The Impact of Spatial Skill Heterogeneity - An Evolutionary Analysis

Harting, Philipp

BIELEFELD UNIVERSITY
Department of Business Administration and Economics
Bielefeld, Germany
philipp.harting@uni-bielefeld.de

Abstract. This paper considers the effects of spatial skill heterogeneity on the economic development. For this purpose, an evolutionary model is developed, which takes into account the important role that the technological change has for economic development and it assumes a positive effect of skills on innovation. For testing the effects caused by regional skill heterogeneity, a spatial distribution of firms is modeled, where the regional endowment with human capital can be unequally distributed. The simulation of the model leads to twofold results: at the industry-wide level, regional heterogeneity concerning human capital has positive effects on the economic performance, but considering the regional perspective a divergence of regional economic performance is observable. From this a major conclusion follows that an exact-weighting of positive macroeconomic effects and the negative divergence is necessary to evaluate the effects of skill heterogeneity.

1 Introduction

The goal of this paper is to find possible effects, which regional skill heterogeneities have on the economic performance. Thus the question is considered whether or not an economy with differentiated regions, which differ due to their endowment with human capital, has a better development compared to economies with an equal skill distribution, and how these inequalities affect the development of the particular regions.

In the last decades, skills and the closely related conception of human capital have been taken into the focus of attention as an important determinate of economic performance, whereby both termini describe the capabilities and qualification in conjunction with the working process. Today it is a mostly common perception in economic theory that skills have a prominent position in association with economic progress.

The impacts of skills and human capital are twofold. Firstly, a higher skill level of the workforce affects the productivity positively. In an empirical study Haskel, Hawkes, and Pereira (2005) examine the relation between skills and productivity, and they find a positive correlation between total factor productivity and skills.

Secondly, a positive effect of skills and human capital on the innovative performance at firm or macroeconomic level is frequently described. The impact of skills on the innovation process is for example shown by Gellatly (1999) who investigates a survey, for which companies belonging to Canadian business service industry were interviewed concerning their innovation profile. Gellatly (1999) finds out that hiring skilled workers is a significant factor for innovative activities at the firm level. Another study by Mohnen and Roeller (2000) finds that the shortage of qualified workers is an important obstacle for innovations.

Rappaport (1999) establishes stylized facts concerning regional growth, where one stylized fact assigns the regional human capital an important role for local growth. Also the regional dimension is an important attribute for the innovation process itself. In this context the cluster concept has a prominent position, which describes the observation of better innovative performance, when firms are spatially concentrated (see for example Malmberg and Power (2003)). Taking the importance of skills for innovations into account, studying of regional skill aspects seems to be meaningful, but the effects arising due to regional skill heterogeneity have not been explicitly considered in the literature so far.

For studying the possible effects of regional skill heterogeneity in this paper, an evolutionary model is built and simulations are implemented. The model is based on the work of Nelson and Winter (1982). The presented model assumes an economy composed of one industry which produces a homogeneous good. The model stresses the prominent role of innovation and technological change for economic development and additionally, it takes into account the important effect that skills have for innovative activities, and the effect of skills on the productivity represented by efficient exploitation of technology. For examination the aims of this paper described above, skills are modeled as spatially unequally distributed.

This paper is composed as follows: in the next section the model is specified and section 3 sets up the model. In section 4 the simulations are conducted and in section 5 political implications are educed based on the simulation results. Finally, section 6 concludes.

2 The Model

2.1 Production, Skills and Regional Endowment with Human Capital

This model considers a market with n firms producing a homogeneous good. The number of firms n is exogenously given. Firms are placed in geographical clusters, whose number m is also exogenously fixed. Clusters are characterized by a certain value of human capital, which stands for the quality of the inherent workforce. In this model the cluster approach is chosen due to two reasons: firstly, the clusters represent individual regions with possibly different characteristics, in particular the human capital. Thus a geographical distribution of firms is considered. Secondly, according to the fact of closer relations of firms in spatial nearness, firms in the same cluster are linked closer than firms outside a cluster.

The workforce required in firm's production process is hired out of the local labor force living in the cluster where the firm was placed. The resulting human capital of firm is composed of two elements: general skills and technology specific skills. General skills are capabilities and knowledge acquired during the formal education and apprenticeship. At firm level they represent the mean qualification of workers employed in a particular firm. The general skill level of firm i is denoted by s_i and is determined by the quality of the human capital of cluster j where firm i is located. Formally, s_i is a normally distributed random variable with mean $\hat{s}_j$ and standard deviation $\hat{\sigma}_j$. These values are cluster specific parameters of human capital, where $\hat{s}_j$ represents the mean level of cluster's human capital and $\hat{\sigma}_j$ denotes the heterogeneity of worker's general skills within cluster j.

The specific skills are closely related to the technology employed by an individual firm. These are experiences and competences of firm's workforce, which are collected by using a certain technology. The level of specific skills in firm i is denoted by B_i. The technology is characterized by a feasible productivity A_i. Productivity A_i and specific skills B_i are related in a complementary way, i.e. without the necessary specific skills it is not possible to take advantage of the full feasible productivity, otherwise the productivity A_i limits the utility of high specific skills B_i. It follows an effective productivity $\min[A_i, B_i]$.

Accumulation of specific skills is largely contributed by collecting of experiences and learning by doing. From this it follows that the adjustment process of B_i must depend on a time path. It is assumed that the pattern of this process is characterized by a deterministic learning curve. This conception describes the frequently empirically observed phenomenon of rising productivity, which increases with proceeding production volume at a declining rate (see for example Argote and Epple (1990)).

The ability to transfer collected experiences into progression of productivity requires a lot of qualifications. On this account it is assumed that accumulating specific skills B_i over time depends on the mean qualification level of employed workers in the particular firm i, s_i. Figure 1 shows this issue.

For producing the output two input factors are used, labor and capital. The factors are complementarily related, so for an increase of input capital a proportional increase of labor is necessary and vice versa. Taking the effective productivity into account, it follows the production function of firm i

$$Q_i = \min[A_i, B_i] \cdot K_i,$$

where the required input labor can be hired without quantitative restrictions. The commodity is dealt on a global market. Transportation costs do not play a role, for this reason spatial aspects on the goods market are unimportant. The demand is represented by an isoelastic inverse demand function

$$P = \frac{\alpha}{\sum_i Q_i},$$

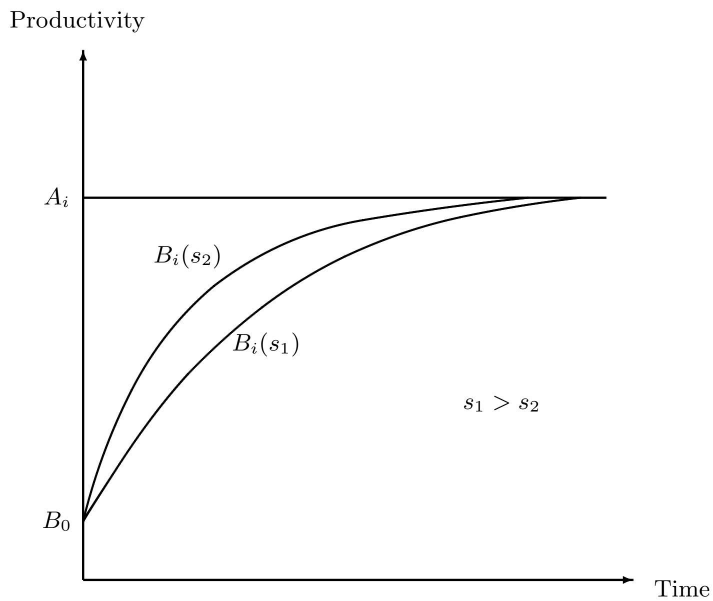

Fig. 1. The adjustment process of specific skills B_i with different general skill level s_1 and s_2

where α is a parameter for the market size. For producing the good a firm must bear costs c_i, which are measured in costs per employed unit of capital. They are assumed as exogenously fixed and they also include the wage bill.

2.2 Technological Progress and Accumulation of Capital

A firm has two opportunities for increasing its output. It can implement a better technology or can increase the stock of physical capital. The former is associated with an increase of the feasible productivity A_i. Hence an adjustment of specific skills is necessary. Because of the introduction of a new technology, the specific skills linked with the old technology would possibly become obsolete. In this model a weaker assumption is made: After implementation a gap between productivity A_i and specific skills B_i appears, but the initial skills linked with the new technology are on the same level as the B_i of the former technology. As a consequence, the new technology can not be used with its full feasible potential, but there is no interim loss of effective productivity in association with the change of technology. In this sense, an incremental evolution of technology is assumed.

Similar to Nelson and Winter (1982), the opportunities for improving the technology are twofold. The first possibility is innovation of a new technology, the second is imitation of better technologies of other firms. Both processes are associated with costs, and concerning the results uncertainties exist.

The innovative activity for developing new technologies is modeled as a two-step random process. In every period t the firm i invests a fraction $X_{i,t}^{IN}$ of its capital stock in innovative research and development. This investment affects the probability of a successful innovation positively. Additionally, a fraction β of the sum of R&D investments from other firms located in the same cluster j as firm i increases this probability in form of technological spillovers.

An assumption is that the firms have explicit R&D departments. The probability of a successful innovation depends on the quality of this department, which is largely determined by the quality of the incumbent workforce s_i. It follows a productivity of the R&D department $a_{i,t}^{IN}(s_{i,t})$ with $\frac{\partial a_{i,t}^{IN}}{\partial s_{i,t}} > 0$.

Altogether, the probability of a successful innovation in period t is given by

$$Pr(d_i^{IN} = 1) = a_{i,t}^{IN}(s_{i,t}) \cdot \left[X_{i,t}^{IN} \cdot K_{i,t} + \beta \hat{X}_{-i,j,t}^{IN} \right],$$

where d_i^{IN} is a binary variable with $d_i^{IN} = 1$ if the innovation is successful else $d_i^{IN} = 0$, and $\hat{X}_{-i,j,t}^{IN} = \sum_{\forall k \neq i \in j} K_{k,t} \cdot X_{k,t}^{IN}$ are the cumulative R&D investments of the other firms in cluster j.

In case of a successful innovation, the productivity of the new technology must be drawn in a second random step. Like the cumulative industry in Nelson and Winter (1982), the productivity of the new-developed technology $\tilde{A}_{i,t}$ is a normally distributed random variable with mean $A_{i,t}$ and standard deviation σ, thus the new technology is based on the former technology.

The second way of improving the process of production, the imitation of better technologies, is also modeled as a two-step random process. The first step appoints whether or not an imitation draw is successful. For this purpose, the firms invest a fraction $X_{i,t}^{IM}$ of the capital into this activity, but in contrast to the innovation process this random draw is independent of general skills $s_{i,t}$ and no spillovers affect the imitation activity.

The probability of a successful imitation is determined by

$$Pr(d_i^{IM} = 1) = a_{i,t}^{IM} \cdot X_{i,t}^{IM} \cdot K_{i,t},$$

where d_i^{IM} is a binary variable representing the success of the activity ($d_i^{IM} = 1$ if successful, else 0), and $a_{i,t}^{IM}$ is a parameter.

The second random draw decides what technology will possibly be imitated. According to the closer link of firms within the same region, the best technology of cluster j will be imitated with an exogenously given probability $p > 0.5$, otherwise the industry wide best practice technology will be implemented. It follows

$$\bar{A}_{i,t} = \begin{cases} \max_{\forall k \in j} A_{k,t} & \text{with prob. } p \\ \max_{\forall l \in [1,\ldots,n]} A_{l,t} & \text{with prob. } 1-p. \end{cases}$$

After completing the innovation and imitation activities, the firm has to decide which technology will be implemented in the next period. A simple decision rule for determining the technology of $t+1$ is assumed: the technology with the highest productivity will be employed, i.e.

$$A_{i,t+1} = \max[A_{i,t}, \tilde{A}_{i,t}, \bar{A}_{i,t}],$$

where for $d_i^{IN} = 0$ holds $\tilde{A}_{i,t} = 0$, accordingly for $d_i^{IM} = 0$ $\bar{A}_{i,t} = 0$.

An important variable affecting the development of firms over time is the profit. Profit per unit of capital is calculated from the sales per capital minus the costs, which include the costs of production as well as the investments into innovation and imitation. Formally, the profit per capital is determined by

$$\pi_{i,t} = P_t \cdot \min[A_{i,t}, B_{i,t}] - c_i - X_{i,t}^{IN} - X_{i,t}^{IM}.$$

If the profit is positive, a fraction φ of π is distributed as dividend to firm's stockholder. Similar to the model of Dawid, Columbo, and Karbus (2006), the remaining amount is deposited on a saving account. In case of negative profits, the total shortage is subtracted from savings. The account balance $S_{i,t}$ is an indicator for the financial standing of firm i, i.e. it shows the level of liquidity or the level of debt.

At every period the physical capital depreciates with a fixed rate ρ. The capital stock $K_{i,t}$ can be increased by investments $I_{i,t}$, where the investment function is modeled similar to Nelson and Winter (1982). There are intended investments $\tilde{I}_{i,t}$, which positively depends on the market share $MS_{i,t} = \frac{Q_{i,t}}{\sum_{\forall j} Q_{j,t}}$ and positively on the depreciation rate ρ. Additionally, a positive impact on the intended investments has the mark up $\gamma_{i,t} = \frac{P_t \cdot \min[A_{i,t}, B_{i,t}]}{c_i}$. What follows is the intended investment function

$$\tilde{I} = 1 + \rho - \frac{2 - MS}{\gamma(2 - 2MS)}.$$

For committing the investments, the financial situation of firm has to be taken into account. Thus it exists a financial restriction $f(\pi)$ with $f(\pi) = S_{i,t} + \rho + 2.5\pi_{i,t}$ for $\pi > 0$, otherwise $f(\pi) = S_{i,t} + \rho + \pi_{i,t}$. In cases of positive profits it is possible to finance the investments, which are not covered by savings, up to 2.5 times of profits by external loans. For losses an external financing is not possible.

The combination of the intended investment function and the finance restriction yields the investment function

$$I_{i,t} = \max\left[0, \min[1 + \rho - \frac{2 - MS}{\gamma(2 - 2MS)}, f(\pi)]\right].$$

After realization of profits and investments the saving account has a balance of

$$S_{i,t}^* = \begin{cases} S_{i,t} + (1-\varphi)\pi_{i,t} - I_{i,t} & \pi > 0 \\ S_{i,t} + \pi_{i,t} - I_{i,t} & else. \end{cases}$$

The capital stock in the next period $t+1$ is the result of an addition of the realized investments and the capital in t less depreciation. Because of measuring investments $I_{i,t}$ in units of capital, it follows for the capital stock in $t+1$

$$K_{i,t+1} = (1-\rho)K_{i,t} + I_{i,t} \cdot K_{i,t}.$$

2.3 The Adjustment of Firm's Human Capital

Due to the production technology, the input factors labor and capital are used in a fixed proportion. Since the capital stock is fluctuating because of investments and depreciation, an adjustment of the employed workforce becomes necessary. This affects the mean qualification level of the incumbent workforce, thus an assimilation of general skills s_i must be done.

In cases of positive net investments new workers have to be hired. For this purpose, the firm randomly draws the needed cohort out of the available labor force of its cluster. Due to simplicity it is assumed that firms have no opportunity to assess the qualification profile of applicants. The mean skill level $\Delta s_{i,t}$ of the hired cohort is a normally distributed random variable with the cluster specific mean $\hat{s}_j$ and standard deviation $\hat{\sigma}_j$. For the resulting mean skill level of the firm in $t+1$ follows

$$s_{i,t+1} = \frac{L_{i,t}}{L_{i,t+1}} s_{i,t} + \frac{\Delta L_{i,t}}{L_{i,t+1}} \Delta s_{i,t},$$

where $\Delta L_{i,t} = \max[0, (I_{i,t} - \rho)K_{i,t}]$ represents the change of workforce and for $L_{i,t+1}$ holds $L_{i,t+1} = L_{i,t} + \Delta L_{i,t}$. The costs for training hired workers are included in investments.

For negative net investments the current workforce has to be reduced. Similar to hiring it is assumed that firms can not identify better qualified incumbent workers, so the firm randomly draws the laid off workers. From this it follows that the skill level in $t+1$ $s_{i,t+1}$ is equal to the mean skills in t.

The specific skills related to the employed technology rises over time. The workers collect experiences in conjunction with the technology, which are the largest contributions for building up specific skills. This learning by doing is described by a learning curve. The level of specific skills B_i is always smaller or equal the productivity A_i, where B_i converges to the productivity. Additionally, the productivity rises as a result of implementing new technologies through innovations and imitations.

When finishing the innovation and imitation processes, the feasible productivity in $t+1$ $A_{i,t+1}$is known. If a gap $A_{i,t+1} - B_{i,t} > 0$ appears, the gap will be closed via learning by doing and training at a percentage rate $\lambda \in [0,1]$. It follows

$$B_{i,t+1} = B_{i,t} + \lambda \cdot (A_{i,t+1} - B_{i,t}).$$

The rate λ consists of two factors. The first element $\mu(s_{i,t}, B_{i,t})$ includes the impact of general skills s_i and specific skills B_i on the learning capacity. The partial derivations are $\frac{\partial\mu}{s} > 0$ and $\frac{\partial\mu}{B_t} < 0$, so the effect of higher general skills is positive. But the effect of a rising B_i is negative, i.e., the higher B_i the less is the absorptive capacity of workers for new specific knowledge.

The second element ϕ includes firm's opportunity for investing in training and schooling, with that the technology specific skills can be increased. The volume of investments in human capital is denoted by $I^H_{i,t}$. These investments are positively affected by the anticipated gap $A_{i,t+1} - B_{i,t}$, but also the current financial standing of firms has to be taken into consideration, thus the saving account balance $S^*_{i,t}$ has a positive effect on $I^H_{i,t}$. Formally, it yields $\frac{\partial I^H}{\partial A_{t+1} - B_t} > 0$ and $\frac{\partial I^H}{\partial S^*_i} \geq 0$. ϕ is a function depending on the investment $I^H_{i,t}$ with $\frac{\partial \phi(I^H)}{\partial I^H} > 0$. Are the investments equal to zero, it holds $\phi(0) = k$ with $k \in [0,1]$. In the limit $\lim_{I^H \to \infty} \phi$ it goes to one.

Altogether, it holds for the adjustment rate λ

$$\lambda = \mu(s_{i,t}, B_{i,t}) \cdot \phi \left[I^H(A_{t+1} - B_t, S^*_i) \right].$$

After investing in human capital, the costs have to be subtracted from savings. It follows the account balance in $t+1$[1]

$$S_{i,t+1} = S^*_{i,t} - I^H_{i,t}.$$

2.4 Adaption of Innovation and Imitation Strategy

An important feature of this model is the commitment of firm's spending in innovation and imitation $X^{IN}_{i,t}$, $X^{IM}_{i,t}$. In Nelson and Winter (1982) these expenditures are exogenously given and are not adapted over time. Since these processes are exposed to high uncertainty and so a persistent review of strategies should be necessary, this might be a critical assumption. In Dawid, Columbo, and Karbus (2006) a simple adaption mechanism is employed, which is the basis of the following adaption of innovation and imitation expenditures. This mechanism is modeled as a two-step process and takes the relative success of both strategies into consideration.

Firstly, the firm decides on intended investments in these activities. The intended investment in innovation is denoted by $\tilde{X}^{IN}_{i,t}$, respectively for imitation $\tilde{X}^{IM}_{i,t}$. In every period, this values are adapted according to the relative success. For this purpose, the estimated returns of both strategies are compared, where $\Delta^{IN}_{i,t}$ stands for the estimated return of innovation and $\Delta^{IM}_{i,t}$ for the return of imitation. Following Dawid, Columbo, and Karbus (2006), these values stay unchanged when the associated activity is not successful[2].

Let's assume an innovation draw was successful in $t-1$, before it the last innovation had occurred in $t-k$. The estimated return of investment in innovation is the ratio of the possibly additional sales because of better productivity

[1] Due to the varying capital stock, the savings must be converted on $K_{i,t+1}$.

[2] An activity is successful, if and only if the corresponding technology will be implemented.

and the cumulated investments which have been spent during the last and the current innovation draw. Formally, for innovations follows

$$\Delta_{i,t}^{IN} = \frac{(A_{i,t} - A_{i,t-1}) \cdot P_t}{\sum_{s=t-k+1}^{t-1} X_{i,s}^{IN}}.$$

and analogously, it holds for the imitation

$$\Delta_{i,t}^{IM} = \frac{(A_{i,t} - A_{i,t-1}) \cdot P_t}{\sum_{s=t-k+1}^{t-1} X_{i,s}^{IM}},$$

when in $t-1$ was a successful imitation and before it a successful imitation had occurred in $t-k$.

If at least one activity was in $t-1$ successful, the estimated returns in t $\Delta_{i,t}^{IN}$ and $\Delta_{i,t}^{IM}$ are compared, and depending on the result of comparison, the intended investments of the activity with the greater estimated return will be increased by a fixed proportion ϵ and the intended investment of the opposite activity will be reduced by the same ϵ. Altogether, it follows either

$$\Delta_{i,t}^{IN} > \Delta_{i,t}^{IM} \begin{cases} \tilde{X}_{i,t}^{IN} = (1+\epsilon)\tilde{X}_{i,t-1}^{IN} \\ \tilde{X}_{i,t}^{IM} = (1-\epsilon)\tilde{X}_{i,t-1}^{IM} \end{cases},$$

or

$$\Delta_{i,t}^{IM} > \Delta_{i,t}^{IN} \begin{cases} \tilde{X}_{i,t}^{IM} = (1+\epsilon)\tilde{X}_{i,t-1}^{IM} \\ \tilde{X}_{i,t}^{IN} = (1-\epsilon)\tilde{X}_{i,t-1}^{IN} \end{cases}.$$

After committing the intended investments, in a second step the firm has to take into account the gap between feasible productivity A_i and specific skills B_i. It seems to be implausible that after implementing a new technology a firm has strong incentives to additionally increase the arisen gap by introducing a better technology. Thus, the firm reduces the intended investments $\tilde{X}_{i,t}^{IN}$ and $\tilde{X}_{i,t}^{IM}$ depending on the gap in t $A_{i,t} - B_{i,t}$. The investments are only realized at a fraction η, so it follows

$$X_{i,t}^{IN} = \eta(A_{i,t} - B_{i,t}) \cdot \tilde{X}_{i,t}^{IN}$$

$$X_{i,t}^{IM} = \eta(A_{i,t} - B_{i,t}) \cdot \tilde{X}_{i,t}^{IM},$$

where η is a function with $\frac{\partial \eta}{\partial (A_{i,t} - B_{i,t})} < 0$, $\eta(0) = 1$, and $\lim_{(A_{i,t} - B_{i,t}) \to \infty} \eta = 0$. The adaption process after a successful innovation is illustrated in figure 2, where the adjustment of B_i follows a learning curve as displayed in figure 1. The adaption in case of a successful imitation looks alike.

2.5 Timing and the Dynamics of the Model

The intertemporal connections of variables are important determinates of the dynamics of model. On this account the chronology of events during a period is an important attribute of modeling. What follows is the timing of the model:

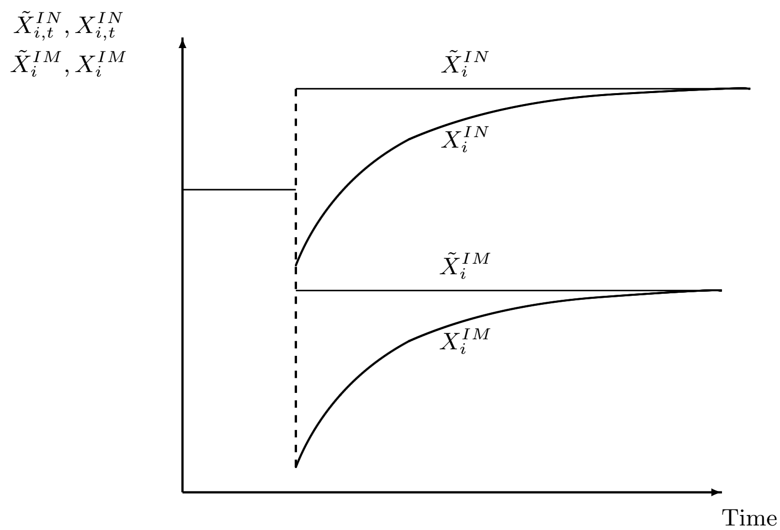

Fig. 2. Adaption of innovation and imitation investments: intended and realized expenditures

1. The firms simultaneously determine their production output $Q_{i,t}$. This yields the good's price P_t.
2. Taking into account the productivity gap $A_{i,t} - B_{i,t}$, the firm determines the realizable investments in innovation and imitation for period t, $X^{IN}_{i,t}$ and $X^{IM}_{i,t}$.
3. It follows the profit per unit of capital $\pi_{i,t}$.
4. The firms decide on the investments in physical capital $I_{i,t}$. The saving account is firstly updated, it follows $S^*_{i,t}$.
5. The innovation and imitation activities are simultaneously conducted. The technology employed in next period is chosen.
6. The progress of learning is determined. Additionally, the firms commit the expenditures in training and schooling of their workforce. Altogether, this leads to $B_{i,t+1}$. After realizing the investments in human capital, the saving account has to be secondly updated, it follows $S_{i,t+1}$.
7. The intended investments in innovation and imitation in $t+1$, $\tilde{X}^{IN}_{i,t+1}$ and $\tilde{X}^{IM}_{i,t+1}$, are determined.
8. The last step during a period is the realization of physical investments, this yields to $K_{i,t+1}$. As an consequence, the workforce has to be adapted, by what the mean skill level in $t+1$ $s_{i,t+1}$ is affected. So, the mean general skills have to be adjusted.

The dynamics of the model emerges from the intertemporal linkages of certain variables. Basically, it results from the variations of both kinds of capital, the human as well as the physical capital, and the improvement of firm's production technology. These variables influence the production volume and profitability of firms, by what the investments are affected again, and so on.

3 The Setup of the Simulations

In order to show possible consequences of different qualities of regional labor forces on the economic development at the industry-wide as well as regional level, computer based simulations of the presented model with different settings concerning certain regional characteristics of human capital are executed. For obtaining statistically strong results, 200 simulation runs for every constellation of parameters are conducted, where the final values of certain variables after 200 time steps are of interest. The parameters, which effects of variation is mainly considered, are the cluster specific skill parameter $\hat{s}_j$. The statistical significance of changes in parameter values are tested with either the Wilcoxon rang sum test or the Kruscal Wallis test.

The variables of interest have to be distinguished in industry-wide variables, and regional or cluster variables. At the industry-wide level the most important variable is the total output $\sum_i Q_i$, which can be used as a proxy for economic performance.

For considering the development of an individual region j, the major indicator is the total output of j, $\sum_{\forall i \in j} Q_i$.

Besides the performance indicators, there are a lot of other important variables, which should be explored. So, the mean profitability of all firms is examined, where it holds

$$\Pi_{ges,t} = \sum_{\forall i} \frac{K_{i,t}}{\sum_{\forall i} K_{i,t}} \pi_{i,t} K_{i,t}.$$

Also, the development of the profitability on regional level is of interest, thus

$$\Pi_{j,t} = \sum_{\forall i \in j} \frac{K_{i,t}}{K_{j,t}^{Kum}} \pi_{i,t} K_{i,t},$$

is considered, where $K_{j,t}^{Kum}$ denotes the total capital stock of cluster j. Total capital of clusters and the economy wide capital stock are variables representing the dimension of the whole economy and the relative extent of clusters concerning the potential of production. For examining the concentration on the goods market, the herfindahl index

$$H_t = \sum_{\forall i} \left(\frac{Q_{i,t}}{\sum_{\forall i} Q_{i,t}} \right)^2$$

is computed. In case of $H_t = \frac{1}{n}$, the market shares are equally distributed and thus the concentration is on its lowest level. For rising H_t the market concentration increases, and for $H_t = 1$ the market is completely monopolistic.

An additional attribute is the technological development of the economy as well as the regions. The technological improvement is characterized by two variables, the economy wide best technology $A_t^{Max} = \max_i[A_{i,t}]$ and the mean level of technology

$$A_t^{Mean} = \sum_{\forall i} \frac{K_{i,t}}{\sum_{\forall i} K_{i,t}} A_{i,t}.$$

For considering the technology at the regional level, these variables are also computed for the clusters.

At last, the relative incentives for innovation and imitation are considered. Here are also both, the regional and the macroeconomic level, examined. For this purpose, the mean intended investments in both activities must be computed. For the cluster level, it holds

$$\hat{X}_{t,j}^{IN} = \sum_{\forall i \in j} \frac{K_{i,t}}{K_{j,t}^{Kum}} \tilde{X}_{i,t}^{IN}$$

and

$$\hat{X}_{t,j}^{IM} = \sum_{\forall i \in j} \frac{K_{i,t}}{K_{j,t}^{Kum}} \tilde{X}_{i,t}^{IM}.$$

The economy-wide variables are accordingly determined. Due to regarding the specific skills $B_{i,t}$ for committing the investments, the realized investments $\tilde{X}^{IN}$ and $\tilde{X}^{IM}$ bias the relative incentives for innovation and imitation, thus the intended investments are used to investigate the incentives.

The simulations are conducted with $n = 32$ firms, which are equally distributed on $m = 4$ clusters. The cluster specific skill level $\hat{s}_j \in [0, 1]$ is the mainly controlled variable. For selecting different values of $\hat{s}_j$ for the particular clusters, a skill heterogeneity is modeled.

Table 1 shows parameter values and needed initial values of some variables, the chosen functions are listed in the appendix. The parameters are oriented on the values established in Nelson and Winter (1982) and Dawid, Columbo, and Karbus (2006).

The firms are ex ante identical. An exception are the initial values of the general skills $s_{i,0}$, which are random variables. The technology employed by all firms in $t = 0$ is assumed as simple, and the initial technology specific skills $B_{i,0}$ are at the same level as the productivity $A_{i,0}$. This means that the starting technology can be used without loss of productivity. From these it follows that all firms produce the same output, where in period 0 an output $Q_0 = 64$ is produced.

4 Simulations

4.1 A Benchmark Scenario: Homogeneous Distribution of Skills

The first simulation considers a setting with homogeneous distributions of regional skills. This scenario is meant as a sample for comparing these results

Table 1. Values of parameters and variables in $t = 0$

Parameter	Value	Variable $t = 0$	Value
n	32	$A_{i,0}$	0.16
m	4	$B_{i,0}$	0.16
α	80	$K_{i,0}$	12.5
$\hat{\sigma}$	0.1	$X_{i,0}^{IN}$	0.005
σ	0.02	$X_{i,0}^{IM}$	0.005
c_i	0.16	$s_{i,0}$	$[0, 1]$
ρ	0.03	$S_{i,0}$	0
φ	0.5		
$a_{i,t}^{IM}$	0.2		
β	0.1		
p	0.75		

with cases of an unequal distribution. In this manner a classification of emerging simulation results could be tried.

For modeling an equal distribution of regional human capital it is assumed that the clusters, which represents the regions, have identical human capital parameters $\hat{s}_j$, thus $\hat{s}_j = \hat{s} \forall j$ follows.

In this setting the impact of an improvement of economy's total human capital can be considered. For this purpose, the simulation are made with three values of total human capital, $\hat{s} = 0.3$, $\hat{s} = 0.5$, and $\hat{s} = 0.7$. The first value represents a low level of human capital, while the second represents a medium and the last a high level of mean skills.

The numerical results of the simulation runs are displayed in table 2. There are listed the means and standard deviations of the economy-wide variables after 200 time steps.

The results displayed in table 2 show a positive impact of a higher mean skill level on the total output. The differences between theses values are strongly statistically significant. The hypothesis of an equal distribution of two samples based on two i arbitrarily chosen $\hat{s}$ can be rejected on a 99% level of significance. This broad difference holds for all variables listed in table 2 with the exception of the total capital, where the difference between $\hat{s} = 0.3$ and $\hat{s} = 0.5$ is insignificant (p-value of the Wilcoxon rang sum test: 0.7408), and between $\hat{s} = 0.7$ and $\hat{s} = 0.5$ the difference is statistically significant on a level of 95% (p-value: 0.0402).

The better economic performance of higher skill regimes can be especially declared by increased innovative activities. Firm's general skills positively affect the probability of a successful innovation draw, as a result innovations occur more frequently on the economy-wide level. This can be deduced by the higher values of technology variables, i.e. the best and mean productivity. Due to better technology and faster adjustment of specific skills, the inputs can be more efficiently employed, and thus the production volume can be increased.

Table 2. The means of the macroeconomic variables computed from simulation of the homogeneous skill distribution after 200 time steps. (standard deviation in parentheses)

	$\hat{s} = 0.3$	$\hat{s} = 0.5$	$\hat{s} = 0.7$
Total output	81.84	90.11	100.02
	(7.85)	(9.80)	(11.67)
Best technology	0.27	0.30	0.33
	(0.03)	(0.04)	(0.05)
Mean technology	0.25	0.27	0.31
	(0.03)	(0.03)	(0.04)
Price	0.99	0.90	0.81
	(0.09)	(0.09)	(0.09)
Concentration	0.16	0.18	0.22
	(0.08)	(0.09)	(0.11)
Mean profit	3.87	4.41	5.75
	(2.13)	(2.44)	(3.28)
Mean intended innovation investments	0.0058	0.0066	0.0080
	(0.0008)	(0.0012)	(0.0025)
Mean intended imitation investments	0.0046	0.0042	0.0036
	(0.0006)	(0.0006)	(0.0008)
Total capital	339.19	338.28	335.38
	(3.91)	(6.55)	(11.51)

Comparing the mean intended innovation and imitation expenditures, a stronger incentive for investing in innovation activities instead of imitative activities is identifiable. The stronger competition referring to technology leads to a diversification of capital stocks, hence a stronger concentration is the consequence. The better technology employed in production process overcompensates the decreasing total capital.

If the total output is used as a proxy of welfare, the simulation yields to a result of positive welfare effects of an increase of the human capital. But also the firms benefit from the higher skills which is observable on the mean profitability. Higher skills lead to faster technological change and a better mean technology employed by firms. The main focus lies on innovative activity.

4.2 Non-Systematic Skill Heterogeneity

The simulation of a variation of the total skill level led to a result of increasing economic performance with higher skills. In the following simulation the effect of an increasing regional heterogeneity of the human capital stock will be considered.

The regional skill level is characterized by the parameter $\hat{s}_j$, which is the mean of the distribution of firm i's general skill level s_i, where the firm is located in cluster j. For modeling the regional heterogeneity this cluster specific skill parameter is also a normal distributed random variable with a mean $\hat{s}$ and a standard deviation $\tilde{\sigma}$. The standard deviation $\tilde{\sigma}$ determines the level of heterogeneity. With $\tilde{\sigma} = 0$ a homogeneous distribution is considered, and the more $\tilde{\sigma}$ increases the more heterogeneous the regional skill distribution becomes. For the simulation $\hat{s} = 0.5$ is chosen, so the case of $\tilde{\sigma} = 0$ is equal to the simulation runs in the previous subsection considering a total human capital of $\hat{s} = 0.5$. The expected value of human capital is medium, due to the stochastic process there could be some regions with superior human capital and other with inferior human capital, but the differences balance to a medium level in mean. Since the cluster specific skill levels are not determined ex ante and so they are drawn at the beginning of every simulation run, this setting is called non-systematic heterogeneity.

The simulation treats three levels of heterogeneity ($\tilde{\sigma} = 0.1, \tilde{\sigma} = 0.2, \tilde{\sigma} = 0.3$) plus the case of homogeneity, where in all cases $\hat{s} = 0.5$ holds. The results are listed in table 3.

Table 3 shows a positive impact of an increasing heterogeneity on the total output. A similar pattern yields the examination of the technology specific variables. Both, the best and the mean productivity, rise with higher $\tilde{\sigma}$, and higher incentives exit for investing in innovation instead of imitation. The effect on the mean profitability is positive, whereas the impact on the total capital is negative. The concentration on the goods market is positively affected by the increasing heterogeneity. An exact statistical analysis is given in table 4, where the arising differences are tested with the Wilcoxon rang sum test. In Table 4 are listed the p-values of a comparison of samples related to the same variable which are based on adjacent values of $\tilde{\sigma}$. The table shows a significant change of the samples according to a stepwise increase of $\tilde{\sigma}$ by 0.1, where the differences are in the most cases significant on a level of 95%.

The results of simulation lead to a possible conclusion of a positive impact of regional skill heterogeneity. The simulation shows that, if the spatial heterogeneity increases, the economic performance represented by total output improves. This development is mainly ascribable by the better technological improvement of certain regions which are endowed with better human resources. Firms placed in such regions employ more skilled workers and thus, as a result of positive relation between skills and innovation, they create innovations more frequently. The better technological development of high skill regions is accelerated by the closer link of firms within the same region. But the opportunity of imitation leads also to diffusion of better technologies to firms settled in regions with inferior human capital. Thus a progress of the mean technology in the whole economy occurs, which contributes the total economic development positively.

Recapitulating the results it could be concluded that the skill heterogeneity has, with the exception of a higher market concentration, predominantly positive effects.

4.3 The Structural Heterogeneity

Whether the preliminary conclusion of mainly positive effects holds is examined with the following simulations. By assigning the clusters ex ante certain values of

Table 3. Means and standard deviation of macroeconomic variables of the non-systematic heterogeneity setting

	$\tilde{\sigma} = 0$	$\tilde{\sigma} = 0.1$	$\tilde{\sigma} = 0.2$	$\tilde{\sigma} = 0.3$
Total output	90.11	92.39	95.73	100.64
	(9.80)	(10.34)	(14.51)	(16.47)
Best technology	0.30	0.31	0.32	0.34
	(0.04)	(0.04)	(0.05)	(0.06)
Mean technology	0.27	0.28	0.29	0.31
	(0.03)	(0.04)	(0.05)	(0.06)
Price	0.90	0.88	0.85	0.82
	(0.09)	(0.10)	(0.12)	(0.13)
Concentration	0.18	0.21	0.23	0.25
	(0.09)	(0.10)	(0.11)	(0.11)
Mean profit	4.41	5.20	5.69	6.58
	(2.44)	(2.83)	(2.97)	(3.34)
Mean intended investments in innovation	0.0066	0.0070	0.0074	0.0085
	(0.0013)	(0.0016)	(0.0020)	(0.0034)
Mean intended investments in imitation	0.0042	0.0040	0.0039	0.0035
	(0.0006)	(0.0007)	(0.0008)	(0.0009)
Total capital	338.28	337.00	336.15	333.72
	(6.55)	(8.39)	(8.75)	(11.21)

Table 4. p-value of Wilcoxon rang sum test. Comparison of samples based on adjacent standard deviations of table 3

Compare	$\tilde{\sigma} = 0$ with $\tilde{\sigma} = 0.1$	$\tilde{\sigma} = 0.1$ with $\tilde{\sigma} = 0.2$	$\tilde{\sigma} = 0.2$ with $\tilde{\sigma} = 0.3$
Total output	0.0260	0.0388	0.0026
Best technology	0.0430	0.0416	0.0011
Mean technology	0.0207	0.0373	0.0023
Price	0.0260	0.0388	0.0026
Concentration	0.0018	0.0689	0.0090
Mean profit	0.0022	0.0746	0.0078
Mean intended investments in innovation	0.0149	0.1478	0.0001
Mean intended investments in imitation	0.0179	0.1153	0
Total capital	0.0984	0.1487	0.0323

$\hat{s}_j$, which are not changed during the simulation runs, it is possible to consider the economic development at the regional level in association with a heterogeneity of skills. Due to interpretable results it is assumed that a cluster have either a high skill level with $\hat{s}_j = 0.7$ or the human capital is inferior for which holds $\hat{s}_j = 0.3$. m_H denotes the number of cluster with superior human capital. Simulations are made for increasing values from $m_H = 0$ till $m_H = 4$.

Firstly, the effects of s stepwise increase of m_H on the industry-wide variables is examined. The simulation results are summarized in table 5 and a statistical analysis is given in table 6. A rising total production volume as a result of increasing number of high skill cluster is observable, where the maximum difference occurs at the first step ($m_H = 0$ to $m_H = 1$). Besides the increase from $m_H = 2$ to 3, all differences are statistically significant on a level of at least 95%. This outcome seems plausible, since a rise of the number of high skill cluster has a similar effect as an increase of the mean total level of human capital. The results concerning the technology look alike: the best and mean productivity increases significantly for low and high values of m_H according to a stepwise addition of high skill cluster, but at a medium level of m_H it has no significant effect. The picture of the remaining variables look slightly different: The effect on profit, concentration, and innovation and imitation expenditures, is significant only for low m_H, and the total capital is affected only for a switch from $m_H = 1$ to 2. The direction, which the impact of an increasing m_H has, is not clear: the profitability and the herfindahl index have a maximum and the total capital stock has its minimum for $m_H = 2$, where the value $m_H = 2$ represents the maximum level of heterogeneity.

The more interesting point of considering this simulation setting is the cluster level. In table 7 the means of cluster variables for all simulation steps of m_H are listed. Additionally, there are given p-values of the Kruskal-Wallis test, which tests the significance of differences among all cluster samples of a variable.

In cases of an equal skill distribution, i.e. for $m_H = 0$ and $m_H = 4$, there are no significant differences between the samples of the variables of different clusters. An unimportant exception is the highest productivity for $m_H = 4$. If there is no unequal skill distribution, the regional economic development are mostly identical.

If the regional skills are unequally distributed, it follows a divergence of regional economic development, where the regions with higher human capital evolve much better than regions with inferior human capital. This proposition is based on a comparison of the cluster output used as a proxy for the regional economic performance. For $m_H = 1$, the output of the high skill cluster is above five times greater than the particular output of the low skill clusters, whose outputs are approximately equal[3]. But also the technological development in the regions is different, where the exact development depends on the endowment with skilled workers. Regions with superior human capital employ in average a technology with higher productivity and the top technology is on a higher level. Also these clusters are more innovative, the mean investments into this activity

[3] There are no significant differences among these samples.

Table 5. Means and standard deviation concerning the macroeconomic variables of the simulation of the systematic heterogeneity

	$m_H = 0$	$m_H = 1$	$m_H = 2$	$m_H = 3$	$m_H = 4$
Total output	80.75	90.98	97.63	98.63	101.50
	(7.01)	(12.95)	(13.01)	(11.01)	(12.89)
Best technology	0.27	0.30	0.33	0.33	0.34
	(0.02)	(0.05)	(0.05)	(0.04)	(0.05)
Mean technology	0.25	0.28	0.30	0.30	0.31
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)
Price	1.00	0.90	0.83	0.82	0.80
	(0.09)	(0.12)	(0.11)	(0.09)	(0.10)
Concentration	0.15	0.22	0.24	0.23	0.24
	(0.09)	(0.11)	(0.12)	(0.10)	(0.11)
Mean profit	3.76	5.51	6.31	5.94	6.05
	(2.44)	(3.06)	(3.53)	(3.04)	(3.21)
Mean innovation investments	0.0058	0.0071	0.0080	0.0077	0.0081
	(0.0008)	(0.0020)	(0.0024)	(0.0017)	(0.0022)
Mean imitation investments	0.0046	0.0040	0.0037	0.0037	0.0036
	(0.0005)	(0.0009)	(0.0009)	(0.0008)	(0.0007)
Total capital	338.35	336.54	334.12	335.51	335.48
	(6.04)	(7.97)	(12.62)	(9.98)	(9.83)

Table 6. p-values of Wilcoxon rang sum test. Comparison of samples based on adjacent numbers of high skill cluster of table 5

Compare	$m_H = 0$ with $m_H = 1$	$m_H = 1$ with $m_H = 2$	$m_H = 2$ with $m_H = 3$	$m_H = 3$ with $m_H = 4$
Total output	0	0	0.2304	0.0248
Best technology	0	0	0.3798	0.0610
Mean technology	0	0	0.4641	0.0561
Price	0	0	0.2304	0.0248
Concentration	0	0.0188	0.5185	0.8807
Mean profit	0	0.0242	0.6017	0.9424
Mean innovation investments	0	0	0.8184	0.4095
Mean imitation investments	0	0	0.915	0.4154
Total capital	0.0948	0.03851	0.4774	0.8056

are significantly higher than the investments into imitations. The firms located in high skill regions realize a higher profit and their cumulative capital is significantly larger. From this it follows that firms, which are settled in regions with higher mean skills, are more profitable and better evolved than their competitors in low skilled regions.

Table 7 shows also the simulation results for several numbers of m_H, so it could be tried to find a trend of regional development in respect to the ratio of low and high skill cluster. Considering the cluster output, the particular production volume in both kinds of cluster decreases due to a rising m_H, where for the same kinds of cluster the values are equal. But as noticed above, the total output rises so the economy-wide effect is positive.

A similar picture occurs by examining the profitability, the capital stock of clusters, and the investments in innovation. The values are higher in regions with superior human capital, where for both cluster types, these values decrease with rising m_H.

Altogether, the simulation of the structural heterogeneity yields to differentiated conclusion. At the economy-wide level it follows positive effects of the heterogeneity. But at the regional level a divergence of the economic development occurs, where the development is mainly determined by the skill level of the region. With rising number of cluster endowed with high human capital, the absolute values of all cluster outputs decline, where the relative position of low skill cluster becomes more degraded.

5 Implications for Economic Policy

What implications for economic policy designer follows from the executed simulations? Firstly, the simulation in subsection 4.1 shows a positive effect of an increasing total human capital. Thus the policy should try to improve the mean skill level of the whole economy without respecting a spatial dimension. But in the reality regional inequalities concerning the endowment with a qualified workforce are frequently observed. Also in many countries with a federal constitution the education policy, which is an important determinate for creating human capital, is a decentralized issue. Additionally, the improvement of human capital is an expensive activity and due to a short fiscal budget a total increase of human capital seems difficult. From this it follows the question of possible implications for economic policy according to an unequal distribution of regional human capital. This question might concentrate on three possible policies: a political intervention for equalization the heterogeneity, the second way is a non-intervention of the government or thirdly, a stimulation of the more developed regions in order to push the less developed regions through externalities.

The simulation of the setting with non-systematic heterogeneity has the result of an increase of economic prosperity due to rising heterogeneity. Also the profitability of firms improves, whereas the concentration on the market is higher. The comparison with the setting with a homogeneous distribution shows a better

Table 7. Means of cluster specific variables for the simulation setting with all possible numbers of high skill clusters. High skill clusters are labeled with (*). Additionally, the p-values of the Kruskal-Wallis test are given. For the standard deviation see the appendix.

$m_H = 0:$	Cluster 1	Cluster 2	Cluster 3	Cluster 4	p-value
Output	20.18	18.87	20.96	20.73	0.6559
Mean $\tilde{X}^{IN}$	0.0054	0.0053	0.0053	0.0053	0.9965
Mean $\tilde{X}^{IM}$	0.0048	0.0049	0.0049	0.0049	0.9583
Best technology	0.25	0.24	0.24	0.25	0.5938
Mean technology	0.23	0.23	0.23	0.23	0.8244
Mean profit	2.14	1.92	2.14	2.20	0.6643
Total capital	83.80	80.14	88.19	86.22	0.6674
$m_H = 1:$	Cluster 1*	Cluster 2	Cluster 3	Cluster 4	p-value
Output	56.36	11.68	11.23	11.70	0
Mean $\tilde{X}^{IN}$	0.0074	0.0052	0.0052	0.0052	0
Mean $\tilde{X}^{IM}$	0.0038	0.0050	0.0050	0.0049	0
Best technology	0.29	0.25	0.25	0.25	0
Mean technology	0.28	0.23	0.23	0.23	0
Mean profit	5.80	1.06	1.04	1.10	0
Total capital	192.95	48.39	46.87	48.32	0
$m_H = 2:$	Cluster 1*	Cluster 2*	Cluster 3	Cluster 4	p-value
Output	41.11	42.92	6.13	7.46	0
Mean $\tilde{X}^{IN}$	0.0071	0.0074	0.0050	0.0052	0
Mean $\tilde{X}^{IM}$	0.0041	0.0038	0.0051	0.0050	0
Best technology	0.30	0.30	0.25	0.25	0
Mean technology	0.28	0.28	0.23	0.23	0
Mean profit	4.23	4.43	0.50	0.65	0
Total capital	136.81	142.12	24.99	30.20	0
$m_H = 3:$	Cluster 1*	Cluster 2*	Cluster 3*	Cluster 4	p-value
Output	32.21	30.96	30.41	5.05	0
Mean $\tilde{X}^{IN}$	0.0068	0.0066	0.0066	0.0051	0
Mean $\tilde{X}^{IN}$	0.0041	0.0042	0.0041	0.0051	0
Best technology	0.29	0.29	0.28	0.24	0
Mean technology	0.27	0.27	0.27	0.22	0
Mean profit	3.57	3.08	2.95	0.39	0
Total capital	106.72	104.70	103.73	20.35	0
$m_H = 4:$	Cluster 1*	Cluster 2*	Cluster 3*	Cluster 4*	p-value
Output	29.37	22.95	26.27	22.90	0.2872
Mean $\tilde{X}^{IN}$	0.0068	0.0064	0.0065	0.0061	0.1988
Mean $\tilde{X}^{IM}$	0.0041	0.0043	0.0042	0.0044	0.2185
Best technology	0.29	0.28	0.29	0.28	0.0714
Mean technology	0.27	0.27	0.27	0.26	0.2131
Mean profit	3.28	2.19	2.60	2.28	0.1178
Total capital	95.79	77.56	85.17	76.95	0.3037

development of the economy, so the policy should accept an unequal distribution of human capital.

The setting with a structural heterogeneity leads to a result of a divergence of the regional economic performance. Starting from a setting with only low skill cluster, the adding of one high skill cluster leads to a strong increase of total output, thus the exclusive support of one region could be a political option for increasing the economy-wide development in cases where the economy wide human capital is inferior. Since the better development of the single high skill cluster leads to a decline of the other regions, the policy should equalize these losses with a form of financial compensation.

But if there are more high skill regions than low skill regions the political implication is not clear, because it both opportunities seems possible: the support of low developed regions as well as the promotion of high developed regions.

So the simulations show a differentiated picture that regional skill inequalities have on the economy. Hence policy designers should evaluate the total effect by taking into consideration both, the possible economy-wide effects which are mostly positive, as well as the occurring impacts at the regional level. But a clear statement in order to consult policy designers is not possible.

6 Conclusions

The goal of this paper was an examination of effects resulting from regional skill heterogeneity. For this purpose an evolutionary model based on the model of Nelson and Winter (1982) was employed, whose simulations yielded to interpretable results.

It could be shown that regional skill heterogeneity compared with the equivalent scenario of a homogeneous distribution has positive effects on economic development as well as a positive impact on the profitability of firms. Thus from the economic-wide point of view a heterogeneity of regional human capital has largely positive consequences.

But at the regional level a divergence concerning the economic performance of the particular regions resulted, which depends on their endowment with human capital. What has to follow is an exact consideration of positive effects due to the technological leader position and possible externalities because of the diffusion of better technologies on the one side, and negative effects due to the declining of economic performance according to the inferior human capital, and so a detailed weighting to investigate a total effect becomes necessary.

Even if some assumptions of the model can be criticized due to simplicity, e.g. the assumption of one industry with a homogeneous good or the non-respecting of labor market feedbacks, this paper shows a possible relevance of regional skill heterogeneity on the development of the total economy as well as the regional development. But for a consideration in greater depth, a microeconomic funding of the demand side of goods market and a regard of the labor market as well as an macroeconomic founding should be done.

References

Argote, L. and D. Epple (1990). Learning Curves in Manufacturing. *Science 247*(4945), 920–924.

Dawid, H., L. Columbo, and K. Karbus (2006). When Do Thick Venture Capital Markets Foster Innovation? An Evolutionary Analysis. Working paper.

Gellatly, G. (1999). Differences in Innovator and Non-innovator Profiles: Small Establishments in Business Services. Analytical Studies Branch research Paper Series no. 143, Statistics Canada.

Haskel, J., D. Hawkes, and S. Pereira (2005). Skills, human capital and the plant productivity gap: Uk evidence from matched plant, worker and workforce data. CEPR Discussion Paper no. 5334., Centre for Economic Policy Research, London, http://www.cepr.org/pubs/dps/DP5334.asp.

Malmberg, A. and D. Power (2003). (How) Do (Firms in) Clusters create Knowledge? Paper, CIND - Centre for Innovation and Industrial dynamics, Uppsala University.

Mohnen, P. and L. Roeller (2000). Complementarities in innovation policy. Discussion Paper FS IV 00-18, Wissenschaftszentrum Berlin.

Nelson, R. and S. Winter (1982). *An Evolutionary Theory of Economic Change*. Belknap, Cambridge, MA.

Rappaport, J. (1999). Local Growth Empirics. Working Paper no. 23, Center for International Development at Harvard Universtity.

A Appendix

A.1 Chosen Functions

The functions are chosen as follows:

- The productivity of firm's innovation department is calculated by

$$a_{i,t}^{IN} = (1 + s_{i,t})^2 \cdot \bar{a}^{IN},$$

  with $\bar{a}^{IN} = 0.055$.
- The human capital investment function is denoted by

$$I^H = 0.3 \cdot \frac{e^{5(A_{t+1}-B_t)} - e^{-5(A_{t+1}-B_t)}}{e^{5(A_{t+1}-B_t)} + e^{-5(A_{t+1}-B_t)}} \cdot e^{\upsilon S_{i,t}^*},$$

  where $\upsilon = 6$ holds if $S_{i,t}^* < 0$, else $\upsilon = 0$.
- The adjustment rate for closing the gap between productivity and specific skills is given by

$$\lambda = \mu \cdot \phi = [(0.1(1 - s_{i,t}) + s_{i,t}) \cdot (1 - B_{i,t})] \cdot \left(\frac{1}{1 + 7e^{-50 I_{i,t}^H}} \right).$$

- The intended investments in innovative and imitative activities are reduced by

$$\eta(A_{i,t} - B_{i,t}) = \frac{1}{1 + (100(A_t - B_t))^2}.$$

A.2 Additional tables

Table 8. Standard deviation of table 7 on page 20

$m_H = 0:$	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Output	18.34	15.60	17.18	17.37
Mean investments in innovation	0.0010	0.0010	0.0009	0.0010
Mean investments in imitation	0.0008	0.0008	0.0008	0.0008
Best technology	0.03	0.03	0.03	0.03
Mean technology	0.03	0.03	0.03	0.03
Mean profit	2.55	2.48	2.36	2.91
Total capital	67.89	60.83	65.56	65.29
$m_H = 1:$	Cluster 1*	Cluster 2	Cluster 3	Cluster 4
Output	33.62	15.05	13.35	15.32
Mean investments in innovation	0.0024	0.0009	0.0009	0.0009
Mean investments in imitation	0.0011	0.0007	0.0007	0.0007
Best technology	0.05	0.04	0.04	0.04
Mean technology	0.05	0.03	0.03	0.03
Mean profit	4.14	1.91	1.81	1.85
Total capital	95.64	56.95	51.71	57.83
$m_H = 2:$	Cluster 1*	Cluster 2*	Cluster 3	Cluster 4
Output	35.94	35.91	8.51	11.82
Mean investments in innovation	0.0024	0.0027	0.0007	0.009
Mean investments in imitation	0.0011	0.0011	0.0007	0.0007
Best technology	0.05	0.06	0.05	0.04
Mean technology	0.05	0.05	0.04	0.04
Mean profit	4.60	4.35	1.01	1.82
Total capital	105.93	104.71	32.33	43.97
$m_H = 3:$	Cluster 1*	Cluster 2*	Cluster 3*	Cluster 4
Output	32.18	31.35	29.18	8.72
Mean investments in innovation	0.0022	0.0018	0.0019	0.0008
Mean investments in imitation	0.0011	0.0010	0.0010	0.0007
Best technology	0.06	0.05	0.05	0.04
Mean technology	0.06	0.05	0.05	0.04
Mean profit	4.45	3.87	3.44	1.11
Total capital	95.93	96.51	91.29	31.37
$m_H = 4:$	Cluster 1*	Cluster 2*	Cluster 3*	Cluster 4*
Output	32.65	27.13	31.99	28.13
Mean investments in innovation	0.0024	0.0020	0.0023	0.0017
Mean investments in imitation	0.0011	0.0010	0.0011	0.0009
Best technology	0.06	0.05	0.06	0.06
Mean technology	0.06	0.05	0.06	0.06
Mean profit	4.39	3.17	3.85	3.21
Total capital	96.17	82.52	91.70	84.24