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# Agent-based Models of Innovation and Technological Change

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AGENT-BASED MODELS OF INNOVATION AND TECHNOLOGICAL CHANGE

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## Contents



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**Abstract**

This chapter discusses the potential of the agent-based computational economics approach for the analysis of processes of innovation and technological change. It is argued that, on the one hand, several genuine properties of innovation processes make the possibilities offered by agent-based modelling particularly appealing in this field, and that, on the other hand, agent-based models have been quite successful to explain sets of empirical stylized facts, which are not well accounted for by existing representative-agent equilibrium models. An extensive survey of agent-based computational research dealing with issues of innovation and technological change is given and the contribution of these studies is discussed. Furthermore a few pointers towards potential directions of future research are given.

**Keywords:** agent-based computational economics, innovation, technological change, evolutionary economics

# 1 Introduction

Innovation and technological change[2] is today generally seen as one of the driving forces if not **the** driving force of economic growth in industrialized countries (see e.g. Maddison (1991) or Freeman (1994)). Whereas this aspect of economic activity has for a long time been largely neglected in mainstream economics, its importance has by now been recognized and a large rather diversified literature has evolved focusing on different aspects of technological change. Based on the fast growing empirical literature on this issue a rich set of well accepted facts concerning technological change have been established. Important concepts like that of incremental/radical innovations or technological paradigms and trajectories have been developed to capture patterns holding across sectors, observations about patterns of industry evolution, the general importance and structure of knowledge accumulation processes, the typical existence of heterogeneity in employed technology and firm size within industries have been established, but also a large degree of sector specificity of patterns of technological change (e.g. Pavitt (1984)) has been observed. The reader is referred to Dosi (1988), Dosi et al. (1997), Freeman (1994), Klepper (1997), Kline and Rosenberg (1986), Malerba (1992), Pavitt (1999), Rosenberg (1994) for extensive discussions of empirical findings about technological change. Likewise, the set of modelling approaches and tools that have been used to gain theory-based insights about origins and effects of innovation and technological change is very wide including dynamic equilibrium analysis, static and dynamic games, theory of complex systems or evolutionary theorizing. Overviews over different strands of theory-oriented literature can be found e.g. in Dosi et al. (1988), Grossman and Helpman (1994), Hall (1994), Nelson and Winter (2002), Stoneman (1995), Sutton (1997) or van Cayseele (1998).

The aim of this chapter is to highlight and discuss the past and potential future role of the agent-based computational economics (ACE)[3] approach in the important endeavor to gain a better understanding of technological change. Two main arguments will be put forward to make the point that agent-based models might indeed contribute significantly to this literature. First, as will be argued below, predictions of standard equilibrium models do not provide satisfying explanations for several of the empirically established stylized facts which however emerge quite naturally in agent-based models. Second, the combination of very genuine properties of innovation processes call for a modelling approach that goes beyond the paradigm of a Bayesian representative-agent with full rationality and it seems to me that the possibilities of ACE modelling are well suited to incorporate these properties. The genuine properties I have in mind are: i) the dynamic structure of the process(es); ii) the special nature of 'knowledge', arguably the most important input factor for

[2]Throughout this chapter the term 'technological change' will be interpreted in a wide sense to subsume processes leading to generation and diffusion of new knowledge, technologies and products.

[3]No general introduction to the field of ACE is given in this chapter. See e.g. Tesfatsion (2003) or Tesfatsion (2005) in this handbook for such an introduction.

the 'production' of innovation; iii) the strong substantive uncertainty involved; iv) the importance of heterogeneity between firms with respect to knowledge, employed technology and innovation strategy for technological change.

Let us briefly discuss these four points. (i) The dynamic aspects of the process of innovation and technological change have been stressed at least since the seminal work of Schumpeter (1934, first published 1911 in German language). Technological change does not only lead to an increase in overall factor productivity but also has significant effects on the way the market and industry structure evolves over time. Schumpeter's trilogy of invention-innovation-diffusion already indicates that the innovation process per se has a time structure which should be taken into account. In particular, the speed of diffusion has important implications for the expected returns to innovation on one hand and for the evolution of the market structure on the other hand. The way innovations diffuse are industry specific and such processes typically involve path dependency and dynamic externalities. Also the other two stages in the trilogy involve truly dynamic processes. Investment decisions about innovation projects are typically not made once and for all but are continuously updated over time. This is necessary due to the substantive uncertainty involved in predicting markets and technological developments as well as the accumulation of own knowledge (see the comments below)[4].

(ii) The success of innovative activities of a firm does not only depend on its current investment but also to a large extent on the size and structure of the knowledge base the firm has accumulated. The stock of knowledge of a firm is not uniform and has a lot of structure[5]. For example distinctions should be made between explicit and tacit knowledge as well as between general knowledge and specific skills. A large body of empirical evidence has demonstrated that the knowledge base (Dosi (1988)) needed for successful inventions and innovations has to be gradually accumulated over time. Several mechanisms have been identified to gain such knowledge among them in-house R & D, informal transfer of knowledge between companies (spillovers) or learning by doing. In all cases the effect of current actions depends crucially on past experience and therefore the entire process of knowledge accumulation has to be considered when studying innovative activities. Studying accumulation of knowledge is however quite different from studying accumulation of physical capital. Knowledge can only to a certain extent be traded on a market. It is often embodied in individuals and groups of people ('tacit knowledge'; see Polanyi (1966)), can almost without cost be duplicated by its owners and has a tendency to flow through several local and global channels of diffusion. Studying such flows means dealing also with issues of local interaction and communication network formation. Incorporation ex-

[4]Also within the literature dealing with fully rational Bayesian decision makers the importance of the dynamic resolution of uncertainty in innovation projects has been acknowledged leading to the application of a real-option approach for such decision problems (see e.g. Grenadier and Weiss (2001) or Smit and Trigeorgis (1997)).

[5]Loasby (1999) provides an excellent discussion of the nature of knowledge and cognition and its role in economic interactions and development.

plicit knowledge accumulation processes and non-market interactions between firms into an equilibrium model of technological change might in principle be possible, but this would most probably destroy any analytical tractability and to my knowledge has not been attempted yet[6].

(iii) The level of uncertainty associated with innovations depends on the type of industry and the type of innovation we are dealing with. Typically a distinction is made between incremental innovations, where minor extensions to existing processes or products are introduced without leaving the current paradigm, and radical innovations which try to open new markets or to employ a new technique or organizational structure for the production of a good. Building beliefs about future returns of an attempt to develop a radical innovation is a very challenging task (see Freeman and Perez (1988)). There is uncertainty not only about the technical aspects (feasibility, reliability, cost issues) but also about market reaction. Whether an innovation turns out to be a market-flop, a solid profit earner or the founder of a new market depends on numerous factors and is ex ante hard to see[7]. More generally, any economic agent operating in an environment influenced by innovations is subject to 'strong substantive uncertainty' (Dosi and Egidi (1991)) in a sense that it is impossible to foresee the content of inventions to be made in the future (otherwise it would not be a new invention) and therefore to anticipate all possible directions of future technological development. Put more formally, the current mental model of the agent cannot include all possible future contingencies. Accordingly, a standard Bayesian approach, which has to assume that the agent ex ante knows the set of all possible future states of the world, is not appropriate to capture the essence of the uncertainty involved with innovation processes. Or, as Freeman and Soete (1997) put it: '*The uncertainty surrounding innovation means that among alternative investment possibilities innovation projects are unusually dependent on 'animal spirits'.* [p. 251]. Furthermore, it has been argued in Dosi and Egidi (1991) that 'procedural uncertainty' referring to the inability of an agent to find the optimal solution in a choice problem – either due to her limited capabilities or due to actual problems of computability – is also of particular importance in many tasks associated with innovation and technological change (see also Dosi et al. (2003)).

[6] A recent example of a dynamic equilibrium model which explicitly takes into account the heterogeneity of knowledge stocks and spillovers is Eeckhout and Jovanovic (2002). Here spillovers work on a one-dimensional stock variable representing *an aggregate of physical and human capital*. The stock of a firm is updated based on the part of the population distribution above the own stock using a weighted average rule. The interaction leading to exchange of knowledge is not explicitly modelled but the weighting function is estimated using stock market data. As usual in equilibrium the (physical-human) capital stock of all firms grows at a uniform rate.

[7] Beardsley and Mansfield (1978) show, based on 1960-1969 data from a multi-billion dollar corporation, that (discounted future) profitability forecasts for new products were wrong by a factor larger than 2 in more than 60% of the cases, although the study was not restricted to radical innovations. Even 5 years after development of new products forecasts were off by a factor larger than 2 in more than 15% of the cases. See also e.g. Cooper and Kleinschmidt (1995), Hultink et al. (2000) or Freeman and Soete (1997) for more recent discussions of the issue.

It seems that a rule-based model of the decision making process which, on the one hand, makes constraints on computability explicit and, on the other hand, restricts usable information to what is available to the agent at a certain point in time, rather than assuming an ex-ante knowledge about the set of all possible future contingencies, is better able to capture decision making under strong substantive and procedural uncertainty than dynamic optimization models with Bayesian updating or even perfect foresight.

(iv) Finally, the study of processes and effects of innovation requires particular consideration of the heterogeneity between firms in a market. Different types of heterogeneity should be distinguished. I will mention here three types of of heterogeneities relevant for understanding technological change, but this is certainly no complete list. First, it has been shown that the basic approach towards innovative activities – e.g. whether to focus efforts on product or process innovation, on incremental or radical innovation or even completely on imitation and reverse engineering – is in many instances quite heterogeneous even within one industry (e.g. Malerba and Orsenigo (1996)). Second, heterogeneity and complementarity of the knowledge held by different firms in an industry is an important factor in facilitating the generation of new knowledge through spillovers as well as in the exploration of the potential avenues of technological development. Third, heterogeneity is not only an important pre-requisite for the emergence of technological change, it is also a necessary implication of innovative activities. The whole point of innovating for firms is to distinguish themselves from the competitors in the market according to production technique or product range, thereby generating heterogeneities. Innovation incentives depend on (potential) heterogeneities between firms. So, whereas heterogeneity of agents is of course an important property in any market interaction, consideration of heterogeneities of firm characteristics, strategies, technologies and products seems essential if the goal is to understand the processes governing technological change. It is well established by now that in general aggregate behavior stemming from heterogeneous agents cannot be properly reproduced by using a representative agent instead (see e.g. Kirman (1992)) and therefore these heterogeneities should be properly represented in the models used to analyze technological change.

Summarizing the brief discussion of properties i) - iv) we conclude that when considering the process of technological change in an industry, we are looking at a highly decentralized dynamic search process under strong substantive and procedural uncertainty, where numerous heterogeneous agents search in parallel for new products/processes, but are interlinked through market and non-market interactions. So already from the purely theoretical perspective that a micro-founded economic model, even if highly stylized, should capture the essential effects influencing the phenomenon under examination, the possibilities offered by agent-based computational models are appealing. The modelling of the dynamic interaction between individuals who might be heterogenous in several dimensions and whose decisions are determined by evolving decision rules can be readily realized using ACE models.

Whereas my discussion so far has focused on the issue of realism of the assumptions underlying a model, there is a second argument of at least the same importance for the use of an ACE approach in this field, namely that of the explanatory power of the model. This is particularly true, if we compare the ACE modelling with neoclassical equilibrium analysis. The problems of neoclassical models to explain and reproduce important stylized facts about innovation, technological change and industry evolution have been discussed among other places in Dosi et al. (1995), Dosi et al. (1997), Sutton (1997) or Klepper and Simons (1997). Here, no extensive discussion of this issue is possible. I restrict myself to sketching a few of the empirically supported observations which are at odds with or at least not satisfactorily explained by a neoclassical approach, particularly if we consider several of these facts jointly (for more details on these 'stylized facts' see the references given above, Silverberg and Verspagen (2004) and a special issue of *Industrial and Corporate Change* (Vol. 6, No. 1, 1997)).

- In almost all industries a relatively stable skewed firm size distribution can be observed, i.e. there is persistent co-existence of plants and firms of different sizes.

- Persistent heterogeneities between firms with respect to employed technology, productivity and profits rather than convergence to a common rate of return can be observed in many industries.

- In general, there is a positive correlation between entry and exit rates of firms across industries. Industry profitability does not seem to have a major effect on entry and exit rates.

- Patterns of industry evolution and demographics vary considerably from industry to industry. On the other hand, there are strong similarities of these patterns across countries in the same technological classes. In particular, the knowledge conditions shaping the technological regime underlying an industry have substantial influence on the observed pattern.

- The arrival of major innovations appears to be stochastic, but clustering of major innovations in a given time interval is stronger than one would expect under a uniform distribution.

As will be demonstrated in subsections 3.4 and 3.5, quite a few of these observed patterns can be rather robustly reproduced using ACE models. This is particularly encouraging since these patterns are in no way explicitly incorporated into these models, but are *emergent properties* of the aggregate behavior in complex models, which in many cases are build upon rich micro foundations incorporating at least some of the key features of the processes involved in actual technological change.

This highlights another important feature of ACE models, namely that due to its reliance on computer simulations, this approach can easily link the interplay of individual innovation strategies, market structure and micro effects to the development of industry-wide or even economy-wide variables like average factor productivity, number of firms or economic growth. The emergence of regular macro patterns based on decentralized uncoordinated micro interaction is an important general feature of agent-based models. The fact that ACE models are well able to reproduce actual aggregate behavior under given economic conditions becomes particularly relevant if ACE models are used to predict and evaluate the effects of policy measures that might change the industry or market environment (see e.g. Kwasnicki (1998) or Pyka and Grebel (2003) for more extensive discussions of the potential of agent-based modelling in evolutionary economics).

Despite the apparent merit of the agent-based simulation approach for the analysis of a wide range of issues in the economics of innovation and technological change, the amount of relevant ACE-based work in this area is not huge. A large fraction of this work has been conducted in the tradition of the evolutionary economics approach pioneered by Nelson and Winter (1982). However, the amount of work in this area substantially increased during the last few years where also several issues outside the scope of evolutionary analyses were addressed. This chapter should give an overview over the issues addressed in the different types of ACE studies in this area and highlight some examples of the kind of models which were developed to do this. The presentation will be organized around the two main arguments for the use of ACE models in the domain of the economics of innovation which were discussed in this introduction. I will first illustrate the different ways how ACE researchers have tried to address each of the four discussed specific properties of technical change processes in their models[8]. Afterwards, I will discuss a number of ACE models which have been successful in reproducing stylized patterns of industry evolution and economic growth. Although there will be some coverage of ACE models of economic growth the overall focus of the chapter is rather on the micro foundations and industry level behavior than on economic growth. A more extensive discussion of the potential of ACE models for the analysis of economic growth from a broader perspective can be found in the chapter by Howitt (2005) in this handbook. It is also important to point out a few topics what will *not* be covered in this chapter in spite of their relevance for the understanding of economic

[8]Actually, I will explicitly deal only with the importance of knowledge, the effect of the strong uncertainty and issues of heterogeneity. By their very nature ACE models incorporate the dynamic nature of innovation and technological change and therefore this point is not separately addressed. It should be noted however that many game-theoretic results characterizing innovation incentives in different market environments rely on static models. Among many others Dasgupta and Stiglitz (1980), D'Aspremont and Jaquemin (1988), Bester and Petrakis (1993), Qiu (1997). Although using vastly simplified settings these papers make interesting points about strategic effects that might influence the firms choice of innovation efforts. A static setting indeed seems to be a useful way to clearly identify some of these effects, although it should also be considered in how far the obtained insights transfer to a dynamic world.

change. I will not discuss issues associated with organizational change (this is at least partly covered in the chapter by Chang and Harrington (2005) in this handbook) and only touch upon the important relationship between organizational and technological change and the crucial role of organizational structure of a firm for the success of its innovative activities. Also, there will only be little discussion of emergence of networks and information diffusion models although such models are of obvious relevance for the understanding of several aspects of the process of technological change (e.g. knowledge spillovers, speed of diffusion of new technologies). Models of this kind are discussed in the chapters by Vriend (2005) and Wilhite (2005) in this handbook, see also Cohendet et al. (1998) for a collection of surveys and papers dealing with this issue.

The plan for the remainder of this chapter is the following. In section 2 the evolutionary approach is briefly discussed and in section 3 I survey some of the existing literature[9] where ACE models have been developed to address issues of innovation and technological change. In section 4 I will briefly discuss whether my statements in this introduction concerning the potential of ACE research in this domain can be justified based on the work surveyed in section 3. I conclude with section 5, where a few challenges and promising topics for future work are highlighted.

## 2 The Evolutionary Approach

The dynamic process of technological change has been extensively analyzed in the field of evolutionary economics. The range of work which is subsumed under the label evolutionary economics is quite broad and heterogenous. According to Boulding (1991) '*evolutionary economics is simply an attempt to look at an economic system, whether of the whole world or of its parts as continuing process in space and time.*' Clearly the notion of some kind of 'selection' process which determines the direction of the dynamics is a key concept for most of the studies in this field which also provides the bridge to theories of biological evolution. The idea that behavior of economic decision makers might be determined by a selection process rather than the application of optimization calculus is not a new one (see e.g. Alchian (1950)) and has even been used by neoclassical economists to make the 'as if' argument in defense of the assumption of perfect rationality of economic decision makers (Friedman (1953))[10]. Schumpeter is generally seen as the pioneering figure in the field

[9] The actual selection of papers which are included in this literature review is of course strongly influenced by the available information and the personal bias of the author. I apologize to all authors whose work is not or not properly represented in this chapter.

[10] It should be stressed that the 'as if' argument is flawed for several reasons. The main reason being that it either implicitly assumes global stability of the state, where everyone uses the optimal decision rule, with respect to the underlying evolutionary dynamics – which holds in only few special cases – or implicitly assumes that the initial condition of the system happens to be in the basin of attraction of such an optimal state.

since he was one of the first to stress the importance of innovation for economic growth and rejected the idea of 'convergence' in favor of a view the economy as an ever changing system. Although he rejected the simple application of biological selection metaphors to economic systems, his ideas about technological competition characterized by the interplay of entrepreneurs advancing technology by introducing innovations (thereby earning additional transitory profits) and imitators aiming to adopt them certainly describe a type of selection and diffusion mechanism. The early contributors were however rather isolated and it is fair to say that 'modern' evolutionary economics gained momentum only about 30 years ago. Since then it has been a very active field of research.

## 2.1 General Characteristics of the Evolutionary Approach

Branches within evolutionary economics have relied on approaches heavily influenced by models of natural evolution to study what kind of behavior emerges in the long run in a population whose members are engaged in some kind of repeated direct interaction. The huge literature on evolutionary game theory falls into this category (see e.g. Weibull (1995)). Like Schumpeterian and neo-Schumpeterian work this approach is based on population thinking and scepticism towards too strong rationality assumptions about economic agents. Contrary to the Schumpeterian approach the focus is however typically on questions of dynamic equilibrium selection for a given strategy set rather than to explore actual innovation dynamics. More relevant in our context is the branch of literature that interprets the process of technological change as an evolutionary process and thereby applies evolutionary ideas to gain insights into industry dynamics and in particular into the co-evolution of technology and industry structure. Much of this literature was inspired by the seminal work of Nelson and Winter (1982) and accepts computer simulations as a useful and suitable tool to study the properties of the considered dynamic process.[11] Accordingly, the evolutionary approach has been underlying a large fraction of the agent-based work on innovation and technological change. Before I briefly discuss the simulation models examined Nelson and Winter (1982) I would like to point out some of the arguments and observations concerning technological change made in the evolutionary economics literature which highlight the merit of agent-based modelling in this field. More extensive recent discussions of the evolutionary approach can be found in Dopfer (2001), Dosi and Winter (2002), Fagerberg (2003), Nelson (1995), Nelson and Winter (2002), Witt (2001) or Ziman (2000).

Evolutionary processes in their most general form might be characterized by three main stages: i) generation of variety by means of individual innovations; ii) selection based on some measure of 'success'; iii) reduction of variety due to diffusion and adaptation. The interpretation of the three stages for biological evolution

[11] Some of the work on industrial evolution and growth has relied on analytical tools and findings from evolutionary biology like results on replicator dynamics or Fishers theorem of natural selection (e.g. Silverberg et al. (1988), Metcalfe (1998)).

is straightforward but this is less so if we are concerned with the evolution of economic systems. In each of these three stages individuals make important decisions but in an evolutionary view the subject of analysis is not the individual but rather the entire population. The question which company is introducing a certain new technology is of less concern than the question when such a new technology will be first developed in the entire population. Obviously, there are however crucial feedbacks between the individual and the population level. Population characteristics are the aggregate of individual decisions, but it is also important to realize that individual decisions on all three stages are in general determined by population characteristics. So, an evolutionary approach always calls for 'population thinking' and highlights the importance of an integrated analysis of the micro and the population level (sometimes called meso level) as well as the feedbacks between the two. The complexity of this endeavor is obvious and calls for simulation methods. This is even more so if one considers the importance of variety (or heterogeneity) for the understanding of evolutionary processes. The interplay between the generation of variety in the first stage and the reduction of variety by some kind of selection is the fuel of the evolutionary process, which comes to a halt once the population becomes homogenous. Therefore, the explicit consideration of heterogeneity in a population of economic agents is indeed a natural implication of an evolutionary approach.

Another aspect of the evolutionary approach which has contributed to the popularity of agent-based simulation models in this field is the way decision making processes within the firm are seen. Particularly for work influenced by Nelson and Winter (1982) organizational routines are at the center-stage of these considerations. This view stresses procedural rationality as the key concept for understanding firm's decision making rather than the neoclassical perfect rationality assumption. Nelson and Winter (1982)[12] argue that firms develop over time routines to deal with situations they are frequently facing. This process is based on feedback learning rather than on perfect foresight or complex optimization arguments. The decision making process of a firm is characterized by the set of its developed routines and therefore routines have an important role as the organizational memory. Hence, this view on the decision making process of firms incorporates in a natural way 'behavioral continuity' of firms, which seems to be an important property of actual decision making in many real world firms (some empirical evidence is cited in Nelson and Winter (2002)).

This behavioral foundation of evolutionary economics has lead to a focus on models where decision making processes are represented in an explicit procedural way rather than by relying on abstract optimization calculus. Such a shift of focus makes agent-based models a natural choice, since they easily allow to incorporate decision processes relying on sets or even hierarchies of rules (e.g. using classifier systems), whereas such attempts are typically cumbersome in pure analytical for-

[12]Nelson and Winter build upon previous work, most notably that by Cyert and March (1963) and Simon (1959)

mulations and in general do not allow for general mathematical characterizations. Nelson and Winter (1982) have a very general interpretation of routines and point out that a firm needs a wide mix of different type of routines, where the content ranges from 'determining the actions needed to keep a production line running' to 'managing conflicts within an organization', 'deciding on the introduction of a new product' or even 'determining how routines in the firm should be adapted over time'. Nevertheless, most concrete implementation of models in this tradition have considered rather simple non-hierarchical rule systems determining output quantity or investment decisions, where in many cases it has been assumed that firms do not change their rules over time.

## 2.2 The Analysis of Nelson and Winter (1982)

In this subsection I will briefly discuss a few selected parts of the book by Nelson and Winter (1982). The reasons to do this is twofold. First the way the analysis is carried out in this book has been quite influential for the way simulation studies of industrial dynamics were motivated, set-up and performed afterwards. Second, quite a few of the agent-based models reviewed in section 3 are more or less directly based on the models presented in this book.

In part IV of their book Nelson and Winter develop an evolutionary model of economic growth. There are two input factors, labor and physical capital, and firms are characterized by the current values of the input coefficients for both factors and the capital stock. Firms can improve the values of the input coefficients by local search and imitation. There is fixed supply of labor and wages are determined endogenously based on the aggregate demand for labor. Gross investment is determined by gross profits. Nelson and Winter argue that an evolutionary model of economic growth should be based on plausible micro foundations and at the same time should be able to explain patterns of aggregate variables like outputs and factors prices. They calibrate their model using data reported in Solow (1957) and show that this very simple evolutionary growth model is able to qualitatively reproduce dynamic patters of key variables for the Solow's data. The focus on the reproduction of 'stylized facts' using micro-founded dynamic models stressed in this exercise has been a main theme of subsequent evolutionary research on industrial dynamics and growth.

In Part V of the book a more complex model of Schumpeterian competition and industry evolution is considered. Firms produce with constant returns to scale a single homogeneous good. Every period each firm is using its capital stock in order to produce output according to its current productivity level. By investing in imitation or process innovation firms can increase their probability to have a successful imitation or innovation draw which leads to the adoption of the highest current productivity level in the industry or the development of a new technique whose productivity is random and might be above or below the current best practice (but is only chosen if it is above the firms' current productivity)[13]. A firm is characterized by its fraction of profits invested for imitation and innovation and by its investment function, which determines desired expansion or contraction of capital based on observed price-cost margin, market-share, profit and the physical depreciation rate. Since the entire capital stock is always employed in production, the investment function is crucial for the determination of the production quantities of the firm. Whereas the first two are numerical parameters, a certain functional form had to be chosen for the investment function in the simulations.

In all sets of simulations these characteristics of firms are fixed over time, however there are initial heterogeneities between firms with respect to their innovation strategies. In particular, it is assumed that the industry is a mix of imitators (investing only in imitative R&D) and innovators (investing in imitative and innovative R&D). The different paces of capital accumulation and exit of single firms therefore lead to selection effects of behavior on the industry level. The analysis of the simulation runs focuses on the long run outcomes (after 100 periods) of industry evolution with respect to the distribution of productivity, the degree of industry concentration and the relative performance of innovators and imitators. In a first step these long run outcomes are compared for a science-based industry across scenarios characterized by different degrees of initial concentration. It turns out that average productivity is larger for more concentrated industries but no strict positive relationship between concentration and cumulative expenditures on innovative R&D can be observed. Innovators are on average less profitable than imitators but some still survive in the industry. In a second step Nelson and Winter analyze the impact of several industry characteristics (aggressiveness of investment policies, difficulty of imitation, rate of latent productivity growth, variability of innovation outcomes) on the degree of long run concentration. The simulations show that among these factors the aggressiveness of investment policies is most crucial for determining the long run industry concentration. More aggressive investment behavior leads to higher concentration. Also the direction of the impact of the other considered factors is quite intuitive but less pronounced.

The model and the analysis of Nelson and Winter (1982) is extended in Winter (1984). Two main changes with respect to the model are introduced. First, the innovation strategies are adaptive, firms increase or decrease spending for innovative and imitative R&D based on the past average success of these activities. Second, if return on capital in the industry is high additional firms might enter the industry. The focus of the analysis is on the comparison of two technological regimes, the entrepreneurial and the routinized regime, which loosely correspond to the differ-

[13]Nelson and Winter distinguish the cases of 'cumulative' and 'science-based' technological advance. Whereas in the first case the expected productivity of a new technology equals the firms current productivity, for science-based industries the expectation of the productivity of a new technology equals an exogenously given parameter called 'latent productivity'. Latent productivity is supposed to represent the technological possibilities created outside the industry (public research labs, universities) and grows at a given rate.

ent descriptions of the innovation process in Schumpeter's early writings and in his later work. The main difference between the regimes is that in the entrepreneurial regime a larger number of innovation attempts is made outside the industry but the success of a single innovation attempt is smaller. The parameters are chosen such that these two effects are balanced and the expected number of potential entrants, who have succeeded with an innovation, are identical in both regimes. The simulations show quite distinct patterns of industry evolution under the two regimes. In particular, the routinized regime results in a much smoother dynamics of the best practice technology in the industry, in a higher degree of concentration and in higher R&D expenses in the long run. These observed qualitative differences match well with Schumpeter's description of industry evolution before and after the 'industrialization' of R&D.

These pioneering simulation studies of the interplay of industry evolution and technological change already nicely highlights some of the merits of the agent-based approach for the study of innovation dynamics. Firms are rule-based autonomous agents which differ not only with respect to capital stock and employed technology but also with respect to their production and innovation strategy. The interplay between the dynamics of industry concentration and the dynamics of productivity distribution generates feedback effects with non-trivial implications on the long run outcome. The consideration of different scenarios characterized by different constellations of technological parameters (difficulty of imitation) or strategy characteristics (aggressiveness of investment policies) allows to evaluate how sensitive results depend on the 'type' of the industry considered. The possibility of such 'laboratory experiments' are indeed an important feature of ACE modelling (see e.g. Tesfatsion (2003)). On the other hand, certain aspects are highly simplified in the original Nelson and Winter model and, due to the large impact this work had on subsequent research in this direction, this holds in a similar way for quite a bit of work in the evolutionary tradition to be reviewed in the next section. I like to mention three points here. First, the assumption that firms never adapt their decision rules[14]. Second, the lack of any explicit-structure governing interactions between firms and the shape of externalities[15]. Third, the representation of the process of technological change leaves a large black box between the inflowing funds and the resulting productivity increase. Innovation probabilities only depend on current investments, there is no accumulation of research investment and also no explicit role for knowledge accumulation at the firm[16]. The mechanistic nature of the innovation process also leaves no room for considerations concerning the direction of the innovative

[14]Of course this point does not hold for the extension of the model in Winter(1984). An extension of Nelson and Winter's model of Schumpeterian competition, where firms can adapt their R&D strategy was recently considered in Yildizoglu (2002)

[15]See however Jonard and Yildizoglu (1998) for a formulation of the Nelson and Winter model in a spatial setting.

[16]For cumulative industries the current productivity of the firm might however be seen as a proxy for the knowledge stock of the firm at the time of its most recent innovation.

activities of the individual firm (and related the direction of technological change as a whole) and issues of the timing of the introduction of innovations. Additional structure on the firm level is needed to address such issues.

# 3 Agent-based Models of Technological Change

In this section I will discuss a number of ACE studies dealing with different aspects of innovation and technological change. The presentation is organized according to the main themes discussed in the introduction. I will first focus again on the four important properties of technological change processes discussed in the introduction. For each of the properties ii - iv[17] I will discuss examples of ACE models addressing this issue. In subsection 3.5 I will then shift focus to the power of ACE models to reproduce stylized facts and discuss the success of agent-based growth models in this respect. The final subsection of section 3 will then be dedicated to a stream of research where detailed models of the evolution of specific industries are developed using an agent-based approach.

## 3.1 Knowledge Accumulation, Knowledge Structure and Spillovers

The success of innovative activities of a firm does not only depend on its current investment but also to a large extent on the size and structure of the knowledge base the firm has accumulated. The stock of knowledge of a firm is not uniform and has a lot of structure. For example, distinctions should be made between explicit and tacit knowledge as well as between general knowledge and specific skills. There is vast empirical evidence (see e.g. Griliches (1992), Geroski (1996)) for the relevance of technological spillovers representing knowledge flows between firms or individuals and Cohen and Levinthal (1989) have provided empirical evidence that the extent of spillovers flowing into a firm depends on the firms own R&D efforts. Rosenberg (1990) argues that different types of research efforts have to be distinguished in this respect and that particularly *basic* research capability is essential to enable absorption of knowledge generated elsewhere. Existing analytical approaches and also papers using the Nelson and Winter framework typically do not consider the dynamic accumulation of a *structured* knowledge base of firms competing in a market. Knowledge accumulation is treated either implicitly, by assuming that all current knowledge is embodied in the technology currently used, or by considering a simple R&D stock variable, which is increased by investments over time[18].

[17] All ACE models discussed are dynamic, so no separate discussion of models incorporating property i) ('dynamics') is provided.

[18] There are a few exceptions like Jovanovic and Nyarko (1996), who develop a Bayesian model of learning by doing and technology choice which explicitly takes into account that agents develop expertise specific to their current technology and also deals with spillover effects. However, they treat competition only in a very rudimentary way. Cassiman et al. (2002), analyze a static dominant

Using agent-based simulations allows to add some of the empirically relevant structure to the standard models of knowledge accumulation and spillovers. Cantner and Pyka (1998) consider a dynamic heterogenous oligopoly model, where firms allocate their R&D expenditures between investment in an R&D capital stock and the increase of their absorptive capacity. Firms might carry out product and process innovations where the probability for a successful innovation of a firm depends on its R&D capital stock and on the size of spillovers. It is assumed that the size of the spillovers flowing into a firm depends on the accumulated absorptive capacity of the firm, on the variance of the unit costs (for process innovations) respectively product quality (for product innovations) and on the relative position of the firm in the industry with respect to process respectively product technology. Motivated by empirical observations a bell shaped relationship is used, where spillovers are small for firms close to the frontier of industry technology and for firms too far behind but large for firms whose gap to the frontier is in an intermediate range. Both the bell-shaped spillover function and the fact that the size of spillovers depends on the heterogeneity of the technologies used in the population stresses the point that received information only increases knowledge if it is complementary to the firms current knowledge. A point often ignored in models of technological spillovers.

Each firm is assumed to choose the price for its product like a local monopolist and the only remaining decision variables for a firm are the total R&D expenditures and the allocation between increasing their R&D stock and their absorptive capacity. The allocation rule is characterized by a parameter determining the minimal percentage[19] invested in building absorptive capacity by the firm and the analysis rests on examining the impact of heterogeneities with respect to this parameter.

The authors run simulations for scenarios where all firms have identical fixed R&D quotas but differ with respect to the share of investments used for building absorptive capacity (the decision rules of all firms are fixed over time). Comparing the firms profits, Cantner and Pyka find that initially the firm with zero minimal investment for building absorptive capacity is most profitable, but if potential spillovers are large this is only a transient phenomenon. In such a scenario firms who accumulated absorptive capacity eventually become more profitable than firms solely relying on the own R&D stock. The long run profitability of building absorptive capacity is however jeopardized if appropriability conditions are relatively high and cross effects between the different markets are relatively low.

Similar in spirit is the work of Ballot and Taymaz (1997) who analyze an extensive mirco-macro simulation model based on a model of the Swedish economy by Elliason (1991). Firms in their model can through training build stocks of specific skills enabling them to increase productivity and stocks of general knowledge which increase the probability for successful radical innovations. One of numerous

firm model where the firm allocates R&D investments between basic and applied research.

[19]This percentage is invested by a firm which is the industry leader both for process and product technology.

of their interesting findings is that there is a positive statistical relationship between a firm's early investment in general knowledge and the profit rate, while, with the exception of a few periods, there is always a negative relationship between a firm's specific human capital and the profit rate. Their conclusion is that R&D investments should be preceeded by a buildup of general knowledge since *innovators with a strong knowledge base fare better in the long run*[p.455]. Also in this paper the firms strategies allocating resources between the different types of training are fixed over time. An extension where the strategies are updated via a classifier system has been considered in Ballot and Taymaz (1999) but the focus there is on growth issues and it is not reported in how far the findings concerning knowledge accumulation change with adaptive strategies.

In their work on innovation networks Gilbert et al. (2000, 2001) have developed a way to model knowledge and capabilities of a firm in substantially more detail. The model is part of a general simulation platform which is intended to be used to simulate and reproduce the evolution of innovation networks in various real world industries. The knowledge base of an agent here is represented by a 'kene' which is a collection of triples, each triple giving a technological capability, a corresponding specific ability and a cardinal value describing the agent's level of expertise for this specific ability. Agents develop innovation hypotheses by randomly selecting a set of triplets from their kene. This selection is supposed to capture the current research direction of the agent. The abilities and levels of expertise involved in this hypotheses determine the financial reward which might be gained by this innovation. To capture learning by doing effects the levels of expertise for abilities involved in the current research direction are increased, whereas the expertise for abilities not currently needed are decreased and might eventually vanish. If the financial reward of an innovation hypotheses is above a certain threshold the hypothesis is considered a success and launched as an actual innovation. The concrete interpretation of technological capabilities, specific abilities and the way financial rewards from innovations are determined depends on the properties of the industry that is examined. A general feature of the map determining financial rewards is however that it changes with the launch of an innovation in such a way such that launching an exact copy of the innovation does not pay, whereas a successful innovation increases the attractiveness of points in its neighborhood.

Agents might change their kenes through their own costly R&D where both incremental research, modifying abilities and expertise within the set of capabilities chosen for its innovation hypothesis, and radical changes, where new capabilities are added, are possible. Agents might also change their knowledge base by cooperating with a partner. In such a case the (capability, ability, expertise) triplets from each agents' kene is added to the partner's kene. The expertise level is given by the max of the two partners for abilities which were present in both kenes and set to one for all abilities which were not previously present in an agent's kene. Partners might decide to start a network, which is a persistent connection and can be extended to more than two partners. Network members share results of their research and always have identical innovation hypotheses, dividing the reward if a successful innovation is launched.

This way of representing the knowledge base allows to study the accumulation of knowledge in the industry in a very structured way. One can not only study the increase in amount of knowledge but also identify patterns of knowledge accumulation, for example whether knowledge is accumulated uniformly across the space spanned by capabilities and abilities or whether concentration on one or maybe a few key capabilities can be observed. Also, since in this approach the exchange of knowledge is modelled explicitly, spillovers only occur if partners with complementary abilities and expertise exchange knowledge. Hence, this seems to be a very promising approach to further examine in more detail the building of knowledge bases needed for innovations in industries.

A stylized fact about technological spillovers with good empirical foundation is the observation that the intensity of bilateral spillovers decrease with the geographical distance between two firms (see e.g. Jaffe et al. (1993), Audretsch and Feldman (1996)). Spatial agent-based models like cellular automata type studies allow to incorporate such spatial effects and to examine the impact on the spatial distribution of knowledge and the resulting innovativeness among firms. Cellular automata have been used by several authors to gain a better understanding of the general issues involved in spatial agglomeration of economic activity (see e.g. Keilbach (2000)). A recent contribution with focus on innovation is a paper by Meagher and Rogers (2004) who develop a cellular automaton model where spillovers have two important properties. First, the extent of spillovers gained from another firm decreases with distance and, second, acquiring knowledge from another firm requires time and, since each firm has a fixed time budget, there arise opportunity costs. Given that, each firm only tries to generate knowledge flows from its immediate neighborhood of finite size. The authors find that, if bilateral spillover intensities are homogeneous among firms of equal distance, the size of the neighborhood each firm considers for receiving knowledge has no significant effect, whereas heterogeneity in this respect implies that larger neighborhoods lead to a larger aggregate number of innovations. The overall number of firms in the industry has no effect on the average number of innovations per firm which is due to the localized interaction structure.

## 3.2 Dealing with Substantive Uncertainty: Design of Innovations, Search in the Technology Landscape and Prediction of Market Response

As discussed in the introduction, the substantive uncertainty associated with innovation processes raises several issues. First, in a world where a firm is not able to conceive all possible outcomes of an innovation project and is even less able to generate the payoff distributions resulting from different innovation strategies, the question of *how* to search for new products and processes is far from obvious.

Associated issues then are how different type of search strategies for innovations compare to each other from the firm's perspective and how their interplay influences shape and speed of technological change, industry development and growth. Second, closely related to these issues is the question how firms can develop models to predict market reaction to the introduction of new products and to estimate the expected returns generated by innovations.

In the analytical neoclassical innovation literature the problem of finding the optimal search strategy is in many instances not addressed at all, since it is either assumed that R&D expenditures transform in a deterministic or stochastic way into cost reductions (among many others e.g. Dasgupta and Stiglitz (1980), D'Aspremont and Jaquemin (1988), Kortum (1997)) or quality improvements (e.g. Grosmman and Helpman (1991), Aghion and Howitt (1992), Bonanno and Haworth (1998)), that there are exogenously given innovation steps the firms are aiming for (like in the patent race literature, e.g. Reinganum (1989), Beath et al. (1995)) or that firms can simply choose degrees of horizontal differentiation of their new product from the rest (e.g. Lin and Saggi (2002)). A few papers on technological change have incorporated search theoretic considerations into equilibrium models (see e.g. Bental and Peled (1996), Kortum (1997)) and in section 4 I will briefly discuss the basic differences between these studies and the ACE work surveyed in this subsection. Finally, also the Nelson-Winter type models abstract from the issues discussed above by modelling innovations as the (stochastic) realization of a change in productivity of capital, which is revealed to the innovator prior to actual introduction.

The agent-based approach allows to explicitly address the issues related to substantive uncertainty of innovations and search on technology and product landscapes. The existing literature aiming in this direction is not huge but a few agent-based models have been developed to study in more detail the process of designing and searching for innovations as well as the interplay of this search process with the industry dynamics and the evolution of consumer preferences[20]. Cooper (2000) makes the point that firms are trying to solve certain design problems when carrying out R&D and that in reality these design problems are typically 'ill-structured' and hard to solve. He considers the example of designing a pin-joined frame with certain properties and minimal mass in order to compare the learning curves if firms try to develop the design in isolation with the learning curves under social learning. Each firm searches the design space (represented by the set of all binary strings of a certain length describing key parameters of the design) employing a simulated annealing algorithm. In the case of social learning, in addition each firm every period collects design bits from a given number of other firms selected by roulette wheel selection and puts them together as a potential new design. This design is adopted if it outperforms the current design of the firm. Cooper shows that social learning

[20]Models of search in complex technology spaces without explicit considerations of involved firms or markets have been provided for example by Ebeling et al. (2000) and Silverberg and Verspagen (2004).

speeds up the process of finding better designs and that partial imitation, where firms combine design bits from several firms on average leads to faster learning than a scenario where firms simply adopt the design of one top performer. The reason for this finding is that with partial imitation (corresponding to something like crossover in Genetic Algorithms (see Dawid (1999)) a lock-in of the industry at suboptimal designs is avoided. Unfortunately, individual incentives are not assigned with these considerations, since firms individually can gain by relying on simple imitation of the best performer rather than on partial imitation. Patent protection might be a way to deal with this problem and Cooper's simulation suggest that, in order to facilitate fast development of good designs, patents should be wide in the initial phase where firms have large variations in designs and loosened afterwards.

Since in Coopers model evaluation of designs is entirely based on their technical characteristics, it is reasonable to assume that new designs which have not yet been adopted can be compared to existing designs. If the evaluation of designs however depends on their success in the market such a comparison is only possible if the firm has a way to estimate the success of a new design in the market. Firms have to build an 'internal model' to be able to estimate the profitability of new designs in the market and, as stressed in section 1, that this is a very challenging task. Internal models have to be developed based on past experience and Birchenhall (1995) points out that this means that there is co-evolution of a population of potential new designs and of the models needed to evaluate them[21]. He models such a situation using two co-evolving genetic algorithms. In the GA governing the search for a new technological design a new design created by mutation and/or crossover is only adopted if it is more profitable than the current technology of the firm according to at least one of estimation functions present in the second population (actually the second population consists of encoded parameters for a parameterized evaluation function). The fitness of strings in the second population, which represent evaluation models, is determined by the evaluation errors of these models in the past. It is shown that the use of such evolved internal models for election of designs to be implemented substantially increases the performance of the firm compared to a case where any new developed design is implemented. A similar point has also been made by Yildizoglu (2001) who introduces firms which develop an internal model of the market into a slightly adapted version of Nelson and Winter's model of Schumpeterian competition.

Natter et al. (2001) consider the co-evolution of several internal models within a firm in a rather detailed model addressing issues of organization and learning related to the new product development process. A market with monopolistic competition

[21]There is also a number of ACE-type market studies, where firms are not able to perfectly understand the (time-invariant) demand structure but update and select innovation strategies based on exogenously fixed evaluation models (e.g. Kwasnicki and Kwasnicka (1992), Adner and Levinthal (2001), Dawid and Reimann (2003)). Since the focus of these studies is neither on the way search in the technology landscape is performed nor on internal model building I do not discuss them in detail here.

structure is considered, where each firm consists of a marketing and a production agent. The production agent builds an internal model about the relationship between the production processes and resulting product features as well as about the relationship between the production process and costs. The marketing agent has to develop a model of the relationship between product features and the attractiveness on the market. Agents build these internal models by training artificial neural networks. Using these internal models the agents have to decide on the type of production process to be implemented. Different organizational forms are compared (sequential or team based structures) where life-cycle returns are used to evaluate performance. Among other insights, the simulations show that team-based structures are superior to sequential decision making and highlight the need to adjust incentive schemes to the organizational structure chosen.

Dawid and Reimann (2004) provide a systematic study of the effect of the interaction of different approaches for predicting the success of product innovations in an oligopolistic market[22]. An industry is considered where several horizontally and vertically differentiated products are offered. Consumers have Chamberlinian love for variety preferences where the utility gained from consumption of a good is influenced by the current attractiveness of this product. The attractiveness parameter of a product changes over time according to a stochastic process resembling the shape of a life cycle. The expected maximal attractiveness depends on the effort which has been invested by the innovating firm in the corresponding product innovation process. Since consumers face a budget constraint, the actual demand for a product depends on its relative attractiveness compared to the other products offered, which yields endogenously determined demand life-cycles for the products. Each firm might offer a whole range of products. Each period a firm can extend its product range either by adding a product, which is new to the firm but already exists in the market, to its range, or by introducing a product innovation which is new to the market. If a new product is taken to the market the consumers utility function is extended accordingly, where the expected value of the attractiveness parameter depends on accumulated investments for this product development. At the same time, a firm might decide to drop one or more products from its range. Additionally, firms have to make output, investment and investment allocation decisions.

The focus of Dawid and Reimann (2004) is on the interplay of different firms' strategies for the evaluation of existing and potential new sub-markets. Market evaluations are based on current profits on the market, current growth rate and anticipated long run potential. The weights assigned by a firm to each of these three factors is seen as part of the firms strategy parameters. Using extensive simulations followed by statistical tests Dawid and Reimann (2004) show that individual incentives induce firms to put the larger weight on market growth compared to profit, where this effect is particularly strong if the horizontal differentiation between prod-

[22] An empirical study analyzing simple decision heuristics for making such predictions can be found in Astebro and Elhedhli (2003).

ucts is strong. This means that in a scenario, where firms adapt their evaluation strategies over time, the firms in the industry become more and more oriented towards sub-markets with high growth rates, which are typically markets for recently introduced innovations. However, if all firms would use evaluation strategies which put higher weight on current profits average industry profits would increase. These findings demonstrate that in a complex uncertain environment dynamic adaptation internal evaluation models of new products might per-se induce inefficiencies with respect to the introduction and adoption of innovations.

In the industry model of Dawid and Reimann (2003, 2004) the endogeneous product life-cycles are driven by the fact that the offered product range has some influence on aggregate demand, but there is no micro-founded representation of the demand side. A more explicit consideration of the interplay between the design of product innovations and the evolution of demand is provided in Windrum and Birchenhall (1998). They consider the search for designs of innovative products as a search problem on a shifting rather than a fixed landscape. In their agent-based model consumer preferences co-evolve with the product designs offered by the producers. The search for designs of producers is modelled via an algorithm similar to a genetic algorithm. Furthermore, there is a fixed and finite set of possible consumer types where the frequency of each type varies depending on how effectively different consumer types have been served by the offered supply. The model reproduces patterns of decreasing (product) innovation activities over the life-cycle which is typically observed in real world industries. Furthermore, in this industry typically several co-existing product designs survive which are interpreted as different niche-markets. The authors argue that this finding – although contradicting the dominant design hypothesis – is consistent with observable patterns in numerous industries and that the dominant design hypothesis should rather be seen as a special case of the more general phenomenon of niche-formation.

Before I move on to the discussion of models focusing on the effects and importance of ex-ante heterogeneity of strategies I like to mention that also several of the agent-based growth models incorporate interesting and rather explicit models of technological search. I will discuss these in subsection 3.4.

## 3.3 The Importance of the Heterogeneity of Innovation Strategies

Heterogeneity of behavior of agents is a prevalent phenomenon in almost any economic setting. As has been stressed in section 1, this is particularly true in the context of innovations. In the framework of neoclassical analysis heterogeneity of behavior can be explained by heterogeneities of agent characteristics or initial endowments, but even in a symmetric equilibrium among agents with symmetric characteristics heterogeneous behavior can emerge if the equilibrium involves mixed strategies. Heterogeneity of *strategies* in a neoclassical world with symmetric agents can however only arise if an asymmetric equilibrium exists. Several analytical studies dealing with innovation have in such a way explained heterogeneity of innovation strategies (e.g. Gersbach and Schmutzler (2003)). In an agent-based approach, where the complexity and substantive uncertainty associated with a firm's maximization problem is taken into account, and strategies are rule-based rather than derived as the solution of a tractable well-posed optimization problem, it is quite natural to deal with heterogeneity of strategies. Several of the models discussed so far, including Nelson and Winters model of Schumpeterian competition, incorporate heterogeneity of strategies not induced by differences in endowments. The point of this subsection is therefore not to survey agent-based models of technological change which feature heterogenous behavior – almost any ACE model does – but to stress that several agent-based studies in this domain have explicitly focused on the effects of strategy heterogeneity from a firm and an industry perspective. They have shown that heterogeneity of innovation strategies in not only induced by individual incentives of firms but also has significant positive effects on the overall evolution of the industry.

Dawid et al. (2001) address the question at the firm level. Using a simplified version of the model in Dawid and Reimann (2003, 2004) described above, they study the question how much inertia firms should show when switching from an established product to a a new one, and under which circumstances firms should primarily rely on imitation of existing designs for product innovation or try to develop own innovative designs. Among other findings, the paper shows that, ceteris paribus, it is advantageous for a firm to deviate with respect to the imitation-innovation weighting from the average industry strategy. Put differently, in any state of the industry with uniform innovation strategies, firms have incentives to deviate generating strategy heterogeneity.

The effect of strategy diversity for overall industry performance is pointed out by Llerena and Oltra (2002). They consider a setup which is based on the Nelson and Winter model but extends significantly the description of the innovation process. Firms' innovation probabilities depend on the stock of accumulated knowledge rather than only on current investment. There are two types of firms characterized by different ways to acquire knowledge and generate innovations. The cumulative firms build their stock of knowledge by own R & D and generate innovations internally, the non-cumulative firms invest in building up their absorptive capacity in order to exploit the knowledge generated externally. Accordingly, the average productivity of a new technology of a cumulative firm is given by its own current productivity, whereas for a non-cumulative firm the productivity is centered around the market share weighted average industry productivity. Loosely speaking the two types might be labelled as innovators and imitators. Firms are not allowed to change their innovation strategy but there is endogenous exit and entry of firms and therefore the number of firms of the two types in the population varies over time. Llerena and Oltra show that in industries where both types co-exist the technological evolution is superior (higher average productivity) to homogeneous industries. Typically such a heterogenous industry ends up in a state with few large cumulative firms plus a fringe of many small non-cumulative ones.

Similar results concerning the importance of strategy diversity have also been obtained in several other agent-based papers on industry dynamics and economic change. Chiaromonte and Dosi (1993) consider an evolutionary agent-based growth model and compare simulation results where technological competence and *parameters of decision rules* are heterogenous with scenarios where these parameters are homogenous with unchanged means. They report that homogenous parameter settings lead to significantly less technical progress and lower long-term aggregate income. Ballot and Taymaz (1997, 1999) which I briefly reviewed in subsection 3.1, consider the interplay between four different types of decision rules in their micro-to-macro model and show that heterogeneity of rules is not only self-sustained but that the absence of strategy diversity reduces total output and the level of technology attained. Ballot and Taymaz' work however also makes clear that ex-ante given strategy-diversity, where firms cannot adapt strategies later on, is not sufficient to yield high productivity levels. Crucial for dynamic efficiency is the interplay of heterogeneity and strategy selection by the firms, so these findings are very much in the spirit of an evolutionary approach.

### 3.4 Micro-founded Models of Economic Growth

The main goal of my survey of innovation-related ACE-work in subsections 3.1 - 3.3 was to highlight how ACE researchers have incorporated important aspects of innovation processes, which have been largely neglected in analytical papers, into their models. Guided by the focus on three of the four important aspects of innovation processes, which I discussed in the introduction, I have reviewed the modelling choices made in order to deal with these issues, the research questions asked, and some insights obtained. Hence my basic approach in these subsections was that of an economic theorist who uses rather abstract models to gain insights into general economic phenomena[23]. In the introduction I have argued that the second main advantage of ACE modelling in the domain of innovation and industrial dynamics, besides the capability to incorporate a larger number of important aspects of the innovation process into the analysis, is the good ability of ACE models to reproduce empirically observed stylized facts. The focus of the literature survey in the following two subsections will be on this aspect. In the remainder of this section I briefly discuss some influential evolutionary growth models with an agent-based flavor. The reader is referred to Silverberg and Verspagen (2005) or Windrum (2004) for a more extensive coverage of this field.

Starting with Nelson and Winters' evolutionary growth model a main concern of evolutionary and ACE-minded scholars working on economic growth has been

[23]To avoid any misunderstanding, I like to stress that quite a few of the papers reviewed in sections 3.1 - 3.3 show that results obtained in the used simulation model match well with empirical stylized facts.

to build models, where well known stylized facts about economic growth emerge as aggregate properties from realistic assumptions about economic interactions at the micro level. An influential series of papers in this respect has been published by Silverberg and Verspagen (1994, 1995, 1996), who develop an agent-based growth model with rich economic structure. The model takes into account several stylized facts about technological change and growth not represented in analytic models, among them the co-existence of diverse concurrent technologies (a vintage capital approach), the exploration vs. exploitation tradeoff of innovation efforts, the importance of innovation diffusion speed and the characteristics of knowledge. A firm's innovation strategy is characterized by its R&D quota, determining which portion of profit is used for R&D. Firms are heterogenous with respect to this strategy which is adapted over time by imitation (proportional to market share) and mutation. Several key points are made in Silverberg and Verspagen (1994). The trajectory of the average R&D quota ends up fluctuating around a positive 'evolutionary equilibrium' which is at least for linear innovation functions independent from initial conditions. Hence, there are endogenously generated positive long-run growth rates. The evolution of the rate of technical change is characterized by a long period of slow increase followed by a sudden 'takeoff' where the rate of technological change jumps up and then keeps fluctuating at this high level. The takeoff is also associated with a sharp decrease in market concentration. This observation makes nicely the point that the connection between R&D activity and market concentration might be characterized by co-evolution rather than by causal relationships in either direction (as suggested in many models rooted in the industrial organization tradition). Silverberg and Verspagen (1996) stick to the same basic setup with the single difference that the innovation strategy of a firm is determined by two parameters, where the first determines which portion of profits and the second which portion of total output is invested in R&D. It turns out that in the long run for most firms in the population the value of the first parameter is close to zero whereas the value of the second parameter is positive. The authors argue that profits are more volatile than output and accordingly this result can be seen as an indicator that firms with strongly fluctuating R&D expenditures have lower survival chances than those with relatively stable investment streams. A comparison of the data generated by the model with R&D expenditures in four US and Japanese industries is made and it is demonstrated that the two seem consistent not only qualitatively but also with respect to the range of the observed values.

In Silverberg and Verspagen (1995) the model of Verspagen and Silverberg (1994) is extended to a framework with two countries and it is demonstrated that complex patterns of technological convergence and divergence between the countries are generated. The authors argue that the data generated by their model matches well several characteristics observable in OECD data. In particular they show that, like in the OECD data, the power spectrum of the coefficient of variation of per capita GDP is an almost linear function with negative slope.

Another string of agent-based evolutionary growth models has been developed in Chiaromonte and Dosi (1992), Chiaromonte et al. (1993) and Dosi et al. (1993). Several differences to the Silverberg-Verspagen models should be pointed out. There is no vintage capital, but there are two sectors, one sector producing capital goods the other consumption goods, where production coefficients in both sectors might change over time yielding dynamics in a two-dimensional technology space. Furthermore, firms do not adapt innovation strategies over time, they follow ex-ante determined behavioral rules with in general heterogenous strategy parameters. Although the papers differ a bit in the details of the micro-foundation of the analyzed models, they all also incorporate technological change through innovation and imitation, where the innovation process incorporates the basic distinction between incremental and radical innovations and diffusion of technologies is modelled explicitly as a time consuming process. Dynamics are open-ended since there is an ever-growing set of notional, only partly explored technological opportunities. Market interaction is modelled in reduced form, where in each sector market share in a given period is determined by a firms' relative 'competitiveness', which depends on the price charged by the firm, the demand for its product and – in the capital good sector – also on the productivity of labor. Chiaromonte and Dosi (1992) provide only results for a few individual runs of the model but argue that the simulations generate plausible time series for income and labor productivity. Furthermore it is demonstrated that persistent heterogeneities in market share and labor productivity emerges among consumption good producers, quite in accordance with empirical observations. The main message of the paper is the importance of persistent heterogeneity of behavioral rules and employed technology for the rate of growth. Chiaromonte et al. (1993) use the same model but focus on the effect of the way prices and wages adjust on growth performance. In Dosi et al. (1994) a multi-country model of similar type is analyzed and again it is argued that in spite of its relatively simple structure the model reproduces several stylized facts, like persistent inter-firm asymmetries in productivities and profits, persistence in aggregate fluctuations of per capita income within a country and increasing differentiation in level and rate of growth of per-capita income between countries.These are indeed emergent properties of the model since there are no country-wide externalities and institutional design, parameter settings and so forth are identical across countries.

An even richer agent-based growth model reproducing a large set of empirical findings has been proposed by Fagiolo and Dosi (2003). In this model several of the micro-aspects of the innovation process discussed in subsections 3.1 - 3.3 are incorporated. They consider a finite population of agents exploring an unlimited two-dimensional lattice which represents the technology space . Each agent every period produces a certain output which depends on a productivity parameter of her current technology and (in an increasing way) on the number of other agents employing the same technology. Agents in this economy every period are in one of three possible 'modes': (i) 'Mining', i.e. producing using their current technology;

(ii) 'Imitating', i.e. moving on the technology landscape towards some other technology which is already in use by some other agents. Such moves are triggered by signals about other technologies received by the agent, where the strength of the signal depends on the productivity of the technology and its (technological) distance from the agent's current technology. (iii) 'Exploring', i.e. moving around randomly in the technology space until a new feasible technology is discovered, where only a subset of the points on the lattice corresponds to a feasible technology. If an explorer discovers a new feasible technology the productivity parameter of the new technology is determined stochastically, where the mean increases with the distance from the origin and accumulated skills of the explorer. While an agent moves around exploring or imitating she cannot produce. This formulation captures several stylized facts about innovation: imitating as well as exploring new technologies is associated with opportunity costs with respect to production using the current technology (exploration vs. exploitation); there is uncertainty about technical feasibility if new technologies are explored; accumulated knowledge plays a central role for the ability to absorb technological spillovers; using a technology generates positive externalities for the other users of this technology; technological learning is a cumulative process. There is no market interaction in this model[24] and the characteristics of the employed technologies translates directly to output and, on the aggregate level, to GDP. The model generates plausible outcomes on several levels. On a technology level the model produces clusters of agents at different co-existing technologies of comparable productivity where the adoption curves of technologies have the typical 'S-shape'. Over time the clusters move slowly towards more and more productive technologies. This persistent movement generates positive GDP growth and the authors identify conditions under which (persistently fluctuating) exponential growth can be obtained. Using a much richer set of simulation data and more sophisticated techniques compared to the ones employed in the analyses discussed so far in this subsection, the authors also demonstrate that their artificial GDP time series shares several well established statistical properties of real world GDP data. In particular, there are persistent fluctuations, where autocorrelation of growth rates is significantly positive for small lags decreasing towards zero as the lag increases (see Nelson and Plosser (1982) and Campbell and Mankiw (1989) for empirical evidence in this respect). Also, it is pointed out by the authors that in spite of the fact that there is sustained growth, growth rates do not increase with the population size and therefore does not exhibit scale effects.

### 3.5 Industry Studies and 'History-friendly' Models

The previous section has demonstrated the ability of agent-based growth models to combine a strong micro-foundation with the reproduction of a number of stylized facts about economic growth. Models in the evolutionary tradition have also been

[24]For a model in a similar spirit which includes market interaction see Kwasnicki (2001).

used to gain micro-founded insights into the structure of industry evolution and to account for stylized facts in that respect. Klepper (1996) proposes an analytically tractable industry life cycle model which is able to explain several stylized facts including the positive correlation of entry and exit rates, the existence of industry Shake-out phenomena and the shift of producers efforts from product to process innovation during the life-cycle[25]. Furthermore, evolutionary industry models by Dosi et al. (1995) and Winter et al. (2000, 2003) reproduce stylized facts concerning the skewed firm size distribution in many industries, the long lasting co-existence of firms with different efficiency in production, the long-term advantages of early entrants and the importance of the technological 'regime' in an industry for the characteristics of the industry evolution. These models are however only in a wider sense agent-based since the focus is on the analysis of the evolution of industry level distributions and interactions between agents and individual decisions rules are only considered in very reduced form. Nevertheless, these models reinforce the conclusion obtained from some of the agent-based growth models, that several of the stylized facts on the industry level emerge quite naturally from industry models based on an the explicit consideration of the dynamic interaction of heterogenous rule-based firms.

However, the argument could be made that some of the models presented in this section, although very sophisticated in structure, are formulated in such an abstract setting that the modeler has enough freedom to adapt the underlying assumptions to generate certain stylized facts. Hence, these models (similarly to traditional formal economic theory) highlight which mechanisms are **potential** explanations for observed phenomena. In order to be more confident about capturing **actual** causalities in given concrete industries it might be necessary to link the building blocks of the model more closely to empirical observations in that given industry. Using similar arguments Malerba et al. (1999, 2001a) argue for the need of a new generation of evolutionary economic models they call 'history friendly' models. These models should be developed based on detailed consideration of characteristics of the industry as known to an empirically oriented scholar in the field. Furthermore, they should be capable of reproducing the main facts in the historic development of the industry. The idea is to start with verbal descriptions of the actual structure of an industry and then to translate the verbal arguments into a formal model. Given the complexity of the topic under consideration we will see that the resulting model typically has the structure of a dynamic agent-based simulation model.

Before describing a history friendly model in more detail I like to mention that an early simulation study in similar spirit was presented by Grabowski and Vernon (1987). They build a dynamic model of the pharmaceutical industry, where specifications of model relationships and parameters are based on empirical data

[25]Explanations at least some of the empirically observable regularities of industry life cycles within dynamic equilibrium models have been given by Ericson and Pakes (1995), Hopenhayn (1992), Jovanovic (1982), Jovanovic and MacDonald (1994).

describing the industry. The model abstracts from a micro-founded representation of described relationships, relying rather on observed statistical relationships. The model is used to evaluate and compare the effects on the rate of innovation of changes in patent duration and in the duration of the regulatory review process which has to be finished before a new drug can be introduced to the market. The simulations imply that these two policy-determined variables have strong influence on the rate of innovation where the positive effect of a reduction of regulatory approval time by a year approximately matches the effect of a patent duration increase by five years.

The new generation of history friendly models gives a much more detailed description of firm and behavior compared to the approach of Grabowski and Vernon (1987). As an example I will here describe in some detail the history-friendly model of the computer industry developed in Malerba et al. (1999, 2001b) and afterwards mention a few other recent industry studies based on a similar approach.

In Malerba et al. (1999, 2001b) many of the issues discussed in the previous subsections, like gradual buildup of technical competence, direction of search and advance of innovations, the importance of the distance of a firm from the technological frontier for its costs of innovation, the influence of supply on consumer preferences and demand, the importance of diffusion of information about new technologies or the implications of firms diversification decisions are incorporated into the model, where the chosen specifications are motivated by empirical observations in the computer industry. The model is supposed to capture main phenomena observed in the transition of the computer industry from transistor to microprocessor technology and the associated emergence of the market for PCs in addition to the original mainframe market. In particular, the authors try to explain the empirical observation that a dominant firm emerges in the original market using 'old' technology which then quickly adopts the 'new' technology and keeps its strong position in the original market. However, this dominant firm is not able to gain a similar strong position in the afterwards emerging PC market. The products in the model are characterized by the two attributes 'cheapness' and 'performance' and it is assumed that there are two types of consumers where one type ('big firms') puts more weight on performance whereas the second type ('small users') is more interested in cheapness. The first type of users form the mainframe market whereas the PC market consists of type two consumers. Both types have minimal demands for both attributes which a firm has to meet in order to enter the corresponding market. A given technology puts certain limits on how much of the two attributes can be delivered by a product. The microprocessor technology extends the limit in both directions, where the potential improvement with respect to cheapness is more substantial. In the initial period a certain number of firms start with the transistor technology, and after a given number of periods a new bunch of firms starts developing products using the new microprocessor technology. Firms invest constant fractions of profits into R&D and advertising and prices are determined by simple markup rules. Firms two main decisions, first, to adopt the new technology and, second, to diversify into the new market, are represented in a very simple fashion. Firms perceive the new technology with some probability which depends positively on the technological level of the firm in the old technology and the current advancement of the best practice firm in the new technology. Once the new technology is perceived the firm adopts it as soon as it is able to cover the associated costs. Based on observations in the computer industry, diversification in this model means that a spin-off firm is created, which inherits parts of the budget and the technical and advertising competence but positions in a spot in the attribute space oriented towards the new market. The spin-off also follows a different trajectory in the product space than the parent company. The decision to diversify is made in a probabilistic manner based on the relative size of the new market.

Malerba et al. (1999) show that under certain parameter constellations the qualitative empirical observations described above are indeed reproduced by the model (history-replication). Deviating from such parameter constellation yields 'history-divergent runs', in particular it is shown that if the number of entrants goes down (e.g. due to smaller initial budgets) mainframe firms do not switch to the microprocessor technology and the PC market never takes off. The authors argue that based on this observation the lack of venture capital in Europe and Japan might be seen as reason for the inability of firms in these regions to take advantage of the new technological and market opportunities in the computer industry. In Malerba et al. (2001b) the descriptive analysis is complemented by an evaluation of industrial policy measures using this model. In particular, the effect of antitrust measures which break up a dominant firm a given period after it has reached 75% market share, and different measures aimed at facilitating market entry of small firms is considered. The main conclusion from these experiments is that large and focused policy interventions would have been needed to significantly change the pattern of market development that has been observed in this industry.

The model developed here is very elaborated in its attempt to put together a large number of stylized facts about development of technology and demand in a specific industry in a manageable and transparent model. One possible concern could be a kind of 'over-fitting' of the model. It seems that some modelling choices might have been influenced by the concrete set of historical stylized facts the authors intended to reproduce. To carry out an 'out of sample' test of the model, if at all possible, takes time, we will have to see how well future industry developments can be explained. Also, following the tradition of formal evolutionary modelling, the representation of firm behavior is very simple relying on fixed percentage investment rules and simple probabilistic rules for technology perception and diversification. Whereas firms actions vary over time their strategies are assumed to be fixed. In particular, for the evaluation of the effect of policy interventions it might however be important to take into account the reaction of firms strategies to given measures. Combining more flexible representation of firm strategies with the 'history-friendly' approach therefore seems to be a challenging but hopefully rewarding task.

Following the successful application of the 'history friendly' approach to the computer industry Malerba and Orsenigo (2002) have developed a simulation model of the pharmaceutical industry along similar lines. Whereas the underlying modelling credo is similar as above the industry model has a very different structure representing the large qualitative differences between the two considered industries. Two main characteristics which clearly distinguish the pharmaceutical from the computer industry are: (i) There is almost no cumulativeness in innovative activities since previous successes in developing drugs are of little help in the search for a drug in a different therapeutic category. This is particularly true for the times before the biotechnological revolution, when random screening of compounds was the typical search strategy for innovations; (ii) The market is fragmented - demands for products in different therapeutic categories are independent. The authors focus on the evolution of the industry as the transition from random screening to science-guided search based on biotechnology occurred. The model is again characterized by an empirically motivated rather detailed description of the innovation process, an explicit description of the demand dynamics and constant linear R&D and marketing investment rules of firms. Key historical features replicated by the model are the small degree of industry concentration, the small impact of the emergence of biotechnology on the market structure, the inability of new bio-tech based firms to replace large incumbent firms and the emergence of cooperations between incumbents and small new bio-tech firms. Counterfactual experiments show on the one hand that the fragmentation of markets is indeed a key factor for the low degree of concentration and, on the other hand, that even under circumstances where bio-tech startups have large comparative advantages with respect to this technology compared to incumbents, they would not be able to displace the firms that have build strong market positions in the random screening era. Finally, the model suggests that without the possibility of cooperative agreements with incumbents biotech startups would not be able to survive in the market. The importance of cooperation between large incumbents and small dedicated biotech firms has also been stressed by Pyka and Saviotti (2000) who develop an agent-based simulation model of biotechnology based sectors in order to study the emergence of innovation networks in such industries.

# 4 Discussion

I have started this chapter by arguing that there are two main reasons why agent-based models should be particularly useful for the analysis of processes of innovation and technological change. First, several of the crucial defining aspects of the process of innovation and technological change are readily incorporated in ACE models but can hardly be captured in neoclassical equilibrium analyses. Second, ACE models seem to be able to reproduce a number of stylized facts in this domain which are not well accounted for by existing analytical work.

I believe that the survey of ACE work in section 3 reinforces this view. Although we are certainly talking about a field of research in its infancy with a large variety of addressed research topics and employed approaches, some general insights emerge from the surveyed body of work. It has been shown that a structured model of the knowledge base allows concrete statements about the effect of the allocation of investments between general and specific knowledge build-up and of the structure of knowledge exchange between individuals and firms on firm success and industry development. Considering that also economic policy makers pay more and more attention to the importance of the structure of the knowledge base for technological change and growth[26] these are certainly relevant issues. ACE studies further have highlighted the importance of the interplay of (potentially heterogeneous) individual approaches of firms towards the search for new products and processes and the estimation of market response to innovations. A conclusion emerging from a number of ACE studies with quite diverse setups is that heterogeneity of innovation strategies has a positive effect on the speed of technological change, a theme not present in mainstream theoretical analyses. For some of the covered issues, it can be argued that these questions could in principle also be posed in an intertemporal equilibrium setting – for example the effect of heterogeneity of strategies could be addressed by comparing the speed of technological change under symmetric and asymmetric intertemporal equilibria in a dynamic industry model. Even if one might have concerns about the underlying assumptions, this could serve as a useful benchmark analysis shedding additional light on the mechanisms underlying this effect. However, analytical tractability is a severe problem as soon as asymmetric dynamic equilibria are considered and hence general analytical results might be infeasible. For other issues, like the analysis of search and prediction strategies under substantive uncertainty, an equilibrium analysis relying on the Bayesian optimization framework does not even allow to properly formulate the relevant question. For sake of illustration let us briefly compare the ACE approaches to technological search reviewed in subsection 3.2 with a well received equilibrium approach, like the 'search theoretic' model of technological change by Kortum (1997). In Kortums approach there is a continuum of individuals, where a certain fraction is engaged in research and accumulates over time a research stock. There is also a continuum of goods, where independence of search across different goods is assumed. This allows the author to basically analyze the search for new production techniques for one 'representative' good. The common research stock is available to all researchers and determines the frequency by which new ideas about production techniques arrive. If a new idea for a production technique arrives, the corresponding productivity of labor parameter is drawn from a random distribution, which is positively influenced by the common research stock. The mapping determining the frequency of new ideas and the distribution of productivity parameters given a certain research stock are common knowledge and the

[26]See for example the extensive literature on regional and national innovation systems (see e.g. Nelson (1993), Freeman (1995), Lundvall et al. (2002)) or the 'European Innovation Scoreboard' project of the European Union (http://trendchart.cordis.lu/).

actual productivity of a new technique is perfectly revealed to the innovator once he has this new idea. Innovators can patent their new idea restricting their competitors to the second best technique, and due to the chosen demand structure it is always optimal for them to set prices such that all competitors are shut out. So, overall we have a scenario where a set of ex-ante identical potential innovators employ some identical but not explicitly specified search strategy to generate process innovations for a continuum of goods. Potential innovators have no proprietary knowledge and the type of technique they use for producing the other goods has no influence on their ability to generate good new techniques. For each product at each point of time all the output is produced by the same technique. All potential innovators share the same correct expectations about the (discounted infinite horizon) future return of engaging in research today. Although all these features are not consistent with most empirical observations, the model is quite successful in explaining empirical observations about the time evolution of research employment, patenting and total factor productivity in the US. Nevertheless, it seems to me that a search theoretic approach of this kind can provide less insight about the type of search problem a potential real world innovator faces, and the effect different type of search strategies have on technological change if we compare it to a micro-founded agent-based model.

To get to my second main argument (reproduction of stylized facts), I like to point out a few features of the *results* of the surveyed agent-based evolutionary growth models, which in my eyes make them attractive alternatives to the growing literature on new growth theory (NGT) (see Aghion and Howitt (1998), Grossman and Helpman (1994)), which shares the desire of these models to provide micro-founded explanations for economic growth. This should be considered *in addition* to the discussion about the appropriateness of the use of representative firms carrying out infinite horizon optimization, of non-structured knowledge variables and technology spaces in models dealing with technological change. An important point in this respect is that, contrary to the evolutionary growth models discussed above, NGT models predict some balanced growth rate, but provide no endogenous explanation of the empirically observable persistent fluctuations. Other issues where evolutionary studies provide empirically plausible results but NGT model are silent or generate implausible predictions are the co-existence of several technologies employed in an industry for the production of the same good, the co-existence of firms of different size, the endogenous generation of persistent cross-country differences in growth rates, the endogenous generation of changing growth episodes and take-off phenomena. Furthermore, as pointed out in subsection 3.4 evolutionary growth models do not exhibit a positive effect of population size on the growth rate. Such a scale effect, which is at odds with much of 20th century data on economic growth, is however present in the most influential early NGT models, in particular Aghion and Howitt (1992), Grossman and Helpman (1991) and Romer (1990). New growth models developed later have avoided this problem and exhibit scale effects only with respect to per capita GDP but not with respect to growth rates (see Jones (1999)).

The discussion in the previous two paragraphs highlights another point often made by evolutionary and ACE scholars, namely that ACE models are able to incorporate many realistic features of interaction and behavior on the micro level and simultaneously produce plausible time series on all different levels, rather than being tailored to explain only a few specific phenomena. Although this is certainly an advantage of this approach, the literature survey above shows that many ACE models in the field focus on some aspect of the process of technological change and rely on agent-based models where large parts of the economic system are represented in a highly stylized way. Is this a 'waste' of the versatile powerful method at hand? In my opinion certainly not. The use of an agent-based approach does not avoid the need to carefully design a model under the tradeoff between a proper representation of the relevant effects and the ability to generate and interpret meaningful results. As pointed out above, ACE modelling allows to simultaneously incorporate many important aspects of the process of innovation and technological change into a formal model, but this does not mean that all of them should necessarily be there. Which of the aspects are actually relevant depends on the underlying research agenda.

Having already briefly discussed whether some of the research questions raised in ACE studies could also be addressed using equilibrium analysis, I close this section by pointing out that ACE scholars have so far pretty much ignored many traditional major topics of theoretical research in the field. These issues include the relationship between mode of competition and innovation, the optimal R&D strategy in patent races or the optimal relationship between length and scope of patents[27], although it seems to me that analyses of these issues in a dynamic heterogenous agent setting could provide interesting complementary insights to the existing theoretical findings.

# 5 Outlook

An important aspect of the overall ACE research agenda is the provision of micro-founded explanations for meso and macro level phenomena. Quite a bit has been done in this respect also with respect to the analysis of innovation and technological change, but obviously there is still much more to do.

The process of technological change and the associated economic processes are extremely rich and many aspects have so far been only touched or even completely ignored in the literature. Accordingly, there is a plethora of potential directions to go and certainly no 'natural' trajectory for the field to follow. On a general level, a promising extension of the current approaches might be to try to link the industry development with closely linked parts of the economy which are up to now typically considered as exogenous in the economics of innovation. I would like to give two brief

[27] A preliminary exploration of the effect of patents in the framework of the Nelson and Winter (1982) model is carried out in Vallee and Yildizoglu (2004).

pointers towards issues in this respect[28]. The first pointer is to study in more detail the co-evolution of innovations and demand. The marketing literature provides models of the impact of product pre-announcements and final product positioning on consumer demand with empirical foundation. Putting together an agent-based demand side[29] based on such models with an agent-based dynamic industry model should allow to capture more realistically the properties of the 'search on a shifting landscape' associated particularly with product innovation. Another challenge is to couple the description of innovation and industry dynamics with developments on the labor market. The role of knowledge for the rate of innovation is by now well accepted but the innovation literature is relatively silent about how exactly a workforce which has the necessary competence is built and knowledge is transferred through the labor market. A proper understanding of the processes governing such a buildup might need to consider private household decisions concerning investment in knowledge acquisition as well as those of firms. There is a significant empirical literature studying the effect of technological change on the demand for different skill levels on the labor market (see e.g. Pianta (2000)). On the other hand, the innovation strategy of a firm and its success depends heavily on the ability of the firm to recruit the 'right' workforce. Therefore there seems to be a feedback between innovative activities and labor market conditions. Developing agent based models which combine the two sides is a challenging but also promising task[30].

To a large degree the agent-based work in this field has been descriptive rather than normative, but it seems that recently more attention has been paid to the potential of this approach for normative analysis on the level of the individual firm, of the market (see Marks (2005)) and of public policy (e.g. Berger (2001)). The agent-based approach has large potential to provide guidance with respect to good (if not optimal) firm strategies and public policies. This potential has been shown in concrete case studies in several areas besides the economics of innovation. The recently developed 'history-friendly' models suggest that this approach can also be successfully applied to think about concrete industrial and innovation policy measures. However, to be able to derive robust and convincing policy recommendations from ACE models important issues concerning model validation and calibration as well as robustness testing of simulation results should be addressed in a systematic way. Recent contributions to the ACE literature have shown increasing awareness of these issues. Many researchers in the field now try to provide statistical evidence

[28]To avoid any misunderstanding, I am not claiming that no work addressing these issues has been carried out, but there is very little in terms of published papers.

[29]There is some agent-based work dealing with the coupling of innovations and demand dynamics, see Aversi et al. (1999).

[30]Some work aiming in this direction exists. The model of Ballot and Taymaz (1997) discussed in subsection 3.1 has an explicit representation of the labor market, but no specific knowledge is embodied in the employees and hence no knowledge is transferred through the labor market. Fagiolo et al. (2004) consider an agent-based labor market model incorporating technical change. The model of the process of technical change is however quite mechanistic and simple without considering firm's decision concerning R&D and innovation.

that reported qualitative findings are significant in a statistical sense and robust with respect to parameter variations. Also with respect to model building, validation and calibration, several concrete approaches have been proposed recently in addition to the history friendly approach discussed in this chapter (e.g. Moss (2002), Duffy (2005), Werker and Brenner (2004)). Hence, it should be expected that we will not only see more insightful descriptive agent-based work on technological change but also a growing use of this technique for the design and evaluation of individual firm strategies and of economic policy measures.

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