Modeling Major Technological Change: The Case of General Purpose Technologies

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The present report deals with theoretical concepts centered around General Purpose Technologies (GPTs), a term introduced by Bresnahan and Trajtenberg (1995). GPTs are characterized by the following features: (1) wide range of applicability: by affecting most sectors; (2) innovational complementarities: by lowering the costs of its users over time; (3) technological complementarities: by stimulating the new design or re-design of products and processes. Before discussing the models that explicitly deal with GPTs, other theories related to major technological change will be briefly reviewed.

Keywords: General Purpose Technologies, Technological Change, Innovations

Introduction

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

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are called General Purpose Technologies (GPTs henceforth). Prominent examples of the past would be the steam engine, electricity, and in the last years information and communication technology (ICT). New generation technologies, and specifically nanotechnology (Youtie *et al.*, 2008), have the high potential to become GPTs in the near future. The term itself was introduced into the economic literature by Bresnahan and Trajtenberg (1995). In their seminal paper they stress the important role of GPTs in causing "innovational complementarities", i.e. raising the R&D productivity in user sectors. In a decentralized economy, however, increasing returns to scale and the generality of purpose also generate coordination problems among up- and downstream sectors. As a conclusion, not only the industrial organization of inventing industries has to be examined closer than what had been done so far in the realm of the new endogenous growth theory, but it is also important to analyze sectoral interrelations more carefully, since "the locus of technical change" matters (Bresnahan and Trajtenberg, 1995, p.85). In a first attempt, the authors restrict their analysis to a partial equilibrium framework, in which one sector supplies the GPT at a specific technology level (or quality) to a set of application sectors. The producer of the GPT is assumed to have monopoly power in setting the price of the GPT as well as its quality level. Subsequently, the downstream sectors determine how much to invest in their own level of technology in order to maximize the rents related to the use of the GPT. Due to these "strategic complements" (Bulow *et al.*, 1985), a dual inducement mechanism sets in: Quality improvements in the GPT-sector lead to rising R&D activities in the application sectors, which in turn increases the returns for the GPT-producer and gives him an incentive for further improvements. The generality of purpose creates another positive externality between the user industries, in so far as the more sectors operate the GPT (and thereby enhance their own technology level), the higher are the investments in the GPT itself and hence the rise in its quality. Bresnahan and Trajtenberg show that in a decentralized economy where only arms-length market transactions take place, i.e. no technological information is exchanged between/among up- and downstream sectors, each Nash-equilibrium results in a lower level of GPT-quality and less innovative activities within the application sectors, compared to the social optimum. Coordination between the players in form of technological contracting would reduce the level of underprovision of the GPT. Even though Bresnahan and Trajtenberg concentrate on the incentive mechanisms for innovations and the role of industrial organization in this context, their notion of General Purpose Technologies has given rise to a bunch of dynamic theories, emphasizing the impact of major technological change on the economic structure and on long-term economic growth, in constrast to models that are restricted to the analysis of technological drifts (Jones, 1981).

The present paper attempts to discuss the body of literature on GPT-models. It thereby extends previous reviews on this topic (most notably by Lipsey *et al.*, 1998, 2005) without claiming completeness. Its remainder will be organized as follows: Section 2 distinguishes the notion of GPT from related theories in the economics of technological change. Section 3 reviews the most prominent models on GPTs. Section 4 entails concluding remarks and suggests specific aspects that future models on GPTs could be directed to.

1 Related Theories

The concept of General Purpose Technologies is not the only approach that tries to capture pervasive technological change; there already exists a variety of theories that center around drastic technological breakthroughs. The present section briefly summarizes the most important ones.

1.1 Techno-Economic Paradigms

Introduced by Dosi (1982) and explicitly by Perez (1983), the notion of Techno-Economic Paradigms (TEP) has been on the agenda of several authors (e.g. Perez and Soete, 1988; Freeman and Perez, 1988; Freeman and Soete, 1994). A TEP entails a much broader concept than the GPT, as it is defined as a "systemic relationship among products, processes, organizations, and institutions that coordinate activity"(Lipsey *et al.*, 2005, p.372). Changes in the TEP, generated by a set of radical innovations and some new technological systems (Keirstead, 1948), thus not only lead to new products or processes, but create whole new industries and organizational forms. They can be understood as the "creative gales of destruction" in Schumpeter's long wave theory (Freeman, 1991, p.223). Similar to Kuhn's theory of paradigm shifts, each era is characterized by certain phases: A new TEP comes up within the old era, provided that the current structure has generated an innovation-sympathetic environment. However, it does not immediately break up the existing regime; it rather takes a long period of gestation in which it competes with the incumbent TEP. In this time, the core innovation is being used in some industries and bit by bit takes over the whole economy, initiating a "crisis of structural adjustments", in which the capital equipment and the skills' profile get adapted, and the firm management, the industrial organization and the institutional landscape change. This process takes some time, since, on the one hand, the present environment may be resistant to the new technological breakthrough, and on the other hand the different parts of the system do not change in a coordinated fashion. Furthermore, one or a set of new key inputs evolve, which are available in abundance and show a wide range of applicability, and whose prices continuously fall alongside with the evolution of the new paradigm. The path-dependent, irreversible transformation of the system is based on an evolutionary approach. As Freeman points out, only the persistent search for minimum costs resembles neoclassical economics (Freeman, 1991, p.225).

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

Relating the concept at hand to general purpose technologies, there are certainly many similarities; both assume that economic regimes are technology-constrained and eventually run to diminishing returns. Like the TEP-theory, the subsequently described macro-economic models of GPT explain long waves where growth is rejuvenated by drastic technological change; however, in the theory of techno-economic paradigms the breakthrough is even more pervasive, since adjustment processes are not only dealt with on the firm and industry level, but also encompass the organizational, institutional and political structure[1]. However, understanding the concept of General Purpose Technologies as one part of the TEP-theory would not do justice to the former. As Lipsey (2005) points out, due to the holistic perspective the framework is not able to capture the technology tree as modeled by Bresnahan and Trajtenberg; while one TEP era is characterized by a set of co-evolving (major and minor) techniques, GPT-models entail a strict hierarchy between the actual key technology and innovational complementarities. Thus, the peace-meal treatment of major technical change in GPT-models allows for a more detailed examination of a techno-economic paradigm, focusing on the economic side.

1.2 Macroinventions

In his book *The Lever of Riches: Technology and Economic Progress*, Mokyr strongly emphasizes the difference between minor innovations and radical technical change and its importance for the study of economic growth. Denying the adequacy of the Newtonian equilibrium approach in this context, he follows an analogy-as-heuristic concept in the field of evolutionary economics (Mokyr, 1990, p.275). In contrast to Boulding (1981) and Nelson and Winter (1982), who defined the commodity respective the firm as the analogon to a species, the technique is the unit upon which selection occurs, and technological change is nothing else than the successive emergence of new techniques. Just as biological evolution shows periods of stasis interrupted by periods of drastic evolutionary changes, technological history has been all but smooth. Mokyr borrows Richard Goldschmidt’s distinction between micro- and macromutations (1940) to explain this uneven path of technological change: Microinventions thereby refer to incremental changes that improve, adapt or streamline existing techniques, reduce costs, material and energy use, improve form and function and increase durability (Mokyr, 1990, p.13). When they cumulate, they are able to cause technological change, i.e. generate a technique that can be sufficiently discriminated from previous ones[2]. Macroinventions, on the other hand, are able to explain the phases of radical

[1] The concept of Lipsey *et al.* (2005) also goes beyond the mere microeconomic sphere, considering the facilitating structure as well.

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

turn-over. They emerge *ab nihilo*, and have no clear antecedent (Mokyr, 1990, p.13). Moreover, they are mostly not location-specific, i.e. they do not depend on particular climatic or topographic conditions. While microinventions represent an improvement within a species, macroinventions are *per se* the new species. However, they can only sustain the selection process, if they are economically as well as technically feasible and if they fit into the institutional setting. The potential of this new technology lies in its impact on subsequent innovations, as it stimulates the emergence of further adaptive microinventions and raises their productivity[3]. Mokyr emphasizes the complementary character of both types of innovations: Without the emergence of macroinventions, microinventions would finally reach a technological ceiling, and without subsequent microinventions, macroinventions would fail to be profitable. Based on an extensive historical survey, Mokyr concludes that technological breakthroughs tend to cluster, so that the existence and the arrival time of some macroinventions can indeed be traced back to other ones. So are the Middle Ages and the Industrial Revolution both eras characterized by a large number of macroinventions, whereas in between evolution was driven by microinventions and gradual change. This can partly be explained by critical-mass models where one agent after the other jumps on the bandwagon of innovation; Drastic institutional or organizational changes might also increase the receptiveness of the economy to macroinventions (Mokyr, 1990, p.298). An important difference between both lies in the fact that microinventions can be (and have already been) examined by traditional economic tools: So they react on price signals and market imbalances and are by-products of learning-by-doing and learning-by-using[4]; thus, given the socio-economic environment, the direction of technical change and the probabilitity of success is more or less explicable. In contrast, a macroinvention – the rise of a genius idea – is by all means unpredictable. Just as genetics in evolutionary biology (Mokyr, 1990, p.287) fails to unravel the mystery of mutation, economic analysis can never fully explain the phenomenon of macroinventions. It can only postulate a certain framework of social, economic and political factors that tend to promote their emergence.

Mokyr's distinction between micro- and macroinventions has faced some critics, the most severe of which concerns the presumption that inventions of the first type are a matter of intention, whereas technologies of the latter can only be created by an act of genius or serendipity (see for example Lipsey *et al.* (2005, p.378) and Sokoloff (1991, p.528). Likewise, the idea that technological breakthroughs have no clear-cut parentage has been contested.

Macroinventions and General Purpose Technologies are evidently very similar concepts: The strong interrelation between micro- and macroinventions is basically reflected by the notion of innovational complementarities. In both theories, the new technology is under continuous improvement over its life-time. Interestingly, they also share the idea that technology is supply-constrained. But whereas Mokyr makes the plea that demand is not able to generate innovations, Bresnahan and Trajtenberg abstract from the demand-side just for the sake of simplicity. What is not explic-

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

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

itly stated in the approach at hand is the pervasive character of the new innovation; while the dynamo and the steam engine spread over the whole economy, the screw propellers or the hot-air balloon, also classified as macroinventions, were not so widely used. Moreover, Mokyr assigns most of the productivity gains to microinventions, simply because they dominate in number. In contrast, general purpose technologies are perceived as the real engine of economic growth. Even more, growth eventually ceases in most of the GPT-models without the arrival of a new big innovation. Whatever the differences, the two concepts unite in proposing radical technological change as the true "lever of riches".

1.3 General Technological Change

A further approach in the line of GPTs (even though not explicitly argued) is the model by Antonelli (2003). The author distinguishes between technical and technological change, where the latter can be further differentiated between general and contingent technological change. According to Antonelli (2003, p.80), four characteristics matter for the direction of change: (1) technological vs. scientific opportunities; (2) internal vs. external sources of new knowledge; (3) learning by doing vs. learning by using; (4) switching costs regarding fixed (tangible and intangible) capital, and the degree of irreversibility. Whenever scientific opportunities are broadly available and easy to access, when learning by doing takes place and the switching costs and irreversibility are low, then entrepreneurs are likely to act in favor of general technological change rather than contingent technological change. The ideas unfold in a neoclassical equilibrium framework with bounded rationality and myopic expectations, where innovations cause and are fed by out-of-equilibrium conditions[5]. This disequilibrium is a direct result of a change in demand and, most relevant, in relative factor prices. In this case, technological change necessarily has to occur in order to adjust to the new market situation. The decision whether to invest in the introduction of a new general technology or a contingent (biased) technology, is taken against the background of a specific factor market. The argument is the following: If a firm operates close to the technology frontier, with a technique that already considers the specific endowments of labor and capital (both being available in abundance), it will introduce a new general technology in order to remain competitive. This general technology is most often only locally neutral, so that if the factor market diverges to a large extent from the original one, firms are likely to shift their research activities to the development of a contingent technology which improves the performance of an existing innovation. They do so by adjusting the general technology to the specific local factor market, instead of inventing a totally new production method. Thus, the approach emphasizes the interplay between adoption (of a new general technology) and adaption (the generation of a contingent technology) and can be used to model General Purpose Technologies alongside with its complementary innovations as a sequence of new general technologies and contingent technologies. The relative factor prices determine the external

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

path-dependence (David (1985) and Arthur (1989)), the irreversibility of capital the internal path-dependence. Moreover, it allows for cross-country comparisons, in so far as it can explain, given specific factor endowments, why some economies always push the technology frontier, while others are more likely to imitate. So location matters. Given diverse factor markets, the new GPT diffuses at a higher rate, the more similar are the factor endowments between the place of origination and the place of adoption. Like Bresnahan and Trajtenberg 1995, Antonelli examines the horizontal and vertical effects, i.e. the effects among different application sectors and between up- and downstream industries. The horizontal effect differs with regard to the type of innovation: Contingent technological change can prevent other firms to imitate, as the innovation is specific to local factor endowments, whereas a general technology evolves over an epidemic diffusion path. When relative price changes matter, it is also important to investigate the vertical relationship between the industry which supplies the intermediary input that is strategic in the implementation of the new technology, and those sectors which introduce the new GPT. Together with the industrial dynamics of monopolistic competition, barriers of entry and exit, etc, the pattern and time path of diffusion can be derived on the basis of absolute and relative factor prices. Assuming that the market for the new intermediary input is monopolistically organized, the production costs in downstream sectors may rise after the introduction of the GPT, whereas the suppliers of capital goods complementary to the old technology face declining demand and decreasing prices for their products. Gradually, they get driven out of the market, while entries in the new intermediary sector lower the price for the new capital good, and thus increase the adoption rate of the new technology in the downstream sectors (due to rising profitability). The result is a sigmoid diffusion path as a sequence of probit diffusion processes that generate Schumpeterian growth cycles.

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

2 Models of General Purpose Technologies

The theory of General Purpose Technologies is very much linked to explaining the long-waves in economic history. It was not earlier than in the mid 90s that pervasive technologies became a widely-debated issue in economics, not last because of the rising impact of the ICT, and because of the fact that the existing theories could explain neither the changing productivity pattern of this technology throughout its lifetime nor its diffusion path over the whole economy. While methodological approaches of technological change due to incremental innovations are available in a vast amount, the theoretical literature on technological breakthroughs is relatively tight. The present section reviews the hitherto existing approaches that exemplify the channels through which a GPT affects economic growth: either through the creation of new (intermediate) products or through upgrades in the quality of the products, both in the line of Schumpeterian growth theory; or through knowledge accumulation modeled in an evolutionary framework.

2.1 Expanding Product Variety

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

Helpman and Trajtenberg (1998b)

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

The formal approach is based upon an endogenous growth model of expanding product variety, developed by Grossman and Helpman (1991a), and entailing Romer's concept of monopolistic competition (Romer, 1990). In order to keep the model simple, it is assumed that one general purpose technology after the other arrives at predetermined time intervals. Thus, the authors abstract from dealing with the innovative activity itself, and basically build their framework upon two production sectors: The final good sector producing a homogeneous commodity by means of a specific general purpose technology, alongside with compatible inputs, the so-called components; and the manufacturing sector, whose in-house research develops blueprints for the new components that are subsequently produced. The demand for components is specified by a Dixit-Stiglitz consumption index (Dixit and Stiglitz, 1977) which imposes an equal and constant elasticity of substitution between any two components, independent of the technology in use. The GPT itself enters the production function only in the form of a productivity parameter, whereby those GPTs that arrive later also perform better. Together with the number of different components available, total final output is determined. All firms in the components' manufacturing sector operate under monopolistic competition: Each firm owns the blueprint for a specific component which is produced by one unit of labor only. As the specification of factor demand values all components equally, profit maximizing behavior results in a single price for all intermediate products. As a consequence, each component is used in equal quantity. Thus, having once successfully introduced the blueprint, enterpreneurs share the market power equally among them and the value of each firm equals the current value of the profits accrued by manufacturing the blueprint. Assuming perfect foresight, the development of the new blueprint will take place whenever the expected profit stream covers at least the research costs. Then, the entrepreneur re-allocates the only primary production factor, homogeneous labor, from manufacturing to developing components. Constant returns to scale together with free entry ensures that the entrepreneur can not pocket excess profits (Grossman and Helpman, 1991a, p.51) by undertaking R&D. The more components are available for a specific GPT, the higher is its productivity (in terms of unit labor input) in the final good production. When a new GPT arrives, it cannot be immediately operated, as the available components are not compatible with it; hence prior to its utilization, the number of components developed and manufactured for it has to exceed a certain treshold that lets the new technology be superior to the incumbent one. Only then the switch from one GPT to the next takes place. However, a technology cannot be infinitely improved, as its average productivity is decreasing with every further product development. The economy moves from one static equilibrium to the next, in each of which cost minimization of the final good producers leads to the utilization of the most productive technology; profit maximization among firms in the application sector determines the optimal labor-allocation; and intertemporal utility maximization of consumers actuates the demand path for the final commodity. Analyzing long-term economic growth implies studying the equilibrium trajectory correlated with the arrival of a GPT until the introduction of the next one. Depending on whether the technology has already been exploited to its full potential or not before the arrival of a new one, the overall cycle assigned to the life-time of a technology can be divided either into three or just two phases (the latter is indicated in Figure 1). Phase 1 is the period where a new GPT enters the stage; perfect foresight makes the firms shifting labor resources to the development of new components, while the final good sector still operates with the incumbent technology and the corresponding inputs. This phase is characterized by constant profits (due to the constant supply of old components), rising nominal wage rates and an increasing product variety. As soon as the number of available components has reached a critical mass, the economy enters Phase 2 of the cycle, in which production takes place under the new technology, and labor is divided between manufacturing new components and continuing the development of blueprints. In this period, suppliers of new components can gain profits while the wage rate is declining again. In the case that the meanwhile established GPT

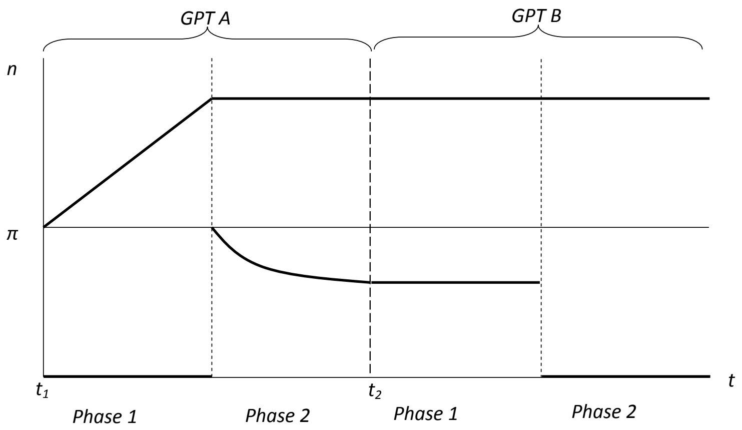

Figure 1: Phases of two successive GPTs (π denotes profits, n the number of components
Source: Helpman and Trajtenberg (1998b, p.66)

can not be further improved before the end of its life-time, a third phase indicates the subperiod, where the final good is still produced with the incumbent technology, but all research activities have ceased and await the arrival of the next GPT. It follows that the wage rate, profits and the number of components are constant. Since the efficiency parameter of the GPT and the arrival rate are exogenous, both phases are of constant length in a stationary equilibrium, i.e. each technology evolves along the same time interval. Real GDP falls at the beginning of each cycle and keeps decreasing throughout the first phase, on the one hand because profits immediately jump to zero (see Fig. 1), and on the other hand because of the negative correlation with the wage rate (which is increasing), as labor resources are redirected to R&D. In phase 2 the growth trend is reversed and output is continuously rising. Thus, the model perceives the slump as an "integral feature" (Helpman and Trajtenberg, 1998b, p.71) of a GPT which results from the necessity of complementary investments and the deployment of resources.

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

In Helpman and Trajtenberg (1998a), the authors go further studying the growth process induced by a GPT by investigating the relation between the order of adoption and the pace of diffusion. The existing framework is modified so as to allow for a multiplicity of final good sectors each of which utilizes tailor-fit components. Every sector is specified by a set of four parameters that defines the order of adoption: (1) a productivity parameter that gives the comparative advantage of the new GPT over the old one, (2) the stock of available inputs compatible with the old GPT; (3) a demand parameter, and (4) an R&D parameter that reflects the costs of new product development. Thus, the sectors are exogenously ranked according to their potential of being early adopters or laggards. Correspondingly, the technology will be adopted the sooner by a final good sector, the better fits the new GPT into the current production structure; and the less components have been developed for the old GPT so far (so that the required "critical mass" is rather small); and the lower is its spending share for intermediate products and the research costs. As before, two GPTs may well co-exist, so that the only primary input labor has to be allocated among manufacturing old as well as new components and the development of new sector-specific blueprints. The mathematical framework is such that not more than one sector engages in R&D at the same time; as a consequence, one final good sector after the other undergoes the two-phase cycle, where prior to the technology switch, the number of new sector-specific components developed in the first phase has to exceed a certain treshold. Thus, the diffusion process over the economy can be described by a sequence of sectoral waves whose length is, in contrast to the former model, endogenously determined by resource allocation. In the basic approach of a single final good sector, the cycle refers to the time period between the arrival of a technology and its replacement by the next one, while in the present model it is determined by the speed of diffusion of one and the same technology over different sectors. As soon as all final good sectors have adopted the new GPT and the economy approaches the steady state, each sector but the last one enters a further round of product development, triggering a second R&D wave (see Fig. 2). The evolution of real wages also occurs in sectoral waves, in each of which the real wage stagnates in the phase prior to the technology switch and rises thereafter. Like in the previous model, real GDP declines in the first phase and rises in the second, and this pattern is repeated for each subsequent sector introducing the new GPT. However, throughout the whole cycle, the average growth rate and real wages are increasing.

To summarize, the model is able to embed the concept of General Purpose Technologies as proposed by Bresnahan and Trajtenberg into a (formally complex) general equilibrium framework. It thus provides a basis for investigating the diffusion process of a pervasive technology across all sectors of the economy and allows deducing its impact on prices of the final commodity and of capital and labor inputs, on the stock market, on the variables of distribution and on GDP in the aggregate. Helpman and Trajtenberg (1998a) further showed that the basic model can be extended to cope with skill-induced wage differentials (which spread with the appearance of a GPT such as in the course of the ICT revolution). However, the present framework still lacks explain-

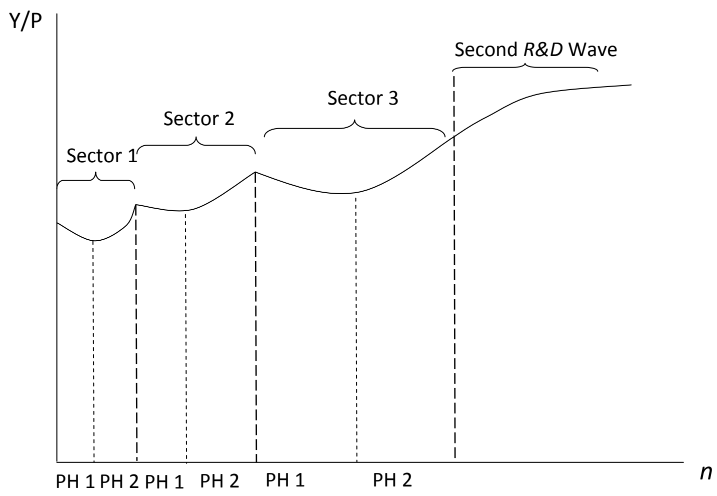

Figure 2: Diffusion of a single GPT over three sectors (Y/P denotes real income, n the number of components
Source: Helpman and Trajtenberg (1998a, p.105)

ing externalities or spillovers between the GPT-using sectors and excludes feedback effects from user sectors to the GPT. Thus, the technology itself does not undergo improvements, as a constant efficiency parameter is assigned to each GPT throughout its life-time. Increasing returns to scale are rather reflected by the productivity of the GPT rising with the number of supporting components. As a direct consequence, what causes the productivity cycle is not the technique itself, but the complements which facilitate its implementation. Moreover, the arrival rates are exogenously determined, so that the model cannot explain why and when a new technology needs to be introduced. Successive GPTs always have the same life-time and just differentiate according to the pre-determined productivity parameter, thus the performance of one technology is an upscaled copy of the preceding one. In this perspective, the history of technological change is a sequence of identically evolving technologies each arriving in equal time-intervals. A severe drawback of the model is the predicted slump of the economy immediately upon the emergence of a new GPT. The feature of the formal framework that real GDP declines whenever one sector, whatever its size and relevance, starts introducing the new technology, can not be defended empirically, and has induced further elaborations in the scope of other theoretical concepts.

Aghion and Howitt (1998a)

On the basis of the model by Helpman and Trajtenberg (HT-model hereafter), Aghion and Howitt (1998a) elaborate a simple Schumpeterian approach comprising three evolution stages of a GPT: innovation, complementary component-building and technological spillovers. This model does not only allow for endogenizing the introduction-timing of a GPT, but also considers the important fact that the adopting process of a firm does not take place isolated, but by imitating other firms that have already implemented the technology successfully. According to Aghion and Howitt, the HT-model bears two inconsistencies concerning the predicted slow-down after the arrival of a new GPT: First, the size of a productivity slump cannot be explained simply by the shift of labor from manufacturing to R&D, as the research sector is in reality too small to induce a fall in output; and second, slumps do not occur immediately upon the emergence of a new technology; controversially, historical studies show a lag of several decades from the point of its arrival, until its far-reaching effects are actually measurable (David, 1990). While the second question can be explained by risky experimentation on a large scale (Atkeson and Kehoe, 2008), increased temporary unemployment, or obsolesence of physical and human capital (Howitt, 1998), the second question is more difficult to answer. As the authors point out, it could be simply measurement problems, because statistical classifications have to be adjusted to the new innovation. Or, more notably, technological spill-overs play a critical role, i.e. firms learn from each other how to adopt a new technology. It is the latter the authors focus upon: In their view, the experience of other entrepreneurs with the introduction of a technology serves as a template upon which firms can start developing their own adoption process. Over all sectors, this type of social learning may – or may not – cause a slump during the first phase of implementation. In order to model technology-spillovers, Aghion and Howitt revert to their basic Schumpeterian growth model with a continuum of sectors producing one final good under constant returns to scale[6]. The discovery of a new technology is subject to a Poisson process with a constant arrival rate. A short time interval between successive GPTs thereby discourages research, as monopoly rents can only be earned over a few periods; whereas a decrease in the arrival rate ensures the diffusion of the technology over the whole economy. After a GPT arrived, each sector has to invent its own intermediate input, in order to use the new technology successfully. However, in contrast to the HT-model, developing a blueprint now requires the afore-mentioned template which prevents the researchers starting from point zero again. After the successful introduction, a new GPT simply scales up the production function of the consumption good; thus, as in the HT-model, the technology directly enters the final good sector(s) as a constant efficiency parameter, so that the increase in productivity along the life-time of the GPT is driven by the number of supporting components. Analogeous to the three stages of the innovation process, the authors differentiate between three states each sector has to undergo: Throughout the first state, the old GPT is in use and no change in output with respect to the new technology occurs. The second state denotes the phase when a new template has already been discovered either independently (given by a Poisson arrival rate equal for each sector) or by imitating similar firms, but still the old technology is operated; and the third state refers to the successful implementation of the new GPT with a corresponding increase in productivity. As concerns the time path, the rate of independent discovery is very low, so that the emergence of a GPT does not have an immediate effect on the economy; rather, agents wait until others have already gained experience with the unknown technology. The probability of a firm moving from the first to the second state thereby increases with the number of its observations of successful firms. Once the template is achieved, the firm has to invest labor in the development of components (the process of which is also subject to a certain success rate), in order to finally reach the last state of introducing the new technology. During this transition phase, no output is produced at all. Since a fixed number of workers is devoted to R&D, the endogenous allocation of labor only concerns the manufacturing of the old and new components respectively, since both technologies are simultaneously operated in the economy. Differential equations give the evolution of the sectors in the second and third state of the innovation process. Figure 3 present both paths on the basis of the simulations carried out in Aghion and Howitt (1998a). Social learning thereby prevents the firms from engaging in experimentation instantly after a new GPT showed up. Instead, entrepreneurs wait, until they can benefit from the experience of others with the new technology, and the likelihood of imitation increases with the pool of successful adopters. Hence, the fraction of sectors with templates rises slowly, peaks in the middle, and diminishes as more and more sectors have succeeded in installing the new GPT. The diffusion process of the new GPT evolves along a logistic curve. These dynamics subsequently determine the growth of aggregate output. In contrast to the HT-model, the slump does not occur immediately upon arrival of the new GPT, but starts delayed due to the externalities of experimentation. If social learning does

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

not take place, if the labor resources required for developing the template are low and uncertainty in this experimentation phase is ruled out, output grows at a constant rate and no slump occurs at all. As can be seen in Fig. 4, technology diffusion over the whole economy causes one entire cycle of GDP-growth, while in the neoclassical model GDP develops in waves where each sectoral adoption induces a fall in output. However, the reason for the slow-down is the same: The higher the number of sectors engaged in R&D, the lower is the output. The magnitude of the recession thereby also depends on the efficiency gains brought by the new technology and the degree of substitutability between the components.

In fact, many further characteristics of the HT-model are inherent in the present framework: The demand function for intermediate goods is also of Stiglitz-Dixit type, so that capital goods are assumed to substitute each other (at whatever degree), while in reality, many components (e.g. soft- and hardware) are complements. One may argue that the sector specific component can be implicitly understood as one whole set of different inputs; but still, this lacks empirical evidence, since for many GPTs like electricity or ICT, there is a number of manufacturing sectors serving different industries with the same products. Vertical feedbacks, in so far as the user sectors can directly improve the design of the GPT, are not considered as well. Increasing productivity can be again traced back to the rising number of components or to technological change itself. Furthermore, the arrival of the new GPT occurs at pre-determined time intervals which are long enough to let (almost) all sectors adopt the incumbent technology before. Thus, Schumpeter's innovator is not really present in this concept; he clearly does not invent the technology itself, and can be best grasped as being the first discoverer of a template.

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

2.2 Rising Product Quality

Quality-ladder models consider the vertical relation between the invented good and the existing one. An entrepreneur is willing to invest in R&D to improve the state-of-the art good, i.e. to enhance its spectrum of services to the consumer. If the innovation process is successful, the firm is able to drive the supplier of the lower-quality-good out

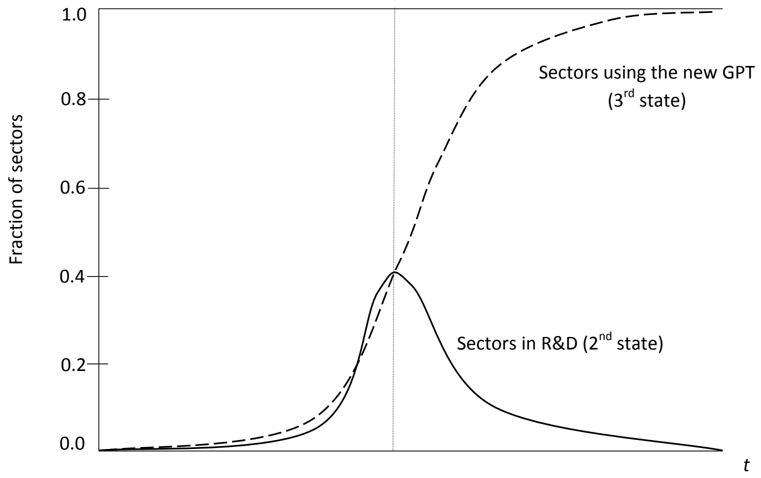

Figure 3: Diffusion of a GPT and related R&D (t denotes time, the dashed vertical line shows the peak in research activities)
Source: Aghion and Howitt (1998a, p.132)

of the market and to set up limit (or quality-adjusted) pricing. However, the stream of monopoly profits lasts only until somebody else comes up with a product of better quality. Step by step, the product thereby climbs up the quality-ladder and the size of the jump reflects the size of improvement.

Petsas (2003)

A further attempt of incorporating the notion of GPTs in a long-run endogenous Schumpeterian growth model was made by Petsas (2003). His approach entails a standard quality-ladder model without scale effects as proposed by Dinopoulos and Segerstrom (1999). Opposed to the previous models of expanding goods variety in intermediate goods, it is the rising product quality of final consumption goods that channels the impact of a new GPT into the economy. The technology itself shows the typical S-shaped diffusion path, however, the rate of diffusion among firms is exogenous to the model. The economy converges to a long-run steady state equilibrium, but during the transition, in which per capita consumption rate falls and the interest rate increases, output growth (measured in GNP) exhibits again a cyclical evolution. The novelty in the approach lies in the fact that population growth is taken into account and leads to diminishing returns with regard to research activities, i.e. with the growing size (or scale) of the market it gets more and more difficult to substitute old goods for

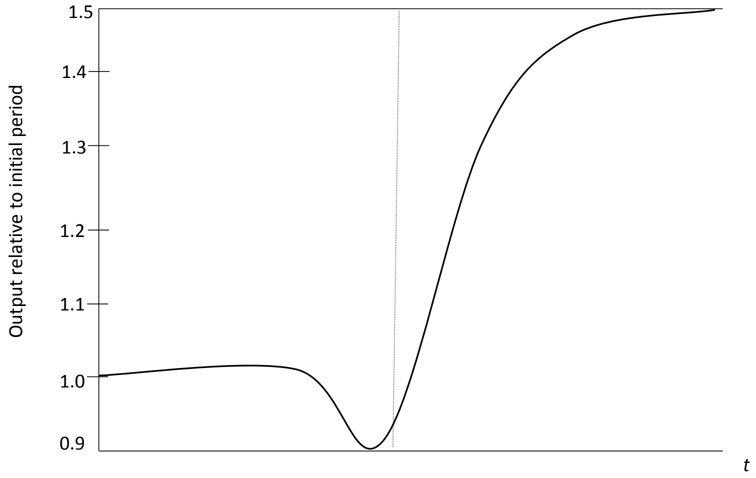

Figure 4: Evolution of output (the dashed vertical line corresponds to the peak in research activities of Fig. 3)
Source: Aghion and Howitt (1998a, p.134)

new products (Petsas, 2003, p.580)[7]. Thus, neither the rate of innovation nor long-run output growth follow the same exponential path of population growth, so that the economy converges again to a steady state.[8]

The framework by Petsas basically features the same setup as the quality-ladder model by Grossman and Helpman (1991b): Final goods are produced by a continuum of industries; and each sector has to allocate the only resource input labor between manufacturing of the goods of highest quality and R&D, in order to foster the innovation of the next generation of final commodities. Households are modeled as dynastic families that maximize intertemporal utility. Each member supplies labor in exchange for wages, consumes only on-top-of-the-line products and saves by holding assets of innovative firms (Petsas, 2003, p.584). The GPT unexpectedly enters the economy in a steady state with constant output growth rates and constant R&D expenditures, where only the old technology is in use, and affects all firms in each sector by increasing (1) the size of all future innovations, and (2) labor productivity in research and thus the arrival intensity of innovations, which in turn enhances the long-run growth rate of the industry. Analogously to Aghion and Howitt (1998a), an epidemic model gives the sigmoid diffusion path of the GPT over all industries at a predetermined rate.

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

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

As to the industry structure, firms in a sector operate under perfect foresight in an imperfectly competitive market and can be differentiated according to the quality of their product. In order to improve the state-of-the art commodity, the agents have to re-direct labor resources to R&D, where free entry applies and production takes place under constant returns to scale. Thus, investments in R&D are undertaken under perfect foresight when the expected returns to research just offset the expenditures. The winner of the R&D race defines and produces the new state-of-the-art good. Each industry follows the same memoryless Poisson process of technical innovation, where the research output is dependent on the GPT under use and the number of workers devoted to R&D. However, with the rising scale of the economy, undertaking research becomes more difficult. Hence, the probability of successful innovation increases with the adoption of the new technology, but falls over time due to population growth. As a consequence, the long run growth rate is affected by the rate of innovation as well as the sigmoid diffusion pattern of the GPT and the economy converges to a new steady state after all industries have switched to the new technology. In contrast to the HT-model and the AH-model, a positive growth rate prevails even in the absence of a new GPT. During the transition to the new steady state, per capita consumption expenditure falls (as more savings are channeled to R&D), and aggregate investments and the interest rate increase. The growth of per-capita-GNP again evolves over a cycle.

Like the HT-model, Petsas' approach allows analyzing the changes on the stock market: As the innovation rate rises with the adoption of the new GPT, the incumbent firm is more likely to be replaced by a challenger, hence the stream of expected discounted profits will cease earlier than before and the stock market valuation undergoes a slump which is more severe, the higher the productivity gain of the new technology. Over the whole life-time of the GPT, the stock market evolves along a U-shaped curve, which is consistent with earlier empirical findings (Jovanovic and Rousseau, 2005) and reflects creative destruction emanating from entrants in R&D.

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

Schiess and Wehrli (2008)

A quality-ladder model of Schumpeterian growth is also used in a recent working paper by Schiess and Wehrli (2008) to examine the effects of a GPT before its arrival, required that economic agents can correctly anticipate its timing and its impact. As in Petsas (2003), the effects of a technological breakthrough are channeled through efficiency gains in R&D. A new technology lifts the economy from one steady state to another with a higher long run growth rate and induces oscillating cycles during the transition. Shortly before the GPT emerges, R&D activities and output growth rise above the initial steady state levels, because agents already know about the technical breakthrough and act under perfect foresight, and immediately upon arrival, R&D related to the old technology slow down drastically.

The framework is based upon the quality-ladder model of Barro and Sala-i-Martin (2004). Final goods are produced by means of labor and a fixed variety of intermediate products, each being on the top of their line. Households earn incomes out of wages and of holding assets and use their budget either for consumption or saving purposes. Firms in the intermediate good sector face monopolistic competition and have to decide whether to manufacture a product of given quality or to invest in R&D in order to improve the commodity and being the sole producer of the new state-of-the-art good. Similar to Petsas (2003), the innovational process takes two stages: In the first stage, firms decide about their R&D expenditures, given that the probability of a successful innovation increases with the amount of resources devoted to research and the operation of the leading-edge technology. Again, difficulties in R&D are taken into account, but opposed to Petsas (2003) they do not depend on the market size, but on the location of the specific firm on the quality-ladder. After having achieved a better quality of the product, they produce and supply the commodity to the final goods sector. The flow of monopoly rents ends with the next successful innovation in the respective industry. The higher is the rate of innovation, the sooner the incumbent is replaced by a challenger and the shorter is the profit stream. As in all other models, free entry to R&D is assumed (so that expected returns on R&D equal zero) and firms are risk-neutral[9]. The arrival of a GPT leads to a new steady state with higher growth and interest rates and a higher level of R&D expenditures[10]. But the question this paper (verbatim) rises is: What happens before the storm? Given the assumption that perfect foresight can be related to the arrival of a GPT, immediately before the technology switch, firms drastically reduce their investments in R&D related to the old technology, as the time intervall in which they can accrue monopoly rents is not sufficiently long. However, if the arrival is far enough in the future, R&D expenditures rise, as all agents know about the imminent slump so that the probability of getting replaced by another firm declines and expected profits increase. The analysis of the transitional dynamics from one steady state to the next is thus carried out by backward induction. Figure 5 shows the corresponding development of interest and growth rates

[9] Risk-neutrality is also present in Petsas (2003), even though each firm is idiosyncratic. However, holding a portfolio of different firms across industries neutralizes the risks for the shareholders.

[10] Schiess and Wehrli (2008) show that the results hold even under the assumption of diminishing returns to R&D.

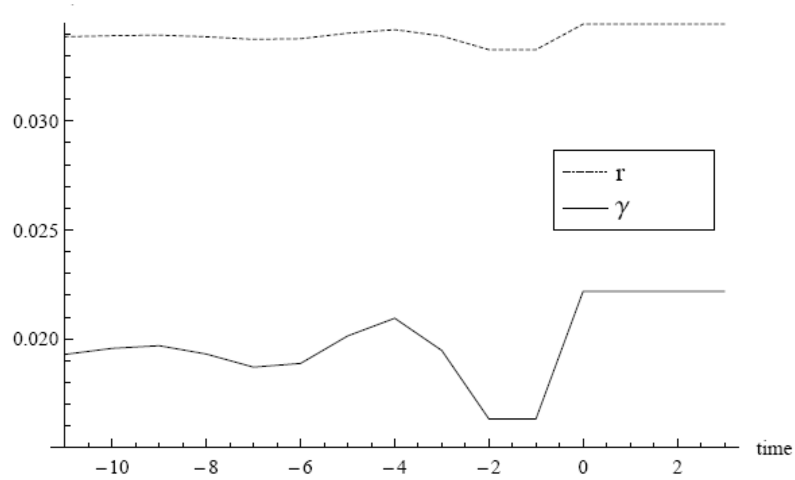

Figure 5: Transitional Dynamics before the arrival of a GPT (r denotes interest rate (dashed line), γ the growth rate)
Source: Schiess and Wehrli (2008, p.19)

between the two equilibria. As the arrival of the new GPT at $t = 0$ approaches, the oscillating cycles become bigger. In the new steady state, both rates are again constant.

The approach differs from all others in so far as a technological breakthrough does not occur unexpectedly. The assumption of knowing the technology before it actually arrives is crucial to the model and the authors justify it in three ways: First, globalization leads to adoption of the same technology across countries, but at different times (see Rosenberg and Trajtenberg (2004) on the corlisse engine and the industrial revolution). Second, many technologies start as a single-purpose technology and unfold their potential only gradually (see Crafts 2004 with regard to the steam engine). Third, the evolution of GPTs itself is path-dependent (ICT would not be possible without electricity, as Lipsey *et al.* (2005) pointed out). The three arguments hold in some cases whereas they have to be denied in others: Type-setting or electricity, for example, were not predictable at all, as they had no clear technological predecessor. It can be argued though (as it is implicitly done in all concepts featuring constant arrival times), that after several decades agents expect the invention of a new all-transforming technology; nevertheless, the exact timing remains uncertain. In general, one could criticize the total absence of uncertainty in this model which firms face in reality with the emergence of a new GPT. Let us take biotechnology as an example: Investments in biotechnology would have never reached the attained high level, if entrepreneurs could have anticipated the strong doubts and even rejection of the broad mass of consumers. So, even if the arrival timing was *a priori* assessable, the impact of a GPT would certainly be not. Compared to the model by Petsas (2003), introducing positive population growth would again lead to scale effects with regard to both innovation and growth rates. As regards the characteristics of General Purpose Technologies, the concept is able to capture the notion of innovational complementarities between the technology and the application sectors, where the GPT enters the production of the final good sector only indirectly over its impact on intermediate products. The model does not deal with the diffusion of the GPT: The technology is *ad hoc* pervasive, because all industries instantaneously adopt it upon arrival, and no *a priori* changes in the production structure is required. As a consequence, just one GPT is operated at any point in time. Finally, the GPT itself does not undergo any further improvements while in use.

All in all, Schiess and Wehrli enhance the existing literature on GPTs by an important aspect, whose further elaboration can give better insights into the phenomenon of GPTs and accomplish the existing concepts. However, tracing the productivity paradox back (or forth) to the next generation technology holds for some GPTs, but not for all, as technological breakthroughs are not always predictable and never in such a scale as the approach at hand assumes.

2.3 Human Capital Accumulation

In a series of papers, Lipsey and Carlaw undertook the attempt to model GPTs in a simple evolutionary framework covering the notion of uncertainty and path-dependence inherent in technological change (Carlaw and Lipsey, 2001, 2003; Lipsey and Carlaw, 2004; Carlaw and Lipsey, 2006). The model allows for successive implementations of different GPTs which are themselves not given from outside of the system, but are developed endogenously and whose creation bears uncertainties concerning arrival times and performance. In contrast to the former models which comprise only two sectors (a final good sector and R&D), it splits the R&D sector into a fundamental research sector which develops the GPT, and an applied research sector where the complementary inputs are created. Agents act on bounded rationality, while in all other models the individuals are able to foresee the whole performance of the GPT already at its arrival. Furthermore, sustained growth does not necessarily imply the invention of a new GPT, which is the case in the first generation of models. The most important difference between the model by Lipsey et al. and earlier models lies in the methodological approach. While the latter used dynamically stationary equilibrium concepts and solve maximization problems under perfect certainty, the former does not imply any concept of equilibrium or balanced growth. In each period a different transitional competitive equilibrium is achieved, and the economy never ends in a steady state. The path dependence of knowledge accumulation and technological change renders the model much closer to evolutionary economics than to the neoclassical perspective.

A first attempt of dealing with pervasive technologies was made by Lipsey and Bekar (1995) under the notion of enabling technologies, which indicates the power of radical innovations in triggering structural change. On the basis of extensive historical studies the authors identify two important features of these technologies which are in common with the concept of GPTs, namely the wide range of applicability and the need of complementary products. Nevertheless, Lipsey and Bekar argue that not all GPTs necessarily have far-reaching effects on the economy in the sense that they induce "deep structural adjustments" of the economic system. Though this first approach has been brought more in line with the existing concept of GPTs, it still retains a more holistic view of technological progress and its impact on structural change. The authors analyse technological change induced by a GPT not only by focusing on its own performance, but with regard to other technologies in use, the facilitating structure and public policy. Thus, examining in great detail the effects on each class of this so-called structuralist-evolutionary (S-E) system, Lipsey *et al.* (2005) differentiate between two types of new GPTs, complementary and transforming technologies, the latter being assigned the motor of drastic structural change. As each of this kind of GPT, such as electricity and ICT, shows similarities in performance and diffusion, a stylized evolution path for a new transforming technology is deducted and embedded into a formal model, with its productivity as well as its number of applications developing in five phases (Lipsey *et al.*, 2005, p.432 ff.). Phase 1 reflects the introduction of the GPT into an S-E system designed for and fully adjusted to the set of technologies in current use. The amount of investment and output attributable to the new GPT is rather small. In Phase 2, the facilitating structure, public policies and policy structure are adapted to the new GPT, the investments are redirected to R&D devoted to the new technology, whereas the corresponding output still lags behind. This phase bears much uncertainty for firms. Phase 3 presents the takeoff of the new technology, in which new products, processes and organization forms are created, and where productivity, real wages, and investments are highest. In Phase 4, the GPT's principles show diminishing rates of application and productivity and the growth rate slows down as the potential of the technology is more and more exploited. In Phase 5, the existing GPT competes with a new technology, which finally partially or fully replaces it, so that conceiving technological change as a sequence of GPTs, more than one technology is on stage at a time. The length of this challenging phase can be either very short, if the new technology is clearly superior or can take some time, when additional R&D is able to boost the productivity of the established technology. It may also be, as in the case of electricity, that the technology in use lays the ground for the next generation of GPT, e.g. electronic computers, revealing the path-dependence of technological change. While Phase one to four appears in chronological order, this last phase can take place at any time in the life-cycle of the incumbent GPT. However, the longer the GPT is in use, the bigger the pressure of inventing a new transforming technology which will re-accelerate the growth rate. This evolution path can be represented by two logistic curves, one related to the efficiency and the other to the set of technological complementarities. Abstracting from further technical breakthroughs complementary to the technology throughout its lifetime, improvements in efficiency come smoothly (so that jumps in the productivity curve do not occur).The applications curve draws the evolution of subsequent technological change with regard to new products, processes and organizational forms or improvements of existing ones, where in the beginning the number of applications is rather small, but rises over time with the increase in efficiency, before the diffusion rate slows down in the last phases of the GPT. Thus, technological change can be presented by a sequence of logistic curves, each assigned to a different GPT, which may overlap during some phases.

The formal model (Lipsey *et al.*, 2005) consists of three different sectors, one producing the single consumption good, an R&D sector, where applied knowledge is used to make the GPT feasible for the specific purpose of producing the final commodity, and one pure research sector, where the GPT itself is developed. Commodity and research outputs are all produced by means of one generic constrained input which has to be allocated between the three sectors and all production functions exhibit diminishing returns to scale with regard to the resource input and constant or diminishing returns to scale to the knowledge stock they use, where (exogenous) depreciation of human capital is accounted for. In contrast to all previous models apart from Schiess and Wehrli (2008), the GPT does not directly enter the production function of the final commodity, but only indirectly, because the new technology (i.e. the current stock of pure knowledge), affects *ad hoc* the stock of applied knowledge, which in turn contributes to the production of the consumer good. The impact of the GPT on the marginal productivity of applied knowledge thereby evolves along the logistic efficiency curve mentioned before, opposed to the linear development of components in the approaches of expanding product variety. Thus, the level of output and the growth cycle is straight-forward determined by the efficiency curve, and not via the diffusion process across firms and sectors (Lipsey *et al.*, 2005, p.442). The third sector is devoted to the development of a new GPT by means of a certain stock of applied knowledge and a generic resource input, and captures the notion of uncertainty threefoldly (Lipsey *et al.*, 2005, p.455): The flow of pure knowledge produced by a given effort is subject to random fluctuations; the arrival of a new GPT fluctuates around a typical length; and the impact of a newly introduced GPT on the productivity of applied knowledge is determined in part endogenously by resource allocation and in part exogenously by two random factors that affect the location and the height of its efficiency curve. It is thus the direct interrelatedness of the applied and the pure knowledge sector which represents technological complementarities and the feedback-effects on the GPT. Under perfect competition, the generic resource is allocated across the three sectors by agents maximizing their expected pay-offs to investments at each point of time. As the discount factor is set to zero, the problem is reduced to dealing with inter-sectoral, but not inter-temporal trade-offs: Shifting resources from the consumption to the applied knowledge sector will lower consumptive output in the current period, but will increase the future productivity in the consumption sector, thus leading to a higher average growth rate of output. Devoting inputs to the production of pure knowledge will affect the impact, but not the timing, of the new GPT. In the absence of perfect foresight, the expectations are formed upon the current marginal products and given the random variables that obstructs the correct anticipation of the future productivity, the economic system results in a non-stationary equilibrium. Unlike all other models on GPT, the present concept addresses the problem of competing GPTs, whereby the new generation still dominates the old one in the long-run, but not necessarily in the short-run, as its full impact is not immediately revealed upon arrival, but evolves along a logistic curve (see Fig. 6). Thus, comparing the innovative technology with

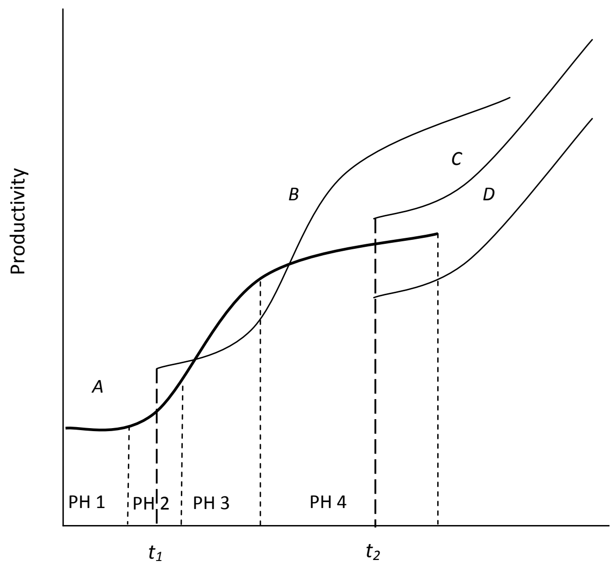

Figure 6: Phases of a single GPT and productivity curves for successive GPTs
Source: Lipsey *et al.* (2005, p.438)

the incumbent one, the first can be either accepted, abandoned or sent back to further development, basically depending on three decision criteria: First, the challenging technology will always beat the technique in use, simply, because it shows up at a later point of time (i.e. B over A in Fig. 6), second, the old and new technology can be ranked according to their current and initial productivity level respectively (A over B), or third, they are compared with regard to their future performance (i.e. B over A). The decision whether to discard the new technology, or to invest in its further development, just concerns the model in so far as if the first option is chosen, the incumbent technology is locked-in until a totally new GPT comes to stage; whereas if the latter occurs, then the present technology is subject to comparison with the challenged GPT in every upcoming period. The choice for a specific transition criterion determines the frequence of arrivals and the rate of technological change. As a consequence, the long-term output growth rate does not necessarily show the cyclical behavior proposed by all previous models, as its path depends here on the timing of the consecutive GPT and the exogenous selection policy.

The concept represents a clear break with all other models, as it does not entail permanent increasing returns to knowledge and does not presume a linear relationship between resource accumulation devoted to R&D and the growth rate. Instead, increasing returns to scale are shown as a jump in the efficiency of a new GPT relative to the established technology. The model predicts sustained growth, also in the absence of a new GPT, and differing average growth rates along the sequence of GPTs. As the authors point out, the application of the model to a range of countries would imply varying growth rates and constant input-output ratios both of which is consistent with the stylized facts in growth theory (Lipsey *et al.*, 2005, p.445). Extensions of the three-sector baseline model is intuitively, not formally, discussed regarding different concepts of expectations' formation and the effects on the facilitating structure. Structural change in the sense that the GPT evolves over different industries is considered in form of a five-sectoral framework, where an additional applied R&D sector serves the production of a further consumption good, i.e. in-house applied R&D takes place. Covering interrelatedness among these industries, the pure knowledge sector is, on the one hand, fed by the different stocks of applied knowledge, and on the other hand exhibits different marginal productivities in the applied R&D sector. Challenged by a new GPT, the incumbent technology might be replaced in one sector, but could have comparative advantages in the production of the other consumption good, which means that two different GPTs are applied simultaneously. Given its holistic view, the approach shows many parallels to the notion of Techno-Economic Paradigms: It not only distinguishes between similar phases, but also the historic specifity and the non-ergodicity of technological innovation is accounted for (Lipsey *et al.*, 2005, p. 461) and unfolds in a spectrum of possible outcomes, in contrast to the general results drawn from the former approaches. The loss in generality is thus outweighted by the gain in explanatory power.

3 Conclusion

The present paper was aimed at discussing the existing literature on major technological change, focusing on the models of General Purpose Technologies. Therein the discontinuities in growth a GPT is able to trigger gets evident in different ways: Either by the switch from one technology to the next, rendering current means of production obsolete, by a jump in the quality-ladder, or by a shift of the efficiency curve (Table 3 compares the models with regard to the most important features). However, as Janssen (1998) indicates, the economic system is an undeterministic, heterogenous, irreversible system which is in constant disequilibrium and contains evolutionary characteristics. This holds *a fortiori* true when a GPT enters the system. The approaches listed in the first section have all considered the path-dependent nature of technological change, whereas most of the models explicitly dealing with GPTs do not. Except for Lipsey *et al.* (2005), technical change is not studied as a phenomenon *per se*, but in the context of neoclassical economics, presupposing Harrod-neutral technical progress to sustain a long-run steady state. More controversially, the present models are not able to encompass the full notion of GPTs as introduced by Bresnahan and Trajtenberg (1995) either. While innovational complementarities, i.e. rising productivity with regard to R&D in the downstream sectors, are accounted for, technological complementarities are covered in the models of expanding product variety and in the evolutionary approach, but not in the quality-ladder models. The positive externalities generated by the introduction of the GPT are undermined; the vertical feedback effects from the user sectors to the GPT itself can be fully captured only in the model by Lipsey *et al.* (2005), since in all other approaches the technology is “frozen” over its life-cycle. Thus, the productivity parameter does not represent the general purpose technology itself but rather the “general purpose principle”(Lipsey *et al.*, 2005; Bresnahan, 2010) behind it. The horizontal externalities, on the other hand, are just present in the model by Aghion and Howitt (1998a), where the number of observations of other firms increases the probability of successful discovery of an own template. However, the original concept has been extended by the models at hand in various ways: Most importantly, the diffusion path of the GPT and its effects on macro-aggregates cannot be modeled within a partial equilibrium framework. Uncertainty was not considered in Bresnahan and Trajtenberg (1995) either, where the main focus lies on the coordination problem linked to asymmetric information and the public-good character of commercial research.

	Expanding Product Variety		Rising Product Quality		Human Capital Accumulation
	Helpman & Trajtenberg 1998a	Aghion & Howitt 1998a	Petsas 2003	Schiess & Wehrli 2008	Bekar, Carlaw & Lipsey 2005
Endogeneity of GPT	no	Poisson arrival process	no	no	endogenous generation of GPT
Evolution of GPT	no	no	no	no	yes
Technological Complementarities	between GPT and CS	between GPT and CS	no	no	between pure knowledge sector and applied knowledge sector between applied knowledge sector and consumption sector
Innovational Complementarities (rising productivity downstream)	yes	yes	yes	yes	yes
Primary Production Factors	labor	labor	labor	labor	unspecified resource input
Sectoral Diffusion	yes	yes	yes	no	yes
Uncertainty	no	arrival time, adoption	R&D race	R&D race	arrival time, size of innovation
Monopolistic competition	CS	CS	final good sector	CS	no

Table 1: Comparison of GPT-models (CS stands for component sector)

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