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The dynamics of firms in a micro-to-macro model: The role of training, learning and innovation*

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Abstract. We analyze the co-evolution of the performances of firms and of the economy in an evolutionary micro-to-macro model of the Swedish economy. The model emphasizes the interactions between human capital (or competences) and technological change at the firm level and their effects on aggregate growth, taking into account the micro-macro feedbacks. The model features learning-by-doing, incremental and radical innovations, user-producer learning at the firm level, and a change in the techno-economic paradigm. We find that there is an optimal sequence for the firm to allocate their resources: (1) build a general human capital stock before the change in the techno-economic paradigm, (2) spend on R&D, and (3) invest in specific human capital. Innovators fare better than imitators on average, not only because they innovate, but also because they build a competence base, which supports the learning from other firms.

Key words: Evolutionary theory – Endogeneous growth – Human capital – Innovation – Diffusion – Learning – Artificial intelligence – Microsimulation

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1 Introduction

We investigate the co-evolution of the performances of firms and of the aggregate economy in a complete micro-to-macro simulation model, placing special emphasis on the interactions between human capital and innovation. Firms decide on the allocation of funds between training and R&D; these decisions in turn affect macroeconomic growth, taking due account of the feedbacks between the firm and the aggregate levels.

Our motivation for a joint modelling of the interactions between technical progress and human capital (specially, firm-sponsored training) comes from a recognition that the two activities have been up to now studied separately. We find this to be an unsatisfactory situation. Integration matters significantly in the explanation of both microeconomic performance and macroeconomic growth. The novel feature of our model is that expenditures in R&D may be a waste of resources if the firm does not have the skills to transform them into commercial success. Engineers' and researchers' human capital is crucial to the discovery of the innovations as well as to an understanding of the innovations of others; managers' human capital is essential to the relation of economic to technology choice. Higher human capital for other categories of workers is needed as well when new technologies are adopted, especially during the implementation phase, during which unexpected problems arise (Bartel and Lichtenberg, 1987).

Typically R&D and human capital are merged under the categories of "receiver competence" (Eliasson, 1990), "knowledge base", or "absorptive capacity" (Cohen and Levinthal, 1989, 1990). These concepts are meant to signify the use of accumulated knowledge to acquire a new technology. While useful, they are not well-defined empirical categories such as education and training expenditures. Yet another reason exists for a distinct treatment. Human capital and R&D have been presented as alternative foundations for endogeneous growth, while interactions are likely to be important (Lucas, 1988; Romer, 1990). Innovations and human capital can be of different types (incremental versus radical innovations, general versus specific human capital…), and these distinctions appear to be important in understanding growth.

To demonstrate the relative importance of human capital and R&D, we build a numerical simulation model with heterogeneous firms and complex relations. It is a microanalytic model in the sense of Orcutt et al. (1961) and Bennett and Bergmann (1986) with each firm explicitly represented. Our model belongs to the evolutionary paradigm that has variety (heterogeneity), learning and selection in its core (Saviotti and Metcalfe, 1991). Technological change is discontinuous, in the Schumpeterian tradition, and the macro system exhibits irreversibility and path dependency. History matters.

The research presented here uses the MOSES model, a complete Micro-to-Macro model of the (Swedish) economy, and adds to it a training-innovation module (Eliasson, 1977, 1991). The MOSES model with the training-innovation module has already offered novel results exposed elsewhere (Ballot and Taymaz, 1994, 1996); the present paper adds new results, some at the macro level. The essential result validates the intuition that the diffusion of radical innovations is important for growth, especially when feedbacks lead to a change in the global technological system of the economy, a change that our model is able to reproduce. At the micro level, we find some interesting results. First, the market share of innovators becomes bounded as diffusion occurs. Secondly, the model confirms that innovators do on average better than the other firms in terms of rate of return, but, since dispersion is enormous, some imitators are the most profitable firms in the final year of the experiment. Thirdly, firms' rates of return are unstable over time but not random. Fourthly, the simulations suggest that the effects of general human capital, specific human capital and R&D evolve over time, each having a positive influence in turn at a certain phase of the change of paradigm. This shows the importance for firms of the timing of their allocation of resources and the necessity to start with training in general human capital (or hiring workers with general training), a topic which will be central to our theoretical framework.

Section 2 of this paper will explain the methodological and theoretical framework embodied in the model. Section 3 will present the main specifications of the model. Section 4 will report on the results of the base run and four experiments. Some conclusions will follow.

2 The theoretical framework

2.1 Training for the innovation rent

We develop a model to explain why firms undertake investment in human capital even if there is some loss through turnover (Ballot, 1994; Ballot and Taymaz, 1993). This we label the *training for the rent* hypothesis. The basic argument is straightforward: Firms that innovate successfully obtain a quasi-rent if they have trained workers at the time of implementation of the new technology. It can then be rational for them to pay for *general* training, and not only specific training, even if some workers quit, because they recoup both the cost of the investment and the cost of higher wages or turnover with the quasi-rent. Of course, the higher the turnover, the less the firms will invest in training.

The competition framework is Schumpeterian, and therefore allows for the existence of rates of profits over the interest rate even in the long run. There is also a dispersion of these rates which is related partly to the stochastic nature of R&D output, and partly to the *race for competence*, where the winner would get all the market in the short run, if it could build the capacity (Ballot, 1994). The framework then allows for factors that influence the level of general investment and the rate of return, such as the rate of turnover or financial constraints. In pure competition, such factors have no influence, since the optimal investment in general training is zero and financial constraints do not exist (Becker, 1964). In the Schumpeterian framework, deficiencies in human capital will then occur and keep the firm inside the production possibility frontier in the short term, while they slow down significantly the outward shifting of this frontier in the long run, i.e. the rate of technical change.

Preliminary tests of the effects of firm-sponsored training and R&D expenditures on profitability support the hypothesis above (Ballot and Taymaz, 1993). In France the human capital stock, measured as cumulated (but discounted) training expenditures, has a very significant positive effect on profitability, while R&D has a negative effect and the interaction of the two variables has a positive effect. This result is only suggestive but it points to the potential benefits of integrating the analysis of innovation and the analysis of training (general and specific) both at the theoretical and the empirical level.

2.2 Types of human capital, innovation and productivity

We use the Beckerian distinction between general and specific human capital, based on the non transferability of the latter when workers move, but we also contrast the roles of these capitals. In our model, specific human capital is necessary to operate a technology and enters in the production function; it is lost when the workers quit, so that hiring a worker means that he arrives with zero specific skills. Human capital is thus acquired through training sponsored by the firm.

Specific human capital allows learning-by-doing to take place. Productivity is improved without physical investment when the specific skill is available. The higher this specific human capital, the faster the average productivity in the firm converges to the productivity of the new equipment. Besides this type of learning-by-doing, we have introduced indirectly the Arrow (1962) type of learning-by-doing, an automatic process by which the production cost is a decreasing function of cumulated past production: the stock of the specific human capital is raised by past production.

General human capital can be understood in two ways. First, it is transferable. Second, it facilitates the accumulation of specific human capital. This captures the cumulative character of competence building and the importance of receiver competence (Eliasson, 1992). Obvious examples are the proficiency in maths or in foreign language, but also the strategic competencies of managers.

We assume that there is only one general competence, which we will call general knowledge (or general human capital). While not a direct factor of production, it has important effects on innovation and diffusion of innovation. *First*, it allows the firm to find new technologies and hence increases the expectation of finding more profitable ones (not all new technologies in our model are more profitable than the existing ones). This competence corresponds to a higher scientific level of engineers and better trained managers who seize opportunities faster. *Second*, it enables the firm to discover more quickly the technologies used by other firms and implement some of them (sometimes after modification). This competence has been given a prominent place in the analysis of the determinants of innovation ("absorptive capacity" in Cohen and Levinthal, 1989, 1990), and depends on prior R&D done by the firm. This concept is important because it introduces the novel idea that the diffusion of technology is not a public good and involves costs and time. We argue that absorptive capacity requires not only prior R&D, but also general knowledge. *Third*, general human capital decreases the cost of acquiring specific skills. Acquiring skills often demands prerequisites, many of a general character such as those mentioned, which means that the absence of general knowledge entails an infinite cost of skill acquisition. Such a feature distinguishes R&D from general knowledge: R&D, when leading to an innovation, makes the skill used in the former technology partly obsolete; general knowledge is not affected by innovation to the same degree.

As regards innovation, microsimulation allows us to distinguish different types of innovation. One of the main contributions of this paper as compared with the previous training-innovation module (Ballot and Taymaz, 1996) is the introduction of a widely used taxonomy of innovation developed by Freeman and Perez (1988).

Firstly, R&D may lead to incremental innovation. In our previous paper, we argued that there is an optimum combination of techniques – called the global technology – which guarantees maximum performance in terms of capital and labor productivities, and introduced innovations moving the firms towards this optimum. We now introduce the idea of *radical innovation*, a change in the global technology itself, clearly superior to those allowed by incremental innovation.

We omit the third type of Freeman and Perez, in which a cluster of radical, interrelated innovations appear in several sectors and give birth to a new sector, without affecting the entire economy, since the sectors in MOSES number only four, and thus are very broadly defined. We integrate the fourth type of innovation called *the change in the techno-economic paradigm*. This change has pervasive effects on the economy, affecting the input cost structure, and conditions of production and distribution throughout the system. Moreover we also introduce in the model *user-producer interaction* which is a potential factor for the diffusion of a radical innovation from one sector to the others (Von Hippel, 1988).

2.3 Firms endogeneous rationality and the jointly evolving macroeconomy

An economy characterized by continuous innovation and a process of creative destruction is very complex, and modelling should not reduce this complexity too much. It is a fundamental determinant of agents' decisions processes, and significantly affects macroeconomic coordination. Firms cannot fully understand the workings of such an economy (the model of the world). To be able to take decisions, they cannot «build a model» to compute their "optimal decisions". The rhythm of innovation and the evolution of market structures generate too much uncertainty to assign probability distributions to key variables in the future (market shares, net profit rates…). The technique of optimization under uncertainty, over a long (or infinite) horizon, however, does not allow the firm to reach highly-valued results, because it cannot take into account variables with a high future variance and unstable and unpredictable interactions.

In the real world, agents thus compensate for the limitations of their information by learning continuously. They are constantly on the alert to identify and correct mistakes, and improve next time. However, if they know *how* they have obtained a good result, they may not necessarily know the reason for this result (the mechanism of the economy) because of the complexity of the environment. A trial and error experimental process allows the agents to learn the *how*. This contrasts with the classical optimization model in which agents «know» the model of the economy (rational expectations) and do not make mistakes in a probabilistic sense (the error distribution has a zero mean); in this model, agents do not learn how to improve their decisions in a fundamental way. However *bounded rationality*, a concept developed by H. Simon, is useful for basing the study of the workings of an economic system on microeconomic foundations *if and only if* tools for modelling the improvement process of decisions are available, which has not been the case until recently. Boundedly rational fixed rules were then very arbitrary, and the choice made likely to determine heterogeneous and arbitrary results. The MOSES model we have used as a starting point contains some adaptive rules. The training-innovation module that we add uses a more powerful tool: *genetic algorithms*.

The idea of Genetic Algorithm (GAs) (Holland, 1975) is to search for an optimum in an environment on which one does not have full information, and in which the objective function is extremely complex. These algorithms have proved their robustness in numerous disciplines (Goldberg, 1989), and have recently been used in economics. However this paper offers a first application to the modelling of a complete micro-macroeconomic system.

The GA is used to search for more efficient technologies. The efficiency of search (according to several criteria) is determined by the level of the general knowledge of the firm, and hence is influenced by its expenditures in general training. This level also influences the capacity to adopt the technologies of other firms. These notions of efficiency of search and capacity can be summarized under the general term of "rationality" of the firm. They are also close to Eliasson's (1990, 1993) concept of «economic competence». The degree of rationality of a given firm is endogeneous because the firms decide on their level of training[1].

Not only information but also rationality differs between firms, which is logical since it is bounded. The heterogeneity of firms has a more fundamental nature than their endowments (physical capital, financial assets ...), which in the long run are endogeneous to their behavior. One can hope to account better for the diversity of firms' behavior, and for the fact that some meet with success and others with failure, generating a Schumpeterian dynamic process with its macroeconomic implications (external competitiveness, unemployment...). In the process, innovation and technological progress are themselves explained.

MOSES, as a micro-macro model in which firms learn through GAs, appears as a basic artificial world (or economy) of the type described by Lane (1993a,b). It might also be labelled a complex adaptive system (as per Holland and Miller, 1991), since it has the three required characteristics: i) it is a network of interacting agents; ii) it exhibits dynamic, aggregate

[1] See Lane (1993a,b) for a plea for modelling rationality as an endogeneous variable.

behavior; and iii) its aggregate behavior can be described without detailed knowledge of the behavior of individual agents. The interesting property of these artificial worlds or complex adaptive systems is the emergence of coordination in the economy. It is self-organizing. Such aggregate variables as the number of firms, the rate of growth, the rate of investment in training, or the rate of technical progress are endogeneous. Relations between these variables are not built into the model, but observed after the simulation. They emerge.

3 The model

We will here only sketch the main features of the model, and present in detail the training-innovation modules[2]. The manufacturing sector is divided into four industries – raw material processing, intermediate goods, durable and capital goods, and consumer non-durables. Each industry produces a homogenous product and consists of a number of firms (225 in total at the beginning of simulation). Many of our industries include the accounts of real Swedish firms, while others are synthetic firms, the accounts of which have been designed so that the aggregate accounts reproduce the real accounts at the beginning of the simulation. The firms take decisions on all markets (products, labor, capital), based on adaptive expectations, and these decisions are revised quarterly, since their plans are likely to be inconsistent. Competition eliminates some firms, but profit opportunities in an industry pushes entrepreneurs to create new firms.

Other sectors (agriculture, mining, services, etc.) are modelled at the aggregate level in an 11 sector Leontieff-type Input-Output structure. There is an aggregate household sector with a Keynesian consumption and saving function. The model includes a Government, and a Bank. The outside world (foreign prices, foreign interest rates, etc.) is exogenous.

3.1 The production function

The production function for each firm in MOSES is of the following form:

$$Q_t = QTOP_t^* (1 - \exp(-TEC_t^* L_t / QTOP_t)) \tag{1}$$

where Q is the potential output (in physical units) for a given employment level in number of hours (L); QTOP the maximum level of output which is approached asymptotically when an infinite amount of labor is used, given a certain level of capital stock; TEC the productivity of the first unit of labor (to be more precise, the slope of the production function at the origin); and exp(.) the exponential function. Subscript t denotes time.

The maximum output, QTOP, depends on the (real) stock of physical capital, the stock of specific skills, and the efficiency of the stock of physical capital as follows.

[2] A short description is given in Eliasson (1991). A set of books give a full description of MOSES and the data base: Albrecht et al. (1989, 1992) and Taymaz (1991).

$$QTOP_t = QTOPFR_t^*\{MINRT + [(1 - MINRT)^*ST_1^* (1 - \exp(-SPECTR_t/ST_2))]\} \quad (2)$$

where QTOPFR is the level of productive capacity (= EFF*PK, where PK is the stock of physical capital and EFF its efficiency), SPECTR the stock of specific skills. ST_1 and ST_2 are industry-specific parameters. MINRT is the minimum (percentage) level of output that can be produced with no stock of specific skills, and shows the productivity level of completely unskilled workers. Thus, if SPECTR = 0, QTOP = QTOPFR*MINRT. On the other hand, as SPECTR $\rightarrow \infty$, QTOP $\rightarrow$ QTOPFR.

As shown in the specification of production functions (equations 1 and 2), there are two critical *technology* variables that determine the performance of the firm: EFF and TEC. There are two methods to upgrade the EFF and TEC variables. In the case of *embodied* change, the technological level is upgraded by investment, since new equipment embodies a higher level of technology, MTEC and MEFF, where MTEC > TEC and MEFF > EFF. The technological level of the capital stock after investment is equal to the weighted average of all vintages of capital. In a sense, the MEFF and MTEC variables reflect the stock of knowledge possessed by the firm. The technological level of the productive equipment actually used (measured by the EFF and TEC variables) is lower than the level known by the firm because of the vintage effect. In the *disembodied* case, the EFF and TEC variables are increased by implementing what is known by the firm (organizational changes, rationalization, etc.). In other words, the EFF and TEC variables converge gradually towards MEFF and MTEC levels, where the rate of convergence depends upon the specific human capital stock of the firm. Thus, we assume that the stock of *specific* skills (those skills specific to the physical capital used in the firm) determines the pace of disembodied change for *a given* level of the MEFF and MTEC variables. The values of the MEFF and MTEC variables, on the other hand, depend on the efficiency of learning which is determined by the stock of *general* knowledge[3].

3.2 Technology

The technology of a firm can be represented by a set of "techniques", $F^P = \{f_1^P, f_2^P, \ldots f_n^P\}$, where F^P is the technology used by the firm, and f_i^P is the i^{th} technique, i = 1,2,...,n. Superscript P denotes the relevant technological paradigm. For simplicity (and without any lack of generality), a technique can be assumed to have only two values/alternatives, $f_i^P \in \{f_i^{1P}, f_i^{2P}\}$.

The best practice technology of a technological paradigm (the "global technology"), which is defined similarly, describes the best *combination* of techniques. The firm which uses *all* techniques in the set of global technology reaches the highest technological "level" defined by that paradigm. A firm can know only *a part* of the global technology (or the opportunity set, see Eliasson, 1990) and its technological level is determined by the

[3] See equations [3] to [6] in Ballot and Taymaz (1996, p. 443).

correspondence between the global technology and the technology applied by the firm.

In our experiments, we use a 40-element vector for the global technology. The technological level of the firm depends on the degree of correspondence (DC) between the global technology and the technology employed by the firm as follows.

$$DC^P = \Sigma a_i w_i \tag{3}$$

$$a_i = \begin{bmatrix} 0 & \text{if } t_i \neq f_i \\ & \\ 1 & \text{if } t_i = f_i \end{bmatrix}$$

where w_i is the weight for the i^{th} technique, T^P represents the global technology of the P^{th} paradigm, and F^P the technology used by the firm. $t_i{}^P$ and $f_i{}^P$ denote i^{th} techniques of T^P and F^P, respectively. The technological level of the firm is computed by an exponential function of the DC value.

$$MTEC^P = \alpha^P \exp(\beta^P DC^P), \tag{4}$$

where α^P and β^P are industry- and paradigm-specific parameters. In our model, we use the same DC function for all global technologies. Differences in α and β values create different global technologies. Thus, the value of $\alpha^P \exp(\beta^P)$, which is obtained when $F = T$, defines the absolute technological limit for the P^{th} paradigm. Although there may be many alternative specifications for the DC and MTEC functions, the one used in our model is quite flexible and sufficient for our purpose. The MEFF variable is also defined in the same way.

3.3 Learning and incremental innovations

Firms use "genetic algorithms" to discover the global technology of a certain technological paradigm. A firm has a memory to retain k alternative technology sets at a time (in our experiments, 3 sets), and actually uses the set that has the highest degree of correspondence. Firms "learn" about the global technology by recombining their own technologies (*experimentation*), by recombining their sets with other firms' sets (*imitation*), or by innovations in some techniques (*mutations*). One of the most important processes of evolutionary dynamics, *selection*, takes place at the sectoral level through the selection of firms. Badly performing firms (and technologies used by them) will be nullified by the competition process in the market. This is the way learning takes place at the national economic system level (see Eliasson, 1992, pp. 36–37).

Our learning specification has four critical parameters: INSEARCH, NSEARCH, PMUTAT and NMUTAT. A decrease in INSEARCH means the firm will have a stronger tendency for out-search (imitation). Intuitively, out-search is usually better than in-search, since the set of available technologies is broader in the case of out-search (the number of firms in the sector being higher than the number of technologies that reside in the firm's memory). Moreover, except in the most advanced firm, at least one firm's technological level is higher than that of the imitating firm. Our simulation experiments with the learning module support this intuition. When the INSEARCH variable is reduced, the learning process goes faster, i.e., firms quickly discover the elements of the global technology. A firm decides to try experimentation with INSEARCH/(INSEARCH + N) probability where N is the number of firms in the sector using the same type of technology. The more the technology is adopted, the less firms try experimentation. INSEARCH depends negatively on the stock of general knowledge. The increase in general human capital thus lowers the probability of experimentation. It may appear as a paradox that the firms with a high stock of general knowledge do more imitation than the others, since they are presumably closer to the frontier. However they simultaneously spend more R&D for radical innovation than other firms, and, in that area, will practice experimentation, since there is no firm to imitate.

The second variable, NSEARCH, determines the extent of the change in the technology. A low value for NSEARCH means the firm can change only a few elements (techniques) at a time. This implies a slow learning process. Experiments with the learning module shows that increasing the NSEARCH variable improves the learning performance.

The PMUTAT and NMUTAT variables, which determine the probability of mutation and the number of elements to be changed in mutation, have positive impacts on learning. We assume that out-search and mutation probabilities depend on the firms' stock of general knowledge (GENTR). The firm with a larger stock of general knowledge will be able to experiment with other firms' techniques and so will achieve a higher rate of learning. The numbers of elements to be changed in experimentation, imitation and mutation is determined by real R&D expenditures. In a sense, the firm buys experiments for R&D activities, and the quality (the probability of success) of those activities depends on the stock of general knowledge.

The learning process, which takes place at the beginning of each year, is executed in four steps for all technologies in each firm's memory. *First*, the firm decides if it will try experimentation or imitation.

Second, if the firm decides to try experimentation, it will select a technology *from its memory* for recombination. The probability of selection depends on the relative degree of correspondence with the global technology. If the firm decides to try imitation, then it will select a technology for recombination *from another firm* in the same market using the same techno-economic paradigm. As may be expected, the probability of adoption depends on the latter firm technological level (the MEFF or MTEC variables).

Third, the firm selects, randomly, NSEARCH number of elements of the technology to be used in recombination. Then, the values of those elements (i.e., techniques) are replaced by corresponding elements from the selected technology vector. If the degree of correspondence improves, the firm keeps the modified technology in memory. Otherwise, the existing technology remains in memory.

The main difference between experimentation and imitation is the source of technology to be used in recombination. In the case of experimentation, the firm experiments by replacing NSEARCH number of techniques of one of the technologies with the corresponding techniques of another technology in its memory. Recall that a firm can keep three different technologies in its memory. In the case of imitation, the firm experiments by recombining the techniques of a certain technology with the corresponding techniques from another firm's technology.

Finally, the firm will try mutation, with PMUTAT probability. In the case of mutation, a randomly selected NMUTAT number of elements of the technology vector are replaced by their opposites ($0 \to 1$, and $1 \to 0$).

A firm can improve its technological level by learning and incremental innovations only within the limits of its global technology (technological paradigm). When the firm feels it is approaching this limit, it starts to allocate more funds to radical R&D, as described below. If the firm discovers a radical innovation, it jumps into another technological trajectory.

3.4 Radical innovations and changes in techno-economic paradigms

Firms, especially those close to the technological frontier, may try to achieve a radical innovation (a new type of technology, a new paradigm) or to imitate a radical innovation from other firms. The probability of a radical innovation (PRINN) depends on real R&D expenditures aimed for radical innovation (RDRAD), and the effective stock of general knowledge (GENTREFF). Effective stock of general knowledge refers to the fact that the firm may be able to benefit from the knowledge accumulated in other firms. It is defined as follows:

$$\mathrm{GENTREFF} = \mathrm{GENTR} + (\mathrm{ABSORB}^{*}\mathrm{SECGENTR}) \tag{5}$$

where SECGENTR is the (weighted) average knowledge stock of the sector, and ABSORB is the absorptive capacity of the firm which, of course, depends on its stock of knowledge, GENTR. Thus, firms with a higher stock of knowledge will be able to benefit more from other firms' knowledge.

The probability of imitation of a radical innovation is defined similarly. In addition to the RDRAD and GENTREFF variables, the probability of imitation depends on the number of firms adopting the new technology. The techniques used by a firm after a radical innovation are determined randomly. The firm will improve its technology by learning and incremental innovations.

In the case of the diffusion of radical innovations, we assume that capital goods producers can imitate a radical innovation from all firms; other firms (users) can imitate from capital goods producers *and* from the (user) firms in their sector. In that way, the capital goods sector becomes a "nodal" industry that facilitates the diffusion of radical innovations.

The first firm to discover and implement a radical innovation may not be very successful, since it may be less efficient at the beginning than the technology in the lower paradigm, which was improved through incremental innovations. However, as the radical innovation is imitated, the new technology reveals its higher potential, and diffusion accelerates. We find here the effect labelled by Arthur (1988) as increasing returns to adoption. An endogeneously generated S-curve characterizes the diffusion of a paradigm in the economy.

3.5 Training and R&D activities

The stocks of general knowledge and specific skills are accumulated as follows.

$$\mathrm{GENTR_t} = (\mathrm{GENTR_{t-1}}*(1 - \rho_g)) + \mathrm{INVGT_{t-1}} \tag{6}$$

$$\mathrm{SPECTR_t} = (\mathrm{SPECTR_{t-1}}*(1 - \rho_s)) + \mathrm{LEARNEFF_{t-1}}* \mathrm{f}(\mathrm{Q_{t-1}}/\mathrm{L_{t-1}}, \mathrm{INVST_{t-1}}) \tag{7}$$

where ρ_g and ρ_s are depreciation parameters, and INVGT and INVST are (real) general and specific training expenditures per employee, respectively. f(..) is an exponential function. LEARNEFF is the efficiency of learning which depends on the stock of general knowledge. The depreciation rate (or the obsolescence rate) of the stock of specific skills, ρ_s, is a function of the rate of improvement in the case of incremental innovations. A different (and much bigger) value is used for radical innovations.

General knowledge, once created, is applicable in all firms and, therefore, transferable. If employees with a high level of general human capital move to another firm, they will increase the stock of general knowledge of the new firm. Firm-specific skills, as the name implies, cannot be transferred from one firm to another. Therefore, firms can increase the stock of specific skills only by specific training and learning-by-doing (Q_{t-1}/L_{t-1}) whereas the stock of general knowledge can be increased by training and hiring highly educated workers from other firms.

In our model, it is assumed that the stock of knowledge of a firm affects its problem-solving capabilities. The PMUTAT, INSEARCH, ABSORB and LEARNEFF variables depend on the general knowledge stock of the firm. Firm-specific skills play a critical role in the application of what is learned about the global technology. There are two aspects of the "application" process. First, a firm learning more about the global technology can update/improve its current stock of productive equipment. The improvement of the existing fixed capital stock as a result of learning global technology depends on the stock of firm-specific skills. Second, the actual use of existing fixed capital depends on the stock of firm-specific skills. A firm endowed with the most productive equipment cannot produce much if employees are not trained in the use of that machinery. Thus, firm-specific skills can be used both in updating existing equipment (of the old vintage), and in effectively operating the (updated) equipment.

The level of desired investment in training depends on three variables: existing stocks of knowledge and specific skills, (the inverse of) the rate of utilization of potential capacity (QTOP/QTOPFR) and sales revenue. Firms tend to increase stock at a certain rate and to spend a part of their sales revenue on training. If the QTOP/QTOPFR ratio is low, the firm will spend more on training, since a low value of that ratio indicates that the firm is not able to use efficiently its productive capacity because of the lack of specific skills.

The desired level of investment in R&D depends on the stock of general knowledge, sales revenue, and the emphasis on radical innovations. If the firm spends a large part of its R&D funds for generating radical innovations, the level of R&D funds will be increased. The emphasis on R&D for radical innovation (RDRAD) depends on three factors. First, when the rate of learning within the existing paradigm (i.e. the rate of improvement of MTEC and MEFF) becomes lower because the firm gets closer to the paradigm frontier, the allocation will increase. Secondly, when the firm lags behind the average of the sector in terms of technology, it spends more on RDRAD. Thirdly, if the firm has adopted a radical technology recently, it will be reluctant to spend on radical innovation. The allocation of R&D between incremental and radical innovation is then endogenous and depends on the technological history of the firm.

In addition to training and R&D, the firm calculates its desired level of investment in physical capital and liquid assets. Then, given the level of net cash flow, the firm decides the level of desired borrowing (desired total investment *minus* net cash flow). The actual level of borrowing depends on the resources of the bank and total demand for borrowing. Finally, after the level of borrowing is set in the credit market, the firm allocates its resources (net cash flow *plus* net borrowing) among four different assets – training, R&D, physical capital and liquid assets – in proportion to their desired levels.

Total investment in training, INVTR, is then allocated to general and specific training. The allocation between general and specific training depends on a distribution parameter and the QTOP/QTOPFR ratio.

3.6 Markets

Firms confront one another on different markets on a quarterly basis. First, they make plans, based on adaptive expectations. The top management sets a target rate of return as a minimum profit margin based on past experience (satisficing rule). This target translates into a minimum labor productivity level. Then, the division head examines this level to see whether it is compatible with the potential production, Q, allowed by the present employment level. If not, the firm will search (through trial and error) for a level of production that satisfies both the minimum productivity level and the (unknown) production frontier. The employment plan is then set. Each firm sets its own wage offer, on the base of expectations about the wage that will prevail. When it needs to hire, it tries to hire either from the unemployment pool, or from other firms. The unemployed accept any wage offer; the employees of other firms quit if they are offered a wage rate at least 10% higher than their present wage. If the wage offer does not attract these employees, the firm may raise the wage offer afterwards. If it is successful, then the raided firm raises its wage. Each firm wishing to increase its labor force tries to raid other firms in the same manner. The process is iterated a fixed number of times. At the end of the quarter, final wages are then set, and there remain unemployed workers and vacant jobs, simultaneously. These mechanisms result in a wage curve and a Beveridge curve.

Domestic prices are set endogeneously in the product market as an outcome of interactions between domestic supply, demand, and foreign prices. Finally, there is a capital market where firms compete each quarter for investment resources. The rate of interest is set endogeneously in the credit market.

4 Experiments

4.1 Specifications

Five simulations are run for «50 years» to analyze the micro and macro effects of heterogeneity in firms' behavior. Table 1 summarizes the differences between experiments. The BASE experiment assumes that i) firms borrow at the same interest rate, ii) the parameters that determine investments in R&D and training is identical for all firms, and iii) firms can imitate radical innovations.

Table 1. Experiments specifications

Experiment	Interest rates paid	Decisions training R&D	Imitation of radical innovation
Base	same all firms	same	yes
EXP 1	firm specific	same	yes
EXP 2	same all firms	heterogeneous	yes
EXP 3	firm specific	heterogeneous	yes
EXP 4	same all firms	same	no

Experiment EXP1 introduces some heterogeneity in the interest rate faced by firms. It is caused by the banks rating, which is based on the risk of failure. The higher the rate of return of the firm, the lower the risk. Hence, $R_i = R_{AVE}{}^* (1 + RR_{AVE} - RR_i)$ where R_i is the interest rate for the i^{th} firm, R_{AVE} is the average rate of interest, RR_{AVE} is the average rate of return in the industry, and RR_i is the rate of return in the i^{th} firm. A firm with a lower rate of return pays a higher rate of interest. Thus, selection is stronger in EXP1 than in the BASE experiment. This is a short-term selection process which may not be optimal from a social point of view, but which nevertheless occurs in the real world.

Experiment EXP2 studies the effects of another type of heterogeneity. Each parameter that determines the firms investments in R&D and training is now randomly determined. At the beginning of the experiment, the mean is the same as in the BASE experiment, but the range is {0; 2*mean}. These firm-specific parameter values are constant during the simulation, but the mean changes as a result of the selection and entry processes. In the third experiment (EXP3), firm-specific interest rates and heterogeneity in investment parameters are introduced simultaneously. Experiment EXP4 differs from the BASE experiment by assuming full appropriability of *radical* innovations. Firms cannot imitate radical innovations in EXP4.

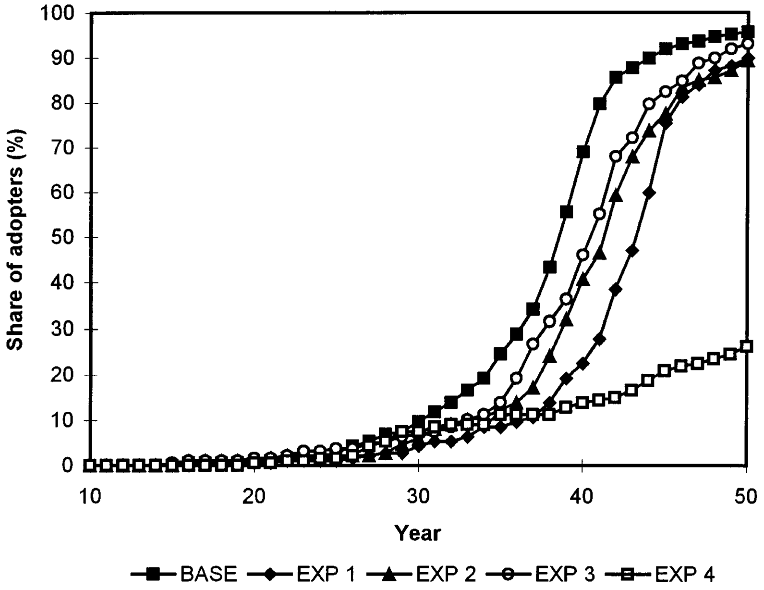

Fig. 1. Diffusion of radical innovations

4.2 The change in techno-economic paradigm

The model displays a change in techno-economic paradigm after some decades (Fig. 1). In BASE, some radical innovations appear in the second half of the second decade. However, the bulk of the radical innovations occur in the third and the fourth decades (Fig. 2). Imitation then occurs essentially in the fourth decade (152 imitators), with some early imitators in the third decade and some latecomers in the fifth decade. Five firms manage to survive at the end of the 50 years period without innovating or imitating (in the radical sense). The change in technology that occurs in the third and fourth decades concerns all four manufacturing industries that are modelled at the firm level. Each of these industries displays a similar diffusion curve, but with a lag from the raw material industry to the consumer goods industry (Ballot and Taymaz, 1994).

User-producer interactions as well as increasing returns to adoption and learning play a major role in the transition to a new technological paradigm. However, EXP4 shows that a crucial determinant is the possibility of imitating radical innovations. When this possibility is denied as in EXP4, the use of the radical innovations that characterize the new techno-economic paradigm increases at a much slower rate, since it occurs only through the exit of the non-imitating firms, the increase in the market share of innovators, and the higher number of radical innovations, since no resources are devoted to radical imitation.

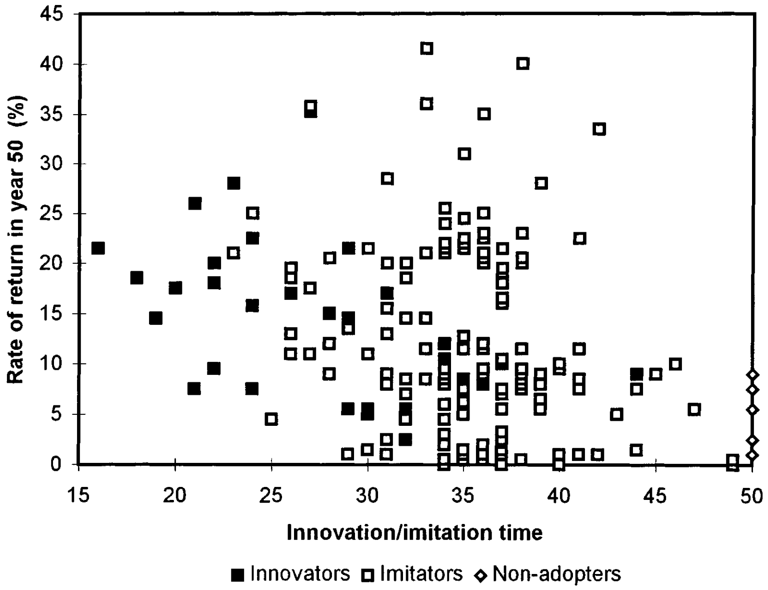

Fig. 2. Rates of return by innovation/imitation time

4.3 Firm heterogeneity and macroeconomic performance

The BASE experiment displays steadily increasing stocks of the general and specific human capital from the start (Table 2). These increase the growth rate of the technological level and the productivity. Investments in general human capital and in R&D trigger radical innovations. Since we model only process innovations, technical progress has a labor saving bias. However, it also increases wages, lowers prices and therefore increases consumption. As a result, the unemployment rate decreases during the change in the techno-economic paradigm. *A contrario* EXP4, which has no such change of paradigm, displays a monotonic increase in unemployment.

Experiment EXP1 links the rate of interest paid by the firm to its performance. Hence it strengthens selection, a key factor in evolutionary theory. Figure 1 shows that the change in techno-economic paradigm is delayed by about five years. The macroeconomic performance is somewhat lower, productivity growth is lower, and so are the manufacturing and GNP growth rates. This is caused by a smaller accumulation of general and specific human capital. Firms have a lower average rate of return and fewer resources to invest. There is also more concentration than in the BASE experiment. One tentative interpretation is that the higher concentration entails less diffusion and therefore lower growth – a standard result in evolutionary theory. Higher unemployment rates reflect more reallocation of manpower as more firms fail.

Experiment EXP2, characterized by heterogeneity in firms' behavior towards investment in R&D and human capital, also yields macroeconomic results inferior to those in the BASE experiment. This may appear

Table 2. Main macroeconomic variables

Decade	Base	Exp 1	Exp 2	Exp 3	Exp 4
GNP growth rates					
1	2.76	2.34	2.49	2.07	2.35
2	2.99	2.55	2.8	2.57	2.93
3	3.53	3.88	3.48	3.44	3.17
4	3.08	3.21	3.59	3.56	2.78
5	4.04	3.25	2.86	3.59	2.78
Manufacturing Industry growth rates					
1	4.15	2.91	3.23	2.29	3.43
2	3.82	3.38	3.65	3.3	4.19
3	4.05	4.67	4.03	4.1	3.72
4	3.78	3.7	4.11	4.16	3.16
5	4.42	3.48	2.73	4.03	1.97
Manufacturing employment growth rates					
1	2.19	1.68	2.63	1.85	2
2	0.84	0.02	0.98	0.76	0.11
3	1.56	0.83	−0.13	−0.59	1.01
4	0.96	1.56	0.37	1.02	1.68
5	−0.6	−0.78	−0.72	−1.1	1.35
Manufacturing productivity growth rates					
1	1.74	1.55	1.05	0.95	1.39
2	3.55	3.4	2.87	2.83	3.9
3	2.61	4.08	4.53	5.04	2.96
4	2.52	2.22	3.8	3.28	1.4
5	4.91	4.29	3.86	5.13	1.54
Average unemployment rates (period average)					
1	9.84	10.39	9.49	11.05	10.46
2	7.56	9.23	6.3	7.6	8.63
3	5.78	9.82	8.15	10.63	9.81
4	2.06	5.07	6.72	10.76	5.15
5	4.25	7.57	9.23	12.32	1.3
Average stock of specific skills					
1	90.77	83.45	82.91	86.86	79.32
2	151.04	145.62	131.65	136.04	156.69
3	159.83	180.01	219.04	223.37	184.17
4	224.9	231.44	267.26	280.59	222.27
5	347.35	300.8	516.59	464.49	161.32
Average stock of general knowledge					
1	103.77	99.1	100.3	102.4	96.25
2	149.11	142.46	128.56	130.43	150.25
3	179.19	199.53	219.26	228.39	199.62
4	245.53	251.23	290.57	322.15	233.23
5	386.87	342.84	551.17	533.63	185.46
Average rate of return (%)					
1	−0.44	0.13	0.7	0.16	−0.79
2	−1.42	−0.94	−3.49	−1.8	−2.66
3	11.72	5.47	6.36	2.87	8.95
4	8.35	5.68	11.53	7.17	7.8
5	8.78	9.04	12.73	11.21	7.82

paradoxical since aggregate investment in both types of human capital is higher. One interpretation is that some firms spend too much and others too little. Decreasing returns then explain the mediocre result. Another factor is the selection process which eliminates firms that make mistakes (investing far too much or far too little). There is a higher concentration and less diffusion.

Experiment EXP3 adds up the two factors of heterogeneity but this does not result in a macroeconomic performance inferior to EXP1 and EXP2, except for unemployment. It may be the case that the harsher selection forces the remaining firms to be more productive, as the high productivity growth shows. As may be expected, the worst macro-performance is achieved in EXP4 where imitation of radical innovations is blockaded.

4.4 Human capital, R&D and micro-performance in Schumpeterian competition

The dynamics of firms' profitability over the paradigm change is studied by an econometric analysis of the micro-data generated by our simulation model. Rates of return over the simulation period are regressed on a number of firm characteristics to test the effects of investments in R&D and training on micro-performance in various phases of the technological trajectory. Since we focus our attention on innovation and human capital, we use 'R&D stock per employee', 'general training stock per employee', and 'specific training stock per employee' as explanatory variables for the rate of return equation. Physical capital stock per employee, number of employees (proxy for firm size), a dummy for the radical innovator/non-innovator position, and industry dummies are included into the model as control variables. A ten year lag of all explanatory variables is used, because the effects of R&D and training are stochastic and long lasting. The regression has been run for every other year, starting in year 2. Figure 3 displays the values of regression coefficients of our main variables of interest for the BASE experiment.

The econometric specification is very crude, and alternative specifications could be tried[4]. Results are certainly sensitive to the assumptions on the parameters, and should be considered as very tentative. Yet they point out to importance of the timing of different types of investments. The effect of an investment depends on its timing relatively to the change in the techno-economic system. General training before the change has a positive effect on profitability, presumably because it gives to the firm the necessary competence base to innovate or imitate radical technologies. Then R&D has to be undertaken to innovate or imitate. Its effect is positive when it is undertaken just before or at the beginning of the change in the techno-economic paradigm; these early innovators/imitators reap the quasi-rents.

[4] R^2 ranges from 30 to 45%. To comment briefly on variables not central to our framework, physical capital has a non significant effect on the rate of return which is negative after the second decade. Size has a positive effect and sectoral dummies are significant.

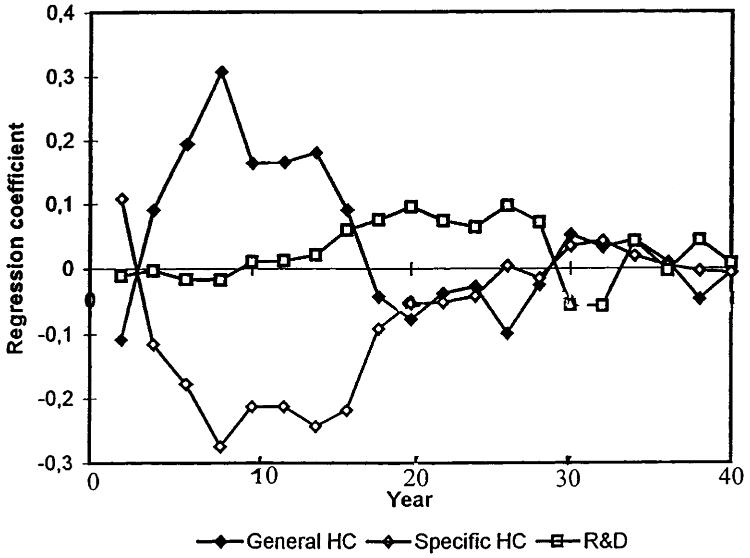

Fig. 3. Effects of general and specific human capital and R&D on the rate of profit

Finally, the specific training stock has a negative effect, except when the training is done during the change in paradigm. The negative effect is somewhat puzzling. One possible explanation, to be explored further, is that the specific human capital stock is only partially a result of the decisions of the firms. Firms that do not spend much on radical innovation or imitation of radical innovations accumulate experience and specific human capital in obsolete technologies. It is quite understandable that the return is not positive except in the fifth decade, when the change of techno-economic system has taken place and the wave of radical innovations has almost disappeared. Then specific human capital invested during the change in techno-economic paradigm improves efficiency in production after the change.

To assess the results correctly, it is important to note that the effects of the investments in human capital and R&D do not go through the discovery of a radical innovation, since this is controlled for by a dummy. Then the effects go through the accumulation of "competence" that favors the improvements of radical innovations, in the line of Cohen and Levinthal's absorptive capacity theory[5].

The preceding results do not distinguish between the innovators and the imitators. However, the dummy for innovators in the estimated equation is consistently positive and significant. We have computed statistics to assess whether innovators are more profitable than imitators (of radical innovations). In the BASE experiment the rate of return of innovators is 15% higher than the industry average in the first decade; this premium rises to

[5] See Gerowski et al. (1993) for econometric evidence.

30% in the last decade. However, the market share of innovators does not rise continuously. During the change in techno-economic paradigm and afterwards, the imitators (which include new firms) gain back some of the market (other experiments yield similar results).

Figure 2 shows the rate of return in the last year of the simulation (year 50) for individual firms as a function of the year of radical innovation/imitation in the BASE experiment. It shows that the dispersion is very wide between innovators, although to a lesser extent than imitators. Many innovators are less successful than some of the imitators, giving an apparent credit to the idea that innovators can be "lambs of sacrifice". However we see no irrationality in the innovators' behavior, since they are on average better off and innovation is obviously a very risky enterprise. Another interesting result is that the rate of return in the last year is on average lower for late innovators. Early innovators not only reap quasi-rents that may vanish over time, but they have also built up a general human capital stock that enables them to accumulate more specific human capital, make more radical and incremental innovations later, and benefit more from learning-by-doing. There are clear first-mover advantages enjoyed by innovators, though some early imitators are actually more profitable.

An analysis of the changes in the rate of profit over time shows both that firms have variation in their rate of return, as one sees in the real world, and that there is some persistence. Technological advantage and market share have also some stability, that, again, can be attributed to the competence base that we approximate by the levels of general and specific human capital. If these long lasting differences did not exist, the model, which does not assume monopolistic competition, could yield a much higher instability in rates of return, since the firms would be very similar.

5 Conclusions

The model has proved capable of reproducing endogeneously different types and levels of innovations contained in the Freeman and Perez taxonomy. As such it offers a challenging alternative to the real business cycle school that invokes exogenous technological shocks to explain the dynamics of the macroeconomy (Nelson and Plosser, 1982). Our model allows a detailed analysis of the factors behind economic growth and fluctuations. A major factor of growth appears to be the efficiency of diffusion of innovations.

We offer a theory of the effects of firms' general training and human capital stock on innovation. Although the theory is compatible with endogeneous growth theory, it has distinct features. First it solves the externality problem posed by firm-sponsored general training, which is avoided in endogeneous growth theory by its high level of aggregation: in Schumpeterian competition, rational firms can invest in general training and so make profits by obtaining the quasi-rent. The simulations show that it is the case. Secondly, it develops a story of how human capital and innovations interact at the microeconomic level to generate macroeconomic growth. This story treats the degree of rationality of firms as an endogeneous variable, which depends on the firms' human capital stock. It also shows that timing at the firm level is important: general training should precede investment in R&D. The simulations confirm that the story is consistent at the micro and macro levels. We suggest that innovators with a strong knowledge base fare better in the long run. Recent econometric work also confirms that competence accumulation has long-run effects on firm profitability which should not be confused with the direct effects of innovation.

An exciting development in micro-simulation is the endogeneization of the rules of resource allocation in firms that learn through classifier systems (Holland and Miller, 1991; Ballot and Taymaz, 1995) or neural networks (Langrognet and Merlateau, 1994). We believe that our model, and, thus, our analysis, can be progressively enriched by incorporating features about learning, and rule generation and selection at the firm level. This is a challenge for future research.

Appendix: Variable names

ABSORB	absorptive capacity coefficient (depends on general knowledge)
EFF	average output/capital ratio
GENTR	stock of general knowledge
GENTREFF	effective stock of general knowledge
INSEARCH	in-search parameter
INV	physical investment
INVGT	general training expenditures per employee
INVST	specific training expenditures per employee
L	employment level (in number of hours)
LEARNEFF	efficiency of learning coefficient
MEFF	output/capital ratio of newly installed capital
MTEC	labor productivity of newly installed capital
MINRT	minimum level of output (with no specific skills)
N	number of firms in a paradigm in a given sector
NMUTAT	number of elements of the technology that are replaced in a mutation
NSEARCH	number of elements (techniques) of a technology that are replaced in an experimentation or an imitation
PK	stock of physical capital
PMUTAT	probability of a mutation
PRINN	probability of a radical innovation
Q	potential output in physical units for a given employment level (in hours) L
QTOP	maximum level of output when infinite amounts of labor are used, for a given level of capital stock
QTOPFR	level of productive capacity (maximum output, for infinite specific skills)
SECGENTR	weighted average knowledge stock of a sector
SPECTR	stock of specific skills
RDRAD	real R&D expenditures for radical innovation
TEC	productivity of the first unit of labor

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