with our intuition. Only highly skilled workers can be employed for basic R&D. These workers have to be trained. Higher education expenditures therefore lead to a bigger pool of possible basic R&D workers and to a higher productivity of these workers. This implies that the outcome of basic R&D is more promising and its share increases. Interestingly, *trade*, which was significantly positive in the single equation approach, is now insignificantly negative. The same argumentation applies for the explanation of this result as for the result for *trade* in equation (1).

Compared to the single equation estimation with *PC* as dependent variable *RNDCAP* is not significant anymore in the *PC* equation (3) and has therefore been dropped in the final estimations. Unfortunately, education expenditures are also not significant anymore. Although countries with higher education expenditures do more research and have a higher share of basic research, they don't seem to adopt PCs faster. *Trade* also turns insignificant, whereas the results concerning per capita GDP, the investment share, the agricultural share and the cyclical behaviour are confirmed.

Education in equation (4) is positively affected by the government share and life expectancy (*lifeexp*). The first result is straightforward because education expenditures are largely paid by the government. The second result says that a government will invest more in human capital (i.e. spend more money for education) when the expected period where the returns can be gained is longer (i.e. when the life expectancy is higher), and therefore the expected lifetime return of education is higher. Per capita GDP is the only other significant variable in equation (4). Surprisingly, it is negative. We would have expected it to be positive. But it seems that taking into account its influence on R&D and the adoption of a GPT, the net effect is negative.

A selection of different alternative specifications of the three-stage least square estimations is shown in Table 5.7. The results are in general consistent with the results

EQUATION	COEFFICIENT	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RNDCAP	PC	0.000589**	0.000634**	0.000570**	0.000622**	0.000651**	0.000567**	0.000526*	0.000643**
		(2.11)	(2.32)	(2.06)	(2.28)	(2.43)	(2.07)	(1.82)	(2.51)
	EDU	0.0607**	0.0662**	0.0599**	0.0663**	0.0642***	0.0701***	0.0801***	0.0848***
		(2.25)	(2.52)	(2.23)	(2.54)	(2.58)	(2.69)	(3.15)	(3.59)
	rgdpch	0.0000141**	0.0000129*	0.0000146**	0.0000133*	0.0000124*	0.0000155**	0.0000167**	0.0000143**
		(2.02)	(1.89)	(2.12)	(1.96)	(1.86)	(2.32)	(2.42)	(2.20)
	trade	-0.00134***	-0.00140***	-0.00136***	-0.00144***	-0.00150***	-0.00131***	-0.00117**	-0.000871**
		(-2.60)	(-2.71)	(-2.64)	(-2.81)	(-3.01)	(-2.61)	(-2.42)	(-2.31)
	ki	0.00588**	0.00600**	0.00641**	0.00682***	0.00614**	0.00672**	0.00631**	0.00587**
		(2.12)	(2.17)	(2.42)	(2.62)	(2.25)	(2.49)	(2.27)	(2.33)
	pop	-0.00000103	-0.00000109	-0.00000102	-0.00000113	-0.00000150**	-0.000000821		
		(-1.17)	(-1.22)	(-1.17)	(-1.28)	(-1.99)	(-0.91)		
	kg	0.000421	-0.00174	0.000860	-0.00185	-0.00280			
		(0.083)	(-0.38)	(0.17)	(-0.41)	(-0.72)			
	cycle	-0.169	-0.164	-0.203	-0.211	-0.161	-0.245	-0.267	-0.196
		(-0.69)	(-0.66)	(-0.84)	(-0.88)	(-0.65)	(-0.97)	(-1.04)	(-0.77)
	time	-0.00392	-0.00436	-0.00375	-0.00424	-0.00417	-0.00421	-0.00448	-0.00636
		(-0.79)	(-0.89)	(-0.76)	(-0.87)	(-0.86)	(-0.83)	(-0.84)	(-1.35)
	Constant	-0.0728	-0.0199	-0.0679	0.00715	0.0248	-0.0607	-0.0985	-0.150
		(-0.29)	(-0.083)	(-0.28)	(0.030)	(0.11)	(-0.28)	(-0.45)	(-0.70)
	R^2	0.9678	0.9656	0.9681	0.9655	0.9659	0.9644	0.9604	0.9577
	Chi2	5194.37	5195.05	5194.98	5196.15	5197.77	4763.27	4513.38	4511.84
SHARE	RNDCAP	-0.972***	-0.915***	-1.009***	-0.956***	-1.147***	-0.909***	-1.052***	-0.997***
		(-4.16)	(-4.51)	(-4.24)	(-4.59)	(-3.76)	(-4.57)	(-4.35)	(-5.72)
	PC					0.000121			
						(0.60)			
	EDU	0.0265**	0.0324***	0.0271**	0.0359***	0.0501***	0.0358***	0.0406***	0.0393***
		(2.10)	(2.81)	(2.06)	(3.08)	(2.63)	(3.09)	(3.00)	(2.90)
	rgdpch	0.0000300***	0.0000283***	0.0000312***	0.0000296***	0.0000321***	0.0000287***	0.0000321***	0.0000309***
		(4.66)	(5.15)	(4.78)	(5.27)	(4.99)	(5.26)	(4.91)	(5.51)
	kg	0.00351		0.00433					
		(0.92)		(1.14)					
	ki	-0.000984	-0.00130						
		(-0.66)	(-0.95)						

Table 5.7: Three-Stage Least Square Estimation of the R&D, PC and Education Equations

	trade	0.000191	0.000111	0.000144	0.00000446	-0.000145	0.0000843	-0.000111	
		(0.45)	(0.28)	(0.33)	(0.011)	(-0.31)	(0.21)	(-0.24)	
	cycle	-0.690***	-0.685***	-0.742***	-0.759***	-0.739***	-0.753***	-0.782***	-0.775***
		(-3.85)	(-4.00)	(-4.40)	(-4.73)	(-3.74)	(-4.71)	(-4.22)	(-4.16)
	time	0.00366*	0.00368*	0.00365*	0.00370*	0.00269	0.00340*	0.00403*	0.00371**
		(1.87)	(1.96)	(1.78)	(1.90)	(0.89)	(1.77)	(1.79)	(2.02)
	Constant	0.424**	0.516***	0.422**	0.543***	0.491***	0.541***	0.534***	0.534***
		(2.43)	(3.81)	(2.31)	(3.97)	(2.86)	(3.96)	(3.38)	(3.37)
	R^2	0.7717	0.7828	0.7566	0.7621	0.6717	0.7773	0.7178	0.7409
	Chi2	880.88	953.26	803.38	889.44	668.01	890.26	670.23	662.14
PC	EDU	36.18	30.47	37.10	29.18	31.92	55.71	52.41	48.49***
		(0.57)	(0.48)	(0.58)	(0.46)	(0.50)	(1.60)	(1.42)	(2.63)
	rgdpch	0.0310***	0.0303***	0.0311***	0.0301***	0.0302***	0.0369***	0.0360***	0.0365***
		(2.90)	(2.84)	(2.91)	(2.82)	(2.83)	(5.10)	(4.74)	(8.30)
	pop	0.00106	0.000919	0.00110	0.000865	0.00105			
		(0.83)	(0.72)	(0.85)	(0.68)	(0.82)			
	ki	-4.367	-4.497	-3.935	-3.792	-4.562			
		(-1.50)	(-1.54)	(-1.39)	(-1.36)	(-1.57)			
	trade	-0.384	-0.465	-0.386	-0.504	-0.387	-0.0602	-0.225	
		(-0.42)	(-0.50)	(-0.42)	(-0.55)	(-0.42)	(-0.10)	(-0.38)	
	agrishare	15.13	13.50	15.20	12.95	12.95	27.71***	24.95**	32.41***
		(0.90)	(0.80)	(0.90)	(0.77)	(0.77)	(2.64)	(2.27)	(5.64)
	cycle	-464.1	-445.2	-486.9	-477.0	-448.7	-749.6***	-734.0***	-736.3***
		(-1.25)	(-1.20)	(-1.31)	(-1.29)	(-1.21)	(-3.04)	(-2.84)	(-4.10)
	time	12.07***	12.28***	11.99***	12.26***	12.03***	11.84***	11.90***	12.65***
		(3.34)	(3.40)	(3.31)	(3.39)	(3.32)	(4.68)	(4.51)	(7.12)
	Constant	-188.2	-157.4	-180.4	-129.4	-160.6	-259.9	-218.4	-289.9
		(-0.47)	(-0.40)	(-0.45)	(-0.33)	(-0.40)	(-0.91)	(-0.73)	(-1.59)
	R^2	0.9289	0.9313	0.9283	0.9314	0.9305	0.9145	0.9163	0.9237
	Chi2	1093.76	1093.34	1093.45	1092.39	1092.18	1484.08	1353.80	2476.02

Table 5.7: continued

EDU	rgdpch	-0.0000752	-0.0000767	-0.0000749	-0.0000773*	-0.0000769*	-0.0000905**	-0.0000903**	-0.0000853*
		(-1.61)	(-1.64)	(-1.60)	(-1.66)	(-1.65)	(-1.96)	(-1.97)	(-1.86)
	pop	-0.00000434	-0.00000254	-0.00000469	-0.00000201	-0.000000733	0.00000242		
		(-0.44)	(-0.26)	(-0.47)	(-0.21)	(-0.076)	(0.31)		
	ki	-0.00222	-0.00214	-0.00378	-0.00623	-0.00178	-0.0276	-0.0294*	-0.0208
		(-0.10)	(-0.097)	(-0.17)	(-0.29)	(-0.081)	(-1.62)	(-1.80)	(-1.02)
	kg	0.0984**	0.100**	0.0983**	0.101**	0.107**	0.0831**	0.0760**	0.0862**
		(2.29)	(2.33)	(2.29)	(2.35)	(2.50)	(2.29)	(2.29)	(2.40)
	lifeexp	0.393***	0.408***	0.389***	0.409***	0.407***	0.413***	0.392***	0.427***
		(3.16)	(3.29)	(3.13)	(3.30)	(3.28)	(3.66)	(3.93)	(4.01)
	cycle	2.986	3.046	3.053	3.267	3.094	4.323*	4.302*	3.978
		(1.16)	(1.18)	(1.18)	(1.27)	(1.20)	(1.72)	(1.72)	(1.56)
	time	-0.0568	-0.0606	-0.0557	-0.0607	-0.0613	-0.0577	-0.0516	-0.0618*
		(-1.41)	(-1.51)	(-1.39)	(-1.51)	(-1.53)	(-1.57)	(-1.52)	(-1.76)
	Constant	-27.41***	-28.47***	-27.19***	-28.72***	-28.61***	-28.93***	-27.31***	-29.80***
		(-2.90)	(-3.02)	(-2.88)	(-3.05)	(-3.04)	(-3.38)	(-3.58)	(-3.76)
	R^2	0.7014	0.7010	0.7015	0.7008	0.7010	0.6965	0.6969	0.6982
	Chi2	450.52	450.53	450.69	450.96	449.79	451.20	448.51	449.98
	Observations	190	190	190	190	190	190	190	190

z statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.7: continued

explained in Table 5.6; the alternative estimations chosen in Table 5.7 illustrate some specific effects due to changes in the independent variables.

The majority of the results in Table 5.7 do not change due to different specifications. Especially the results concerning the two R&D equations, i.e. the equations for *RND-CAP* and *SHARE*, are very robust.

In the equation for *PC*, only *rgdpch* is very robust and *pop*, *ki* and *trade* are always insignificant. *Agrishare* and *cycle* only turn significant after dropping the insignificant variables *pop* and *ki*.

Kg and *lifeexp* are always significant with the same sign in the equation for *EDU*. *Rgdpch* is only insignificant for the less relevant cases where some clearly insignificant variables in the equation on *PC* are included. For very few specifications *ki* is significantly negative and *cycle* significantly positive. But these last two results are not robust to changes and should therefore not be overemphasized.

The major results that during the diffusion process of the PC per capita R&D expenditures increase and that the share of basic R&D expenditures decreases are also robust to changes in the proxy for the diffusion of the GPT, i.e. when *INT* is used instead of *PC*. The biggest change is that *trade* looses its significant influence on *RNDCAP* in equation (1). The important results on the influence of the GPT, per capita R&D expenditures, human capital and per capita GDP are unchanged.[12]

5.5 Conclusions

In order to investigate the behaviour of R&D expenditures during the diffusion process of a new GPT, we estimate different empirical specifications. We use single equations with fixed effects, and three-stage least squares with a system of simultaneous equations, consisting of equations for the endogenous variables per capita R&D expenditures, share of basic R&D expenditures, a proxy for the diffusion of a new GPT (either PC per 1000 persons or internet users per 1000 persons), and human capital.

[12]The results of the three-stage least square estimations with internet as GPT are available from the author upon request.

We find that the diffusion of a new GPT has a significant impact on R&D expenditures: Overall per capita R&D expenditures increase during the diffusion process. This finding is consistent with the prevalent theories of General Purpose Technologies, which show that the economy has first to adapt to the new technology through research and development activities, developing templates and learning, before the new GPT exhibits its positive effect on productivity.

By distinguishing between the different types of R&D expenditures, it can be shown that the share of basic R&D expenditures declines during the diffusion process of a GPT. This is a new result that adds to the existing theoretical literature, which does not consider this distinction. It gives new insights for the further development of GPT growth models that consider the type of R&D. It follows from our results that basic R&D is especially needed in a first period of the adoption of a new GPT, in order to set the basis for applied research to exploit the whole possible productivity gains of the new GPT.

Human capital has a positive impact on per capita R&D expenditures and on the share of basic R&D expenditures. Unfortunately, its positive impact on the adoption of a GPT can only be shown in the single equation approach with personal computers and excluding per capita R&D expenditures as independent variable.

Richer economies, measured by per capita GDP, undertake more research and adopt new GPTs faster. They also appear to have a higher share of basic R&D expenditures if estimated with three-stage least square. Otherwise when a single equation approach is used, the effect on the share of basic R&D is negative.

Per capita R&D expenditures have a robust positive impact on the diffusion of PC and Internet in a single equation approach. Although it turns insignificant in the three-stage least square estimations, we recommend that it should be included in studies that concentrate on the diffusion without taking care of the possible endogenous variables. Otherwise some of the results may suffer from the omitted variable bias.

This paper also adds to the discussion of whether R&D expenditures are cyclical. In the panel at hand, overall per capita R&D expenditures do not show a cyclical behaviour. But the share of basic R&D and the adoption of a GPT seem to be counter-cyclical.

This study has shown that basic R&D is especially important after the arrival of a new GPT because applied R&D only becomes productive after basic R&D has set its foundation. Therefore, policy makers should take care that there is enough basic R&D when a new GPT is diffusing into the economy, so that the potential growth effects of a new GPT are fully exploited. Basic R&D should be supported by the government, which can either provide basic research by itself or set the correct incentives that allow the firms to profitably undertake this more uncertain type of R&D. Additionally, this study confirms that human capital is very important for R&D and that a responsible government should adequately invest in education.

A limitation of this kind of study is that R&D expenditure is not a perfect measure for technological progress, because it is only an input measure and non-R&D inputs, such as for example learning by doing, learning by designing and foreign knowledge, are also important for improving a GPT. Hence, R&D expenditures underestimate technological activities, but it is hard to find a perfect R&D measure as there are no satisfactory output measures (Patel and Pavitt, 1995, Smith, 2003). R&D expenditures are chosen because they have been collected over a long period and the harmonization across countries is good. For further research, other non-R&D inputs that affect the applicability of a GPT could also be included, or patent data could be considered as an output measure for all the different productivity-enhancing activities.

5.6 Appendix

5.6.1 R&D Estimations dependent on the Diffusion of the Internet

In this appendix, the R&D estimations of Section 5.4.1 using as dependent variable per capita R&D expenditures as in Figure 5.2 and the share of basic R&D as in Figure 5.3 are redone with *INT* as proxy for a GPT.

COEFFICIENT	(1) RNDCAP	(2) RNDCAP	(3) RNDCAP	(4) RNDCAP	(5) RNDCAP	(6) RNDCAP	(7) RNDCAP
INT	0.000417***	0.000465***	0.000467***	0.000452***	0.000450***	0.000448***	0.000439***
	(10.8)	(10.6)	(10.6)	(10.6)	(10.5)	(10.4)	(10.5)
rgdpch	0.00000622**	0.0000110***	0.0000120***	0.0000105***	0.0000117***	0.0000103***	0.00000991***
	(2.04)	(2.97)	(3.30)	(2.85)	(3.25)	(2.77)	(2.69)
pop	-0.00000187	-0.00000161	-0.00000141			-0.00000144	
	(-1.59)	(-1.38)	(-1.22)			(-1.23)	
trade	-0.000393	0.0000665	0.000309			0.00000264	
	(-0.96)	(0.15)	(0.76)			(0.0058)	
EDU	0.0329***	0.0353***	0.0343***	0.0354***	0.0334***	0.0353***	0.0355***
	(4.85)	(5.19)	(5.08)	(5.28)	(5.09)	(5.16)	(5.27)
kg	-0.00691	-0.00512		-0.00528		-0.00766*	-0.00737**
	(-1.64)	(-1.20)		(-1.38)		(-1.91)	(-2.06)
ki	0.00188	0.00274*	0.00341**	0.00245	0.00323**		
	(1.20)	(1.71)	(2.27)	(1.55)	(2.17)		
cycle	-0.0861	-0.302	-0.319	-0.266	-0.270	-0.176	-0.158
	(-0.51)	(-1.56)	(-1.65)	(-1.39)	(-1.41)	(-0.97)	(-0.89)
time		-0.00543**	-0.00598**	-0.00516**	-0.00512**	-0.00441*	-0.00439**
		(-2.22)	(-2.49)	(-2.37)	(-2.34)	(-1.85)	(-2.06)
Constant	0.325*	0.455**	0.331*	0.364*	0.235	0.437**	0.353*
	(1.66)	(2.24)	(1.89)	(1.94)	(1.44)	(2.14)	(1.88)
Observations	221	221	221	221	221	221	221
Number of countries	19	19	19	19	19	19	19
R^2	0.74	0.74	0.74	0.74	0.74	0.74	0.74

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.8: Fixed Effects Estimation of Per Capita R&D Expenditures with *INT*

COEFFICIENT	(1) SHARE	(2) SHARE	(3) SHARE	(4) SHARE	(5) SHARE	(6) SHARE	(7) SHARE
INT	-0.000164***	-0.000154***	0.0000462	0.0000372			
	(-3.73)	(-3.57)	(0.78)	(0.68)			
RNDCAP			-0.406***	-0.398***	-0.359***	-0.355***	-0.355***
			(-5.13)	(-5.28)	(-8.02)	(-7.94)	(-7.95)
rgdpch	0.00000989***	0.0000106***	0.0000165***	0.0000163***	0.0000148***	0.0000150***	0.0000146***
	(2.81)	(3.17)	(4.37)	(4.67)	(5.18)	(5.24)	(5.23)
pop	0.00000110		-0.000000287		0.000000585		
	(1.09)		(-0.27)		(1.25)		
trade	0.000876**	0.000820**	0.000596	0.000665*	0.000696**	0.000570**	0.000571**
	(2.10)	(2.32)	(1.39)	(1.91)	(2.52)	(2.22)	(2.22)
EDU	-0.00965	-0.0107*	-0.000303	-0.000512	-0.00290	-0.00422	-0.00406
	(-1.56)	(-1.76)	(-0.047)	(-0.081)	(-0.74)	(-1.11)	(-1.07)
kg	-0.00102		-0.000581		0.00239	0.00178	0.00172
	(-0.26)		(-0.15)		(1.01)	(0.77)	(0.75)
ki	-0.00152	-0.00113	0.000488		0.000467	0.000624	
	(-1.05)	(-0.85)	(0.34)		(0.49)	(0.65)	
cycle	-0.626***	-0.645***	-0.675***	-0.645***	-0.509***	-0.515***	-0.472***
	(-3.25)	(-3.37)	(-3.64)	(-3.85)	(-3.54)	(-3.58)	(-3.69)
time	0.00244	0.00243	-0.000571	-0.000448	0.000605	0.000902	0.00116
	(1.03)	(1.08)	(-0.24)	(-0.21)	(0.42)	(0.64)	(0.86)
Constant	0.730***	0.776***	0.852***	0.802***	0.563***	0.617***	0.594***
	(3.75)	(5.01)	(4.41)	(5.72)	(4.39)	(5.09)	(5.13)
Observations	158	158	143	143	206	206	206
Number of countries	18	18	16	16	18	18	18
R^2	0.34	0.33	0.46	0.46	0.52	0.52	0.52

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.9: Fixed Effects Estimation for Share of Basic R&D Expenditures with *INT*

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