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FIRM-SPONSORED TRAINING, TECHNICAL PROGRESS AND AGGREGATE PERFORMANCE IN A MICRO-MACRO MODEL

by

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Firm-sponsored training, technical progress and aggregate performance in a micro-macro model

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1. Introduction. The intellectual framework[1]

1.1. Training, innovation and Schumpeterian competition

Industrial countries have increased their rate of intangible investment in the 80s and decreased their rate of tangible investment. The measured intangible investment comprises R&D, software and marketing, but generally not training expenditures[2]. Yet at the same time productivity growth and income growth have declined. This productivity paradox and the often heard complaint by firms that have difficulties in hiring skilled workers suggest that training may be a required complement to tangible and intangible investments to obtain a high level of productivity, and that its supply might be insufficient. Even in countries like Sweden where the government has an active training policy, deficiencies in skills appear (OECD (1993)). This hypothesis receives some support from the success of Japan where firms devote considerable investments in training.

At the same time, the lack of skilled workers is clearly not caused by a global excess labor demand, since unemployment is rising. However in a perfectly competitive world, it is not clear why education or training would be insufficient. According to standard human capital theory, workers should pay for investment in general human capital while workers and firms should share some of the expenditures in specific human capital. The rates of return should be equal to the rate of interest, and profits should be zero.

The predictions are not confirmed. The classical explanations are that workers face a moral hazard problem when they borrow because of a lack of collateral, are risk averse, or more subtly would have difficulties in signaling to other firms the general character of the training acquired while working in the firm. These arguments may explain why workers invest too little. They do not explain why firms invest in general human capital, except the signaling story. However signaling cannot be the whole story. That firms invest in general training has been documented by various studies which show that in France, US, and Sweden, firms pay much of the training, and do not lower the wage to recoup the cost (see Stern and Ritzen (1991) for some evidence).

We have developed elsewhere a theoretical framework which justifies that firms accept to do such an investment even if there is some loss through turnover (in Ballot, 1992a and Ballot and Taymaz, 1993). It can be labeled the *training-for-the-rent* hypothesis. The basic idea is the following. Firms that innovate successfully obtain a quasi-rent. For that purpose, firms need trained workers at the time of implementation of the new technology. It is then optimal for firms to pay the general training. It recoups the investment with the quasi-rent.

Such a Schumpeterian competition framework admits rates of profits over the interest rate, and a dispersion which is related partly to the stochastic nature of R&D, and partly to the race for competence, where the winner gets the market. It then allows for factors that influence the level of general investment and the rate of return, such as the rate of turnover or the financial constraints. In pure competition, such factors could have no influence since the optimal general investment is zero and the financial constraints do not exist.

Deficiencies in human capital then occur and keep the firm inside the production possibility frontier set by physical capital and labor. At the same time, it gives a rationale for the firms to decide on the level of general training, a rationale that does not exist in a purely competitive static framework.

Ballot and Taymaz (1993) have made preliminary tests of the effects of firms' sponsored training and R&D expenditures on profitability, which support the hypothesis stated above. 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 out to the interest of integrating the analysis of innovation and the analysis of training (general and specific) both at the theoretical level and in empirical analysis.

While the analysis at *individual firm's level* reveals the importance of training for successful innovation, well-known diffusion effects of innovation indicate that the social rates of return are much higher than the private rates of return (see Gomulka, 1990, Ch.3 for a summary of evidence). Although some analytical work at market level exists on R&D and diffusion, it cannot encompass the multiple channels by which general training might affect the process of innovation and diffusion among heterogeneous firms and their effects on aggregate behavior. The game theoretic R&D literature does not discuss training. Numerical methods are required, and among them, microsimulation is the adequate tool to model complexity. Moreover it is not clear that the concept of equilibrium that is necessary to solve an analytical model is adequate in an environment characterized by innovation and Schumpeterian competition, which means as we will see now, learning by firms and continuous changes in the market structure. More will be said on the particular brand of microsimulation which is required.

1.2. Knowledge versus skills

The traditional distinction between general and specific human capital, based on transferability from one firm to another, gets its value from the predictions for the sponsoring the investment. As we have shown, in a Schumpeterian framework, the firm shares both types of investment. Although the determinants of the shares remain in part different, and could be used to distinguish the two types of investment, we propose another criterion related to innovation.

Specific human capital of one sort is necessary to operate a technology. It becomes obsolete when the technology is no longer used. It is technology specific. We name it a skill. There are as many skills as technologies. A firm may operate more than one technology at a time.

We model firms' competencies, not individuals. A skill represents the competence of a team of workers who operate a technology. Such a competence may be obtained from the interaction of partial competencies of the team members. Hence we consider that a skill is not transferable, unless the complete team is transferred, which may be difficult.

Another type of human capital has a general nature in a double sense. First it is transferable. Second, it is a competence which facilitates the learning of skills. Obvious examples are the proficiency in maths or in foreign language. Some other competencies do not correspond to a precise curriculum and are acquired partly through training, partly through experience, such as strategic competence of managers.

Since our purpose is mainly theoretical and qualitative, we will assume that there is only one general competence, which we will call general knowledge. It is not a direct factor of production. However, it has important effects on innovation and diffusion of innovation[3]. *First* it allows to find new technologies and hence increase the expectation of finding more profitable ones (not all new technologies in our model are more profitable than 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 search faster the technologies used by other firms and implement some of them (sometimes after modifying them). This competence has been given a prominent place in the analysis of the determinants of innovation under the name of absorptive capacity coined by Cohen and Levinthal (1989, 1990). These authors state that this competence is given by prior R&D done by the firm. The 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 is not only allowed by prior R&D expenditures, but also by general education and training.

Third it decreases the cost of the training investment necessary to acquire the skills (specific human capital). This is a well-known mechanism. Acquiring skills often demands prerequisites, many of a general character like those we have mentioned, which means that the absence of knowledge entails an infinite cost of skill acquisition.[4] We remark in passing that such a feature distinguishes R&D from knowledge. R&D, when leading to an innovation, has the consequence of making the skill used in the former technology obsolete. Knowledge has only indirectly - by increasing innovation - this scrapping effect.

It should be stressed that the knowledge we have defined does not correspond to learning-by-doing (Arrow, 1962). The latter corresponds to an automatic process by which the firm acquires experience. The production cost is a decreasing function of cumulated past production. It is technique specific and could be modeled as a change in the production process at that level. However, for this first version of the training block in MOSES, we want to restrict the many types of learning to the essential innovation and diffusion effects of general education and training knowledge[5]. We will now be more precise on how innovation and diffusion occur in our simulation model.

1.3. Learning, boundedly rational decisions and training

We have started to paint an economy characterized by continuous innovation and a process of creative destruction of heterogeneous skills, jobs and firms. This is a very complex world, but one suspects that each feature might have a significant aggregate effect, alone or through interaction. It should be recognized that agents in such a world (hence in the model) do not understand the workings of the economy and hence cannot compute optimal decisions[6]. This situation is made worse by uncertainty. First there is uncertainty on innovation and its profitability. Reasoning in terms of a frequency distribution has not much meaning. Second the insufficient understanding of economy by other firms also makes their behavior difficult to predict, and this is an endogenous source of complexity.

Classical optimization under uncertainty then does not provide in general the adequate way of reaching decisions with high values, since it takes into account only a subset of the environment. *In the real world agents compensate the limitations of their information by learning continuously. They are adaptive agents.* They know that they have not taken the best decision, and try to improve the value next time. Moreover, when they do increase their value, they do not generally understand well why they have succeeded, but only *how* they have managed to succeed. The basic mechanism is trial and error which permits learning *how*. In classical optimization under uncertainty, agents know the model of the world (rational expectations) and do not make mistakes in a probabilistic sense. Hence they cannot learn.

Classical optimization uses the tools of calculus. *Bounded rationality* or *adaptive behavior* is worth discussion only if adequate modeling tools can be designed. The current version of the MOSES model uses some rules by which firms try to improve their rate of return (see description in the Appendix). The training/innovation block we add in this paper uses a recent and more powerful tool: *genetic algorithms*. The idea of these algorithms has been invented by Holland (1975) to study adaptation, optimization and learning (see Goldberg, 1989). They have shown their robustness through their application in many fields but are now just being used in economics.[7] We do not know of any application to a complete micro-to-macro model so far, and this is a qualitative step that this paper undertakes.

In our training/innovation block, a GA is used to invent new technologies and select the most profitable of them. A technology is coded as a finite length string over some finite alphabet[8]. We have adopted the usual binary alphabet where a position on the string takes the value of either 0 or 1. Each position may be interpreted as a technique, and a technology has a certain number of techniques as components. Yet for the workings of the model, techniques do not have to be identified with their real world counterparts.

Each string is assigned a measure of performance, which is based on the performance of the corresponding structure (the technology) in the economic environment. At a given date, there exists a set of technologies in the economy and a subset in each firm, and the GA manipulates this set to produce a new set where some technologies perform better.

GAs have proved very efficient in search spaces characterized by many peaks and discontinuities that are likely to be the case in the complex environment of MOSES. However all agents (here firms, since innovation is a team production) are not alike in their level of bounded rationality. Knowledge provided by general education or training is a factor that determines some of the search parameters, and, as we said above, first it makes firms experiment more techniques both through mutation and experimentation, and secondly, it enables them to search for and adopt other firms' techniques. More knowledge allows to reach (stochastically) closer to the best performance, that an omniscient firm would select.

GAs offer an operational tool for making the degree of rationality of an agent endogenous and depend on his level of general knowledge. The latter is itself an endogenous variable, depending on past decisions of the agent, but also on the knowledge of the other agents[9].

In the process, innovation and technological progress are themselves explained[10]. We have looked at microdecisions until now. It is time to describe briefly how the microdecisions of a population of firms interact to yield interesting macro-coordination.

1.4. Micro to macro links: Externalities and aggregate outcomes

MOSES is a complete micro to macro model and one of the very few to contain already some learning by firms. These are inside their production possibility frontier, and can improve their efficiency (see Appendix for a short description of the model). The model also contains the possibility of failure and reorganization of the economy through exit and entry. This made the rate of technical progress endogenous at the aggregate level under the constraint of the pace of scientific advance (the global technology).

The present training/innovation block makes both training and technical progress endogenous at the micro level. Interactions between firms through diffusion and competition/selection effects allow for a much more realistic modeling of the determinants of technical progress and of its effects at the aggregate level.

Our model then includes many dynamic competition aspects of the recent simulation models of innovation initiated by Nelson and Winter (1982), and developed by Silverberg, Dosi and Orsenigo (1988) in a one industry framework, and by Chiaramonte and Dosi (1992) in a two-sector environment.

MOSES as a micro-macro model with firms adapting through GAs appear as a basic artificial world (or economy) of the type described by Lane (1993a, 1993b). It might also be labeled a complex adaptive system according to Holland and Miller (1991), since it has the three required characteristics: i) it is a network of interacting agents, ii) it exhibits a dynamic, aggregate behavior, and iii) its aggregate behavior can be described without detailed knowledge of the behavior of the individual agents.

The interesting property of these artificial worlds or complex adaptive system is the emergence of a coordination in the economy. It is self-organizing. Such aggregate variables as the number of firms and the rate of growth, the rate of investment in training, or the rate of technical progress may be endogenous. The relations between these variables are not built into the model, but observed after the simulation. They emerge.[11]

However these relations may be unstable. Collapses may occur and the aggregate economy might stay for a long time into some seemingly permanent state to move away from it. Lane labels these phenomena meta-stability and also speaks of punctuated equilibria (a term from biology). This open-ended dynamic behavior, rather than bounded rationality/learning, might be the major departure from the standard modeling methodology which imposes asymptotic equilibrium not only when analytic results are searched for, but also in large computable equilibrium models that are solved numerically.

The model displays two important features of real economies that are not seriously integrated in the analytical models. The first is the set of externalities coming from diffusion and imitation. However diffusion is assumed to be costless in endogenous growth models (knowledge is a public good) or, at another extreme, costs the price of the patent. In fact it has a cost that varies with the knowledge of the imitating firm, and this allows the innovating firm to keep a quasi-rent without patent. In our model, diffusion also improves the technologies because it increases the number of crossovers. These occur between firms as well as within firms. Such inter-firms crossovers emphasizes the importance of variety for diffusion to be fruitful (Jovanovic and Rob (1989)). Variety and diffusion then contribute to the rate of technical progress.

The second major feature is selection[12]. Diffusion is unequal and firms that spend more on R&D and general training will have an advantage in the long run, and even often drive out of the market those that spend less either because of lack of funds, high turnover, or give a priority to other allocation of funds (financial or physical investment). Selection among heterogeneous firms has important effects on the aggregate rhythm of technical progress and growth. However it may not be the simple positive effect one would think of. If selection effects are so strong that the industry is dominated by a monopoly, there will be little diffusion, and the rhythm of technical progress will be slower.

A real economy, and our model, is characterized by a complex set of interactions between training, knowledge, innovation, diffusion and market structure which determine (hopefully) some self-organizing aggregate patterns. Through their mediation, patterns depend in fine on the more stable cultural and institutional environment, and history of the economy (including stochastic shocks). The patterns are emerging properties, often not predictable from building blocks

The present version of MOSES should then be a richer story about the determinants of growth, because, for the first time, it adds the endogenous creation of competencies to innovation and technical progress, and dynamic competition on markets.

1.5. Policy issues

The model has two important general features that make it suitable for policy experiments. First it is a complete micro-to-macro model with feedbacks and micro-macro compatible accounts for a real economy (Sweden). As is the case with other microsimulation models, it allows to simulate institutional policies (taxation, laws) at the proper level, which is microeconomic. Externalities and feedback effects occur and transform the micro effects to dampen or amplify then. Secondly, the model is rich and allows to study the effects of important and debated policies such as government intervention in education/training matters. The paper will study one such policy.

Section 2 presents the specification of the training and innovation/learning block. Section 3 discusses the results of the base run, some variants and policy experiments.

2. Model

The Model of the Swedish Economic System, the MOSES model, which is summarized in Appendix is a micro-to-macro, firm-based, model of the Swedish economy (see Eliasson 1977 and 1985; Albrecht et al. 1989 and 1992; Bergholm 1989; Taymaz 1991). The modeling project was initiated in 1974 by IBM Sweden and work began in 1975. Two databases for the model have been prepared by using 1976 and 1982 real micro and macro data. 225 firms or divisions are defined explicitly in the manufacturing sector in the 1982 database which is the database used in simulation experiments summarized in this paper. 154 of those firms are real, i.e., data about those firms come from the Planning Survey conducted by IUI. The model simulates the behavior of firms in four manufacturing industries (namely, raw materials, intermediate products, durable and capital goods and consumer goods). Others sectors and the household sector are modeled at the macro level within a Leontieff-type I-O structure.

Learning and training (the accumulation of knowledge and skills) were not explicitly modeled in MOSES. In this study, we develop new modules for learning and training activities. In the following section, we will first describe the technology to explain how (general) knowledge and (specific) skills affect the performance of the firm. Then, learning and training modules will be explained.

2.1 Technology

The technology used (or known) by each firm can be represented by a set of "techniques." For simplicity (and without any lack of generality), a technique can be assumed to have only two values/alternatives.

$$T=\{ABC...\}$$

$x \in \{x_1, x_2\}$, where T is the technology of the firm, A,B, C, ... are different techniques, and x is any technique in T that can be either x_1 or x_2.

Under certain conditions, there is a "global technology" which describes the best *combination* of techniques. The firm which uses *all* techniques in the set of global technology reaches to the highest technological "level". The global technology can be interpreted in different ways. It may the best combination of techniques for a certain technological paradigm a là Freeman (Freeman and Perez, 1988). It may be the best combination of techniques that can be achieved given the current level of scientific and technological development. In any case, *one* firm can know only *a part* of global technology and firms' technological progressiveness is determined by the correspondence between the global technology and the (part of) technology known by the firm.

For example, let's assume that the global technology for the "petrochemical" industry consists of two techniques, "A" and "B". "A" and "B" may refer to the wall thickness and size of cooling towers, respectively. "A" can be either 1 or 2 cm, and "B" can take two values, 10 m and 20 m. Then we have four alternatives with corresponding "pay off"s (or, "productivity" levels) as follows.

T	A	B	Pay off ("productivity")
T_1	2	20	100
T_2	2	10	50
T_3	1	10	60
T_4	1	20	-70

When the length of tower is 20 m and the wall thickness 2 cm, the firm achieves highest performance level (100 units). When A=1 cm, B=10 m, the pay off is 60 units. But if the firm uses a thicker wall that is not necessary for 10 m tall towers, the pay off is lower because of the extra cost involved. Finally, if the firm builds a 20 m tall tower with 1 cm thick wall, the pay off is negative which means that the tower may collapse due to thin (weak) walls.

The global technology, as defined here, can be represented by a binary array where 0's and 1's will denote alternative techniques. The technology, known and applied by the firm, can also be represented by a firm-specific array. A correspondence function between the global technology and firm-specific technology can easily be defined to determine firm's technological level.

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.

$$DC = \sum a_i w_i$$

$$a_i = \begin{cases} 1 & \text{if } T_i=F_i \text{ and } T_{i+1}=F_{i+1} \\ 0 & \text{if } T_i \neq F_i \\ -1 & \text{if } T_i=F_i \text{ and } T_{i+1} \neq F_{i+1} \end{cases}$$

where w_i is the weight for the i^{th} technique, T the global technology, F technology used by the firm. T_i and F_i denote i^{th} techniques of T and F, respectively. The last line of the a_i specification is used to have a nonlinear DC function originated from the interdependence of techniques.

This specification allows simple non-linearities in the correspondence function. Then, the technological level of the firm is computed by an exponential function of the DC value as follows.

$$P=\alpha\ exp(\beta DC),$$

where α and β are industry-specific parameters, and P the technological level, and *exp*(..) the exponential function. (Although there may be many alternative specifications for the DC and P functions, the one used in our model is quite flexible and sufficient for our purpose.)

In the MOSES model, there are two critical firm-specific technology variables that determine the performance of the firm: the INVEFF variable which is, in a sense, (inverse of) the incremental capital-output ratio, and the MTEC variable which represents the level of labor productivity that can be achieved in new investment (for details, see the Appendix). Thus, in our experiments, we use two global technology vectors, one for the INVEFF variable, and the other for the MTEC variable. The INVEFF variable of a firm depends on the correspondence of that firm's technology vector and the global technology for the INVEFF variable, as explained above. The MTEC variable is computed similarly. The firm then tries to "discover" the global technology by learning to improve its INVEFF and MTEC variables. (In our experiments discussed in the paper, elements and the length of the global technology vector is constant. It is, of course, possible to have a changing global technology vector.)

2.2 Learning

Firms use "genetic algorithms" to discover the global technology. A firm has a memory to retain n-number of 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 technology sets (*experimentation*), recombining their sets with other firms' sets (*imitation*), or by mutations (*innovation*). 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.

The learning process which takes place at the beginning of each year is executed in four steps for all technologies in firms' memory.

First, the firm decides if it will try experimentation or imitation. The firm decides to try experimentation with INSEARCH/INSEARCH+1 probability. For example, if the INSEARCH variable of the firm is equal to 1, the firm will try experimentation with 50% probability.

Second, if the firm decides to try experimentation, it will select a technology from its memory for recombination with the set under consideration. 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 firm in the same market for recombination. As may be expected, the probability of selection depends on firms' technological levels (the INVEFF or MTEC variables).

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

Finally, if the firm cannot find an improved technology in a NOTECH number of trials, then it will try a mutation. The firm can achieve a mutation with PMUTAT probability. In the case of mutation, randomly selected at most NTRIAL number of elements of the technology vector are replaced by their opposites ($0 \rightarrow 1$, and $1 \rightarrow 0$).

Our learning specification has three critical variables: INSEARCH, NTRIAL and PMUTAT. (The fourth variable, NOTECH is constant and equal to 3. That is, if the firm cannot improve any one of technologies in its memory in a year, it will try a mutation.) 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 (because the number of firms in the sector is higher than the number of technologies that reside in firm's memory). Moreover, for all but the most advanced firm, at least one firm's technological level is higher than that of the experimenting (imitating) firm. Indeed, our simulation experiments with the learning module supports this intuition. When the INSEARCH variable is reduced, the learning process goes faster, i.e., firms quickly discover the elements of the global technology.

The second variable, NTRIAL, is another critical variable for the performance of the learning process. A low value for NTRIAL 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 NTRIAL variable improves the learning performance. Finally, the PMUTAT variable which determines the probability of mutation after a certain number of unsuccessful experiments have a positive impact on learning.

The learning *module* based on genetic algorithms as specified here creates "standard" results. For example, the diffusion of new innovations follows usual S-curves. Learning process has also "decreasing" returns if the global technology is constant in the sense that when firms get closer to the (constant) limits of technological frontier, it becomes difficult to improve firms' technological levels.

2.3 Training

Training in a firm generates two types of assets: general knowledge and firm-specific skills. It is assumed in our model that both types of assets are created by training and embodied in personnel employed by firms.

General knowledge, once created, is applicable in all firms and, therefore, transferable. If employees with high general human capital move to another firm, they will increase the stock of general knowledge of the new firm. The firm-specific skills, as the name implies, cannot be transferred from one firm to another.

In our model, it is assumed that the stock of knowledge of a firm affects its problem-solving capabilities. To be precise, the INSEARCH, NTRIAL and PMUTAT variables explained in the preceding section depends on the knowledge stock of the firm. Accumulation of knowledge in a firm either by general training or by hiring highly qualified employees from other firms will improve those variables so that the firm will be able to learn rapidly the global technology. In other words, firms with a large stock of general knowledge, on average, will rapidly learn the global technology and will improve their technology variables, INVEFF and MTEC.

Firm-specific skills then play a critical role in the application of what is learnt about the global technology. There are two aspects of the "application" process. First, a firm learning more about the global technology can updates/improves current stock of productive equipment. The improvement of 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 any output at all if employees are not trained how to use those machinery. Thus, firm-specific skills can be used both in updating existing equipment (of the old vintage), and in effectively operating the (updated) equipment.

For our specification of the accumulation of knowledge it is assumed that the knowledge and skills generated by a unit of training expenditure is constant in real terms and equal for all firms. In other words, we do not assume "learning by learning" or "learning to learn": the "productivity" of training does not change by time and by firm. For future modeling work, we plan to have the accumulation of skills depended on the stock of general knowledge as discussed in Section 1.

3. Experiments

In order to gain an understanding of the impact of general and specific training and different institutional and behavioral settings, we designed a set of simulation experiments on the Swedish micro-to-macro model. In each case we analyze the impact at the macro level, i.e., the impact on macro-performance. In this section, a brief description of the nature of the experiments will be given. The modeling of training and learning modules are not yet complete. More work is planned especially for the calibration of parameters. Therefore, our results should be considered as a first, exploratory phase of the modeling effort.

Experiment BASE. The first experiment is the base experiment. In this experiment, firms desire to spend for training an amount .4% of their total stock of human capital and 1% of the wage bill every quarter if they fully utilize their productive equipment. Otherwise, those numbers are multiplied by the inverse of utilization ratio. Thus, the quits rate does not have any effects on training expenditures. The unemployed people are trained by the government to the extent that the growth rate of the stock of general knowledge of unemployed is equal to the industry average.

In the BASE experiment, firms cannot properly monitor the stock of general knowledge in each other so that when they try to hire employees from each other (when they "attack" to each other to get the people they need), they can neither target firms with high human capital stock nor can hire employees with above-average knowledge stock. Employees in the attacked firm do not accept the offer from other firms if the average wage bill in the attacking firm is at least 30% higher.

Experiment NOEXT. The second experiment, NOEXT, differs from the BASE experiment in the specifications of the labor search and training decision functions. In the NOEXT experiment, firms can, at least to some extent, observe the level of human capital in each other. Thus, when a firm wants to hire new employees, it tries to attack those firms with high human capital stock. If the wage level of the attacked firm is lower, then the attacking firm gets employees with above-average human capital stock. Thus, hiring skilled employees from other firms may be more profitable than training firm's own employees. Moreover, firms training decisions depend on the quits rate as well as variables mentioned before. If a firm has high quits rate, then it will spend less on training. As may be expected, firms spend less on training in this experiment than the BASE experiment.

Experiment GOVTR. The third experiment is similar to the NOEXT experiment. However, in this experiment, government tries to solve the problem of inadequate training in firms by training the unemployed people. Government trains the unemployed to the extent that the human capital stock of unemployed is higher than all firms. Thus, firms can increase their average stock by hiring from the pool of unemployed.

A group of selected macro-performance indicators are shown in Table 1. This table reveals that stocks of both skills and general knowledge become much smaller if the externality problem is significant for training activities. Low level of training expenditures has considerably slowed down the learning process as shown in very low levels of technology variables (the MTEC and INVEFF variables) for the NOEXT experiment. Since the accumulated value of the specific skills is low, actual productivity gains are lower in the NOEXT experiment during the whole simulation period. Note that the stock of skills is less than the stock of knowledge in both the BASE and NOEXT experiments although firms spend more for specific training. In the BASE experiment, for example, firms spent 15% more on average on specific training than on general training. The *stock* of skills is lower because it is lost during inter-firm transfers whereas general knowledge is not lost if workers leave their firms.

As may be expected, the growth rates of real GNP and manufacturing output are considerably higher in the BASE experiment than in the NOEXT experiment. A paradoxical result seems to be generated for the unemployment variable. In spite of high real growth rates achieved in the BASE experiment, the average unemployment rate is much lower in the NOEXT experiment. However high growth rate of labor productivity attained in the BASE experiment can, at least partially, explain this seemingly abnormal result. The labor saving character of technological progress may cause relatively high unemployment rates. This argument is supported by the fact that the average growth rate of wages in the BASE experiment is much higher in both the first and second 15 years of the simulation run.

The macro-performance of the economy in terms of real growth rates of GNP and manufacturing output is marginally better when the government trains the unemployed people considerably (the GOVTR experiment). The growth rate of labor productivity of this run is also marginally better than that of the NOEXT experiment. The training of unemployed people did not increase the macro-performance since firms did not spend much on specific-training because of high quit rates. Although firms received highly qualified employees from the pool of unemployed and became quite successful in learning about the global technology (high MTEC and INVEFF variables), they were not able to apply what they have learnt. A comparison of the values of the SPECTR and GENTR variables for the BASE and GENTR experiments shows that general training of unemployed people by the government can be a method to increase the stock of general knowledge. But rather small stock of skills may impede the use of advanced technologies. We must emphasize here that the assumption about the level of training the unemployed receive in the GOVTR experiment may not be realistic.

4. Conclusions

Our experiments show that if firms behave rationally, i.e., if they appraise the effects of quits, the macro-performance will deteriorate because of low "on-the-job" training. A government policy in the form of training of unemployed people may not be sufficient to solve this problem because firms need specific skills to (effectively) apply what is learnt. We must emphasize the role of "virtuous cycles" in economic growth. In our case, an increase in training generates rapid and sustained macro-economic growth through its effects on the process of innovation and imitation. Innovativeness (cost reductions, etc.) improvess the cash flow which, in turn, means enhanced possibilities for financing training activities. Growth also allows firms to keep their employees so that firm-specific skills are kept in the firm. The "virtuous cycle" is the essence of the growth engine. A complete dynamic micro-macro model like MOSES allows the study of those "cycles", and the role of various factors in economic growth.

Experiments presented here should be considered as a first attempt to model complex activities like learning and training which are certainly very important for the long-run performance of all economies. The model needs further work in two major directions. First, the specification of various functions (for example, training expenditures, effects of quits, etc.) should be based on detailed and, if possible, econometric studies. A parallel study on the relationship between micro-performance and training may shed a light on the subject (Ballot and Taymaz, 1993). Second, there remain a number of functions/relationships that cannot be observed in reality (learning the global technology, etc.). Therefore the model needs to be calibrated to produce reasonable results and to be used in policy experiments.

Genetic algorithms used in our model seem to be very effective to model learning processes. Genetic algorithms are very realistic, flexible and suitable in analyzing seemingly unrelated phenomena. For example, the learning module as modeled in this study can easily be used for the study of "development blocks", long-waves, etc.

Table 1. Experiment Results

	BASE	NOEXT	GOVTR
First 15 years			
GNP growth	4.47	3.32	3.46
Manufacturing growth	6.56	5.50	5.53
Rate of unemployment	6.51	5.02	4.04
Wage growth	7.74	4.56	4.70
Productivity growth	4.51	2.95	3.12
MTEC	15.21	13.07	15.26
INVEFF	2.37	2.10	2.33
SPECTR	121.14	39.82	35.87
GENTR	148.88	88.88	138.71
Last 15 years			
GNP growth	4.07	3.42	3.45
Manufacturing growth	4.36	3.90	4.16
Rate of unemployment	5.72	2.95	4.27
Wage growth	7.73	3.80	3.67
Productivity growth	5.56	4.38	4.43
MTEC	26.22	19.64	26.63
INVEFF	3.30	2.62	3.21
SPECTR	155.79	64.01	83.41
GENTR	196.93	83.67	178.32

Notes: BASE is the base experiment. In the NOEXT experiment, quits negatively affect firms' training expenditures. GOVTR is similar to the NOEXT experiment but now the government trains unemployed people to a very significant extent.

MTEC and INVEFF are model variables that represent labor productivity of the latest equipment and (inverse of) the incremental capital-output ratio, respectively. SPECTR and GENTR are average values of the stocks of skills and general knowledge, respectively. All variables except MTEC, INVEFF, SPECTR and GENTR are in percentages and show period averages. Other variables are in levels and show their values at the end of the period.

APPENDIX
The MOSES Model

Overview of the Model

The MOSES model is a micro-to-macro simulation model of the Swedish economy. It has been constructed primarily to analyze industrial development. Therefore, manufacturing is modeled in greater detail than other sectors. The manufacturing sector is divided into four sectors (raw material processing, intermediate goods, durable and capital goods, and consumer non-durables). Each industry is consists of a number of firms, some of which are real (with data supplied mainly through an annual survey),and some of which are synthetic. Together, the synthetic firms in each industry make up the difference between real firms and the industry totals in the national accounts. There are approximately 150 real decision-making units covering about 30% of industrial output and employment, and about 75 synthetic units in the 1982 database used in our experiments.

Firms in the model constitute short and long-run planning systems for production and investment. Each quarter, each firm begins by forming price, wage,and sales expectations and a profit margin target. These expectations and targets are then used as inputs into the production planning process in which each firm sets a preliminary production/employment plan.

The firm's initial (*ex ante*) production and employment plans need not be consistent with those of other firms in the model. If, for example, the aggregated employment plans for all the firms exceed the number of workers available at the wage levels the firms intend to offer, an adjustment mechanism is invoked to ensure *ex post* consistency. In case of labor, the adjustment takes place in a stylized labor market,where the firm's employment plans confront those of other firms as well as labor supply. This process determines the wage level, which is thus endogenous in the model. In a similar manner, firms' production plans are revised after a market confrontation in the domestic product market, and domestic prices are set.

There is also a capital market where firms compete each quarter for investment resources and where the rate of interest is determined. Given this interest rate, firms invest as much as they find it profitable to invest, in view of their profit targets.

The model is quite complex and we refer the reader to other publications for details (see Eliasson 1977 and 1985; Albrecht et al. 1989 and 1992; Bergholm 1989; Taymaz 1991). The parts of the model most pertinent for our present purposes are presented below. In the following presentation, each variable is calculated for each firm in each year or quarter. To make reading easy, we drop time and firm subscripts if it does not cause any confusion.

Expectations, Targets

Expectations are generated on an annual basis with quarterly modifications concerning percentage changes in sales, prices, and wages for each firm according to a simple "adaptive expectations" formula. The profit target, TARGM, is defined as the share of non-wage value added in total value added is also generated by adaptive expectations.

The production function

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

$$Q = QTOP*(1\text{-}exp(\text{-}TEC*l/QTOP))$$

where Q is the potential output (in physical units), QTOP the maximum level of output which is approached asymptotically when infinite amounts of labor are used , given a certain level of capital stock, TEC the state of technology, L firm employment level (in number of hours) and *exp*(.) the exponential function.

The only factor of production which is explicit in this function is labor. However, the potential output, and hence the productivity of labor, is determined by the state of technology, TEC, and QTOP.

The state of technology in each firm is determined by the previous period's state of technology, the amount of capital, and the level of productivity of new capital:

$$TEC_t = [(TEC_{t-1}*QTOPFR_{t-1})+(MTEC_t*\ \Delta QTOPFR_t)]/(QTOPFR_{t-1}+\Delta QTOPFR_t)$$

where δ = the (constant) rate of depreciation,

$QTOPFR_t = [QTOPFR_{t-1}*(1-\delta)]+\ \Delta QTOPFR_t,$

$\Delta QTOPFR_t = INV_t*INVEFF_t,$

INV_t = investment realized in period t,

$INVEFF_t$ = the efficiency of newly installed capital,

$MTEC_t$ = the level of labor productivity associated with new capital.

In a sense, the INVEFF and MTEC variables reflect the technological level of the firm. They show the stock of knowledge possessed by the firm. Technological level of the productive equipment actually used (TEC and EFF=QTOPFR/PK where PK is the physical capital stock) is less than the level known by the firm because of the vintage effect.

The maximum output attained asymptotically when infinite amounts of labor are used, QTOP, depends on the (real) stock of specific skills (SPECST) and the maximum potential output level (QTOPFR) as follows.

$$QTOP = QTOPFR*\{MINRT+(1-MINRT)*ST1*[1\text{-}exp(\text{-}SPECST/ST2)]\}$$

where MINRT is the minimum (percentage) level of QTOPFR that can be produced with no stock of specific skills, ST1 and ST2 are industry-specific parameters.

Thus, as $SPECST \rightarrow \infty$, $QTOP \rightarrow QTOPFR$.

Investment is the most important mechanism to increase the EFF and TEC variables since newly installed capital embodies INVEFF and MTEC levels of technology. However, we assume that the firm can gradually update its existing equipment without any investment in physical capital stock by applying what is learnt as follows.

$$TEC_t=TEC_{t-1}+(MTEC_t-TEC_{t-1})*ST3*[1\text{-}exp(\text{-}SPECST/ST4)]$$

$QTOPFR_t=EFF_t*PK_t,$

where $EFF_t=EFF_{t-1}+(INVEFF_t-EFF_{t-1})*ST5*[1\text{-}exp(\text{-}SPECST/ST6)]$

ST3, ST4 , ST5 and ST6 are industry-specific parameters.

Thus, as $SPECST \rightarrow \infty$, TEC and EFF (so, QTOPFR) variables are updated to the amount equal to ST3 and ST5 per cent of the difference between known and applied knowledge.

Learning

The critical technology variables, INVEFF and MTEC are determined each year by using the following equations.

$$INVEFF=LT1*[1\text{-}exp(\text{-}DCEFF/LT2)]$$

$$MTEC=LT3*[1\text{-}exp(\text{-}DCTEC/LT4)]$$

where DCEFF is the degree of correspondence between GLOBEFF and $FIRMEFF^m$,

DCTEC the degree of correspondence between GLOBTEC and $FIRMTEC^m$,

LT1, LT2, LT3 and LT4 industry-specific parameters.

GLOBEFF and GLOBTEC are 40-element global technology vectors for the INVEFF and MTEC variables, respectively. FIRMEFF and FIRMTEC are the sets of corresponding firm-technology vectors. There are three (40-element) vectors in each sector and the superscript ^{m} denotes the vector that has the highest degree of correspondence to the relevant global technology vector.

The degree of correspondence for the GLOBEFF vector is defined as follows.

$$DCEFF = \sum a_i w_i$$

$$a_i = \begin{cases} 1 & \text{if } GLOBEFF_i=FIRMEFF_i \text{ and } GLOBEFF_{i+1}=FIRMEFF_{i+1} \\ 0 & \text{if } GLOBEFF_i \neq FIRMEFF_i \\ -1 & \text{if } GLOBEFF_i=FIRMEFF_i \text{ and } GLOBEFF_{i+1} \neq FIRMEFF_{i+1} \end{cases}$$

where w_i is the weight for the i^{th} element. (In our simulations, w_i =i.) $GLOBEFF_i$ and $FIRMEFF_i$ denote i^{th} elements of the GLOBEFF and FIRMEFF vectors, respectively. DCTEC is defined similarly.

Firms try to "discover" the GLOBEFF and GLOBTEC vectors by modifying their FIRMEFF and FIRMTEC variables by using genetic algorithms as explained in the text. The critical variables of the learning process, INSEARCH, NTRIAL and PMUTAT variables are exponential functions of the stock of general knowledge.

$$INSEARCH = GT1*[1\text{-}exp(\text{-}GENST/GT2)]$$

$$NTRIAL = GT3*[1\text{-}exp(\text{-}GENST/GT4)]$$

$$PMUTAT = GT5*[1\text{-}exp(\text{-}GENST/GT6)]$$

Thus, GT1, GT3, and GT5 parameters are asymptotic values of corresponding variables.

Training and the stock of human capital

Stocks of specific skills and general knowledge are accumulated by investment in training.

$SPECST_t = (SPECST_{t-1}*(1-\rho))+INVST_t$

$GENST_t = (GENGT_{t-1}*(1-\rho))+INVGT_t$

where ρ is the depreciation parameter, and

INVST and INVGT are real specific and general training expenditures per employee, respectively.

Firms can increase the stock of specific skills only by training whereas the stock of general knowledge can also be increased by hiring highly educated workers as explained in the section on the labor market.

Short-run production planning

The (quarterly) production planning in the firm starts with the profit margin target and expectations on changes in sales, prices, and wages. The firm try to find a production plan that is both satisfactory (satisfies the profit target) and feasible (under the production function). A simple iterative search algorithm is used for this purpose. The production plan gives the level of (planned) output and employment. If the firm needs more employees, it then in the labor market tries to hire people from other firms or from the pool of unemployed. If it has more employees then it needs, it starts the firing process.

Labor market

In the labor market, firms are first ranked by their relative labor requirements. Then, from starting the firm that wants to hire relatively more people, they attack each other or the pool of unemployed to get people they want. The probability to be attacked depends on the size and (the inverse of) the wage level of the firm in the BASE experiment and the stock of general knowledge in the NOEXT and GOVTR experiments.

In the BASE experiment, if the wage level in attacking firm is at least 30% higher than the level in the attacked firm, then CHL number of workers are transferred from the attacked to attacking firm where CHL=min{DEMAING,KSI*LATTACKED} where DEMANING is the number of workers demanded by the attacking firm, LATTACKED is the number of employees in the attacked firm, and KSI is a parameter. The average stock of general knowledge of transferred workers is equal to the average stock in the attacked firm. The new stock of general knowledge in the attacking firm is computed as the weighted stocks of existing and transferred workers.

In the NOEXT and GOVTR experiments, if the wage level in attacking firm is higher than the level in the attacked firm, then CHL number of worker are transferred where CHL is as defined above. The stock of general knowledge in the attacked firm is assumed to be uniformly distributed within the range {DIST*GENST, (1+DIST)*GENST} where DIST is an industry-specific parameter. The average stock of knowledge of transferred workers is equal to the stock of the top CHL/LATTACKED percentage of workers in the attacked firm. The new stock of knowledge in the attacking firm is computed as the weighted stocks of existing and transferred workers. This specification implies that the attacking firm is, at least partially, able to observe stocks of general knowledge in other firms.

The quits rate is calculated after the adjustments in the labor market as follows.

QUITRT = SUMQUITS/L

where QUITRT is the quits rate, SUMQUITS is the number of employees left the firm in current quarter, and L is the number of employees in the last quarter. Then the quits intensity is computed as follows.

$QUITINT_t = (QTPR*QUITRT_t)+[(1-QTPR)*QUITINT_{t-1}]$

where QUITINT is the quits intensity variable and QTPR is a parameter.

Determination of investment

There are four kinds of assets in MOSES: fixed assets (K1=PK), liquid and other current assets (K2), inventories (K3), and educational assets (SPECST and GENST). The demand for funds and borrowing is found from investment demand and cash flow.

DEMFUND=DESINVK1+DESCHK2+DESINVTR

DESCHBW=DEMFUND-CASH

where DEMFUND = the demand for funds,

DESINVK1 = the desired investment in fixed assets,

DESCHK2 = the desired change in liquid assets,

DESINVTR = the desired investment in training,

DESCHBW = the desired change in debt (or borrowing), and

CASH = the (quarter's) cash flow.

The desired investment in training (training expenditures) is computed as follows.

DESINVTR = (QTOPFR/QTOP)*{[ALFATR*PSER*(GENST+SPECST)]+[BETATR*W*l]+[GAMMATR*QUITINT]}

where PSER is the price of raining services, and ALFATR, BETATR and GAMMATR are parameters.

Depending on the resources of the bank and total demand for borrowing ($\Sigma DESCHBW_i$), the firm borrows CHBW from the bank and allocates its funds proportionately between DESINVK1, DESCHK2 and DESINVTR. The investment in training, INVTR, is divided between specific and general training as follows.

INVGT = [1-(DELTR*QTOPFR/QTOP)]*INVTR/PSER

INVST = [DELTR*QTOPFR/QTOP]*INVTR/PSER

where DELTR is an industry-specific parameter.

Note that if the difference between potential to actual capacity increases, the firm will spend more on specific training to exploit what is learnt.

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