EUROPEAN NETWORK OF
ECONOMIC POLICY RESEARCH INSTITUTES
WORKING PAPER NO. 43/MARCH 2006

KNOWLEDGE CAPITAL AS THE SOURCE OF GROWTH

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ISBN 92-9079-611-1
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Knowledge Capital as the Source of Growth

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Hannu Piekkola*

Abstract

Regional disparities in the growth rates of GDP and total factor productivity (TFP) are a major policy concern in the European Union, not least because of the inclusion of new transition economies in the EU. The growth rate of a nation's TFP especially depends on its level of human capital rather than the increasing rate of human capital. The growth that is driven by innovation and the catching-up process spurred by technology imitation relies on education-based human capital and related agglomeration. This explains why education provides a permanent advantage, which over time may increase in importance in the labour market.

This paper examines the role of knowledge agglomeration in productivity growth in Finland. The analysis rests on a very detailed assessment of knowledge capital in firms, using linked employer-employee data at the micro level. It shows that the agglomeration of education-based human capital explains the regional divergence in the growth rates of GDP and TFP in Finland since 1995. High-growth firms are observed to have highly paid occupations and intangible capital – characteristics that are vital for growth to continue in firms that are far from the leader firm at the frontier of their industry in terms of productivity. In low-productivity firms, knowledge capital that is derived from sources other than educational attainment is also found to be essential for growth.

Theme: 18. Regional labour market

JEL classification: J240, R110, O300, O400, O520

Keywords: regional growth, endogenous growth, catching up, technology transfer.

* Hannu Piekkola is with the Research Institute of the Finnish Economy (ETLA) (e-mail: hannu.piekkola@etla.fi). Support by the Proact programme initiated by the Technology Agency Tekes and the Ministry of Trade is gratefully acknowledged. The author would like to thank Rita Asplund, Edvard Johansson, Mika Maliranta and Petri Böckerman for very helpful comments. The individual data were received from the Confederation of Finnish Employers and financial balance data from the Suomen Asiakastieto and Balance Consulting Oy on condition that they are not disseminated.

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1. Introduction

Regional disparities are a major policy concern in the European Union, not least because of the inclusion of new transition economies in the EU (see Tondl & Vuksic, 2003). Until the 1990s, disparities in growth between countries were on the decline. Around that time, however, increased migration to large cities led to a population concentration in urban areas. As a result, large agglomeration effects in labour productivity could be seen in Europe, as shown by Ciccone (2003). Even in countries that have received EU Cohesion Funds and experienced higher overall growth, such Spain and Portugal, variation in growth among the regions can be observed (Quah, 1997). Further, Cappelen et al. (2003) note that within the old EU member states, very little convergence has occurred among the regions since the 1980s. In Finland, Ottaviano & Pinelle (2004) find there has been a divergence of GDP growth among the Finnish regions since 1994, despite clear convergence prior to that time.

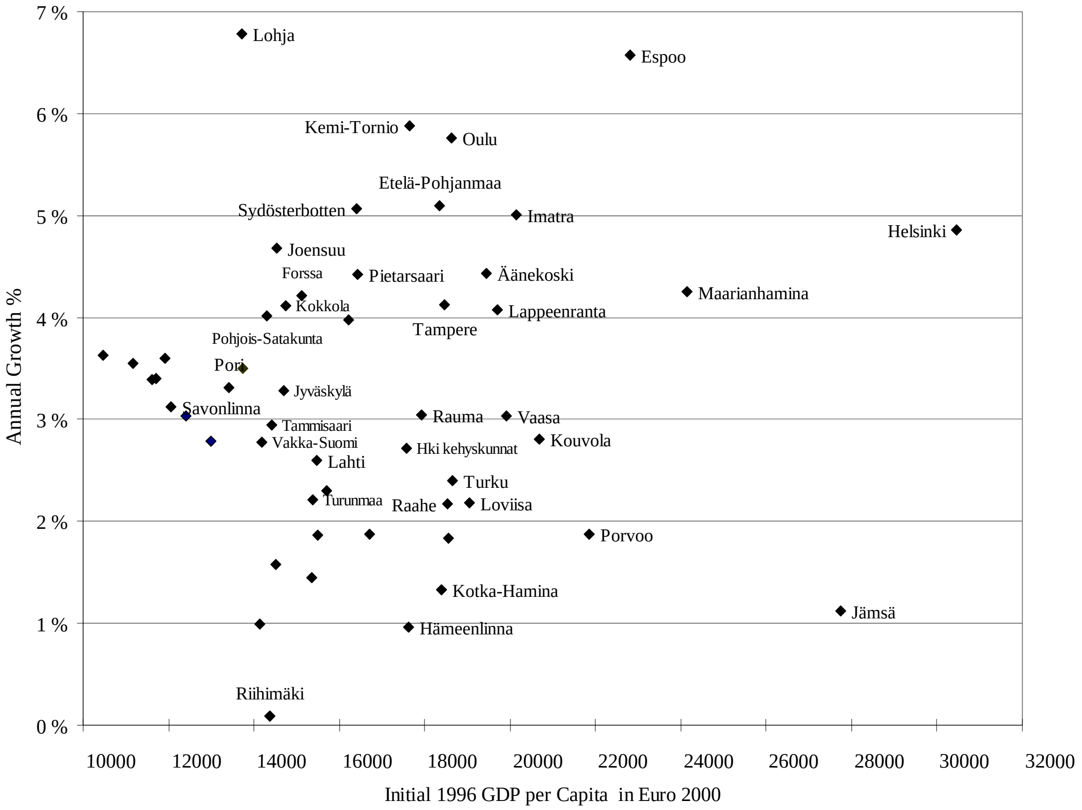
The growth rate of a nation's total factor productivity (TFP) especially depends on its level of human capital and not on the growth rate of human capital (Benhabib & Spiegel, 1994) and Brunello & Comi, 2004). This explains why education provides a permanent advantage, which over time may increase in importance in the labour market. The share of the labour force employed in activities related to innovation is also an important part of knowledge capital. Romer (1990) was one of the first to describe technological innovation as non-rival and stemming from monopolistic competition. Benhabib & Spiegel (2005) separate the growth driven by innovation from that of the catch-up process, which is described as a Romer-type of imitation of new technology. At the regional level, Faberberg, Verspagen & Caniels (1997) show evidence of superior growth performance explained by the share of the business-sector workforce employed in R&D and Wieser's survey (2005) shows the same at the firm level.

Finland is ranked as one of the most competitive countries, according to the Global Competitiveness Report 2004-2005.[1] One attributive factor behind this is its high degree of tertiary enrolment, since Finland exhibits clear growth in higher educational attainment levels relative to the rest of Europe (see, for example, comparisons across countries at the NUTS-2 level in Badinger & Tondl, 2002a). Finland can also be said to be an R&D-driven economy and thus innovative activities are an important source of regional growth (Lehto, 2000). The average GDP growth of 2.5% in the period 1980-2004, which exceeded the average of 2.2% in the euro area, has been accompanied by rapid growth of 3.6% since 1996 and also regional divergence. Figure 1 shows the GDP growth in NUTS-4 level areas in the period 1996-2002.

While growth has been rapid, Figure 1 reveals that the Finnish regions have exhibited no clear tendency towards income convergence over the period under consideration. Large cities such as Espoo (6.6%) and Helsinki (4.8%) have grown more quickly, while the average growth rate has been 3.6%. The findings on growth rates in Finnish regions presented Loikkanen & Susiluoto (2002) are very similar.

[1] See the World Economic Forum's Global Competitiveness Report 2004-2005 (retrieved from www.weforum.org/gcr).

Figure 1. Initial GDP per capita and GDP growth per capita in Finnish regions 1996-2002



Source: Statistics Finland.

This paper examines the role that knowledge plays agglomeration in productivity growth in Finland. Firms represented in the data are members of the Confederation of Finnish Employers and 75% of them belong to the manufacturing sector. Manufacturing industries in particular can explain regional disparities in growth in Finland, as revealed by Kangasharju & Pekkala (2001).

This study uses linked employer-employee data for Finland. The linked data is extensively used in the study of human capital formation, starting with Abowd, Kramarz & Margolis (1999). Linked employer-employee data allow the estimation of wider concepts of knowledge capital that include returns from individual- and firm-specific experience and occupational careers. Three main firm- and regional-level growth determinants are examined: i) the productivity growth effects of education, experience and unobserved human capital and the related agglomeration of these factors; ii) the growth effects of firm-specific, occupation-based human capital and R&D work; and iii) the catching-up process at the firm and regional levels. We categorise firms according to the share of workers below the 25th and above the 75th percentile of the particular type of human capital, as was done for overall human capital in Abowd et al. (2003).

The rest of the paper is structured as follows: section 2 details the model applied and section 3 describes the data that is used along with the procedure for assessing individual- and firm-specific human capital. Section 4 presents the results of the estimation. Finally, section 5 concludes.

2. The model

Benhabib & Spiegel (2005) integrate two types of processes often studied in the context of disaggregated models of technology diffusion.[2] The first one is the Nelson-Phelps model of technology diffusion:

$$\frac{\dot{A}_{jt}}{A_{jt}} = g(KC_{jt}) + c(KC_{jt})\left(\frac{A_{Mt}}{A_{jt}} - 1\right), \tag{1}$$

where A_{jt} is TFP, $g(KC_{jt})$ is the component of TFP that depends on the level of knowledge capital KC_{jt} in firm *j* at period *t* (presented as human capital in a country in Benhabib & Spiegel's model) and $c(KC_{jt})\left(\frac{A_{Mt}}{A_{jt}} - 1\right)$ shows the catching-up with the leader firm *M* in the industry. The knowledge KC_{jt} affects the speed of catching-up so that $c(.)$ and $g(.)$ are increasing functions. The alternative model formulation presented by Benhabib & Spiegel uses a logistic model of technology with different spillover effects given by

$$\frac{\dot{A}_{jt}}{A_{jt}} = g(KC_{jt}) + c(KC_{jt})\left(1 - \frac{A_{jt}}{A_{Mt}}\right) \tag{2}$$

$$= g(KC_{jt}) + c(KC_{jt})\frac{A_{jt}}{A_{Mt}}\left(\frac{A_{Mt}}{A_{jt}} - 1\right).$$

The difference in the dynamics under the logistic model is the extra term A_{jt} / A_{Mt}. The distance between the firm assessed to the 'frontier firm' (the leading firm in productivity in the industry) slows down the adoption speed, which creates a non-linear relationship between the technological capital and the catch-up. An example of this is new technology in some other industry. This can be more easily adopted if the industries resemble each other in knowledge structure. It is clear that the steady-state growth relationship depends on the catch-up rate $\mathrm{c(KC_j)}$ and the difference in the growth rate owing to innovative capability $\mathrm{g(KC_j)\text{-}g(KC_M)}$.

By defining $B_{jt} = \frac{A_{jt}}{A_{jt_0}} e^{-g_M t}$ we can express the growth equation in terms of stationary variables:

$$\frac{\dot{\mathrm{B}}_{\mathrm{jt}}}{\mathrm{B}_{\mathrm{jt}}} = \mathrm{c(KC_j)+g(KC_j)\text{-}g(KC_M)\text{-}c(KC_i)B_{jt}} \quad . \tag{3}$$

Let $d \ln A_{j,t}$ represent the growth rate in log TFP of firm *j*. The empirical testable specification may be written, following Benhabib & Spiegel, as

[2] An endogenous growth model such as that by Badinger & Tondl (2002b) also links human capital explanations to the catching-up theory. Griffith, Redding & Van Reenen (2003) include a positive spillover from the assimilation of existing R&D capacity.

$$d\ln A_{j,t} = b + \left(g - \frac{c}{s}\right)\ln KC_{j,t} + \frac{c}{s}\ln KC_{j,t}\ln\left(\frac{A_{M,t}}{A_{j,t}}\right)^{s} + \varepsilon_{j}, \qquad (4)$$

where *s* equals 1 if the pure catch-up model holds, following a Nelson-Phelps type of model for technology diffusion and *s* equals -1 if the logistic form of technological diffusion is appropriate. In the Nelson-Phelps type of model (*s*=1), knowledge capital enhances the catching-up process but also exhibits decreasing returns. In the logistic specification (*s*=-1), the relative importance of the catching-up process is decreasing at the knowledge capital level. For a high enough catch-up rate, the leader will pull others towards the same technological level and productivity differences will converge. At a low enough catch-up rate, the knowledge base is too low and growth rates continue to diverge. The logistic type of technological diffusion thus allows the emergence of non-converging industries. Benhabib & Spiegel also discuss the Romer-type (1990) of split of human capital to raise returns to either innovation g_j or imitation, increasing catch-up c_j.

In this paper, knowledge capital $KC_{j,t} = \xi(h_{j,t}, l_{j,t,h>h(Q3)}, \psi_{j,t})$ is a function of the average individual- and firm-specific human capital $h_{j,t}$, a function of the fraction of workers in the highest skill category $l_{j,t,h>h(Q3)}$, and a function of the firm effect $\psi_{j,t}$. The fraction of workers above the 75th percentile for human capital across firms over the period is represented by $l_{j,t,h>h(Q3)}$. (We also use the fraction of workers below the 25th percentile and interactions.) $\psi_{j,t}$ is a firm effect in addition to the time-specific, firm-level human capital explained by seniority, performance-related pay, R&D work and occupations. These capture intangible human capital engaged in the human resource management and innovative capabilities, which are not transferable across firms. In knowledge capital we include regional knowledge capital spillover, $SPIL_{r,t}$, which is independent of the catching-up process, where subscript r indicates region *r* (1,…,R). This consists of the spillover from educated human capital in region *r* and the influence of other regions. Spatial weights are based on a negative exponential function with the distance decay parameter depending on the distances between neighbouring regions, following Funke & Niebuhr (2000). The half-decay distance that reduces the spatial interaction by one-half is set, on average, at 122 kilometres for educated human capital (twice as high as in Northern Finland with its long distances).

The leading technology is assessed in 19 industries. The firm with frontier technology is the one with the highest average productivity in the industry. TFP in firm *j* is also measured relative to other firms and time periods. We apply the multilateral TFP index introduced by Caves et al. (1982). (For an analysis using a similar productivity measure in Finnish data, see Ilmakunnas et al., 2004.) Firm *j* is compared with a hypothetical average benchmark firm so that

$$d\ln A_{j,t} = \ln(TFP_{j,t}) - \ln(TFP_{j,t-1}) \text{, where} \qquad (5)$$

$$\ln(TFP_{j,t}) = \ln\left(\frac{V_{j,t}/L_{j,t}}{\overline{V}_{j,t-1}/\overline{L}_{j,t-1}}\right) + \frac{S_{j,t}+\overline{S}_{j,t-1}}{2}\ln\left(\frac{K_{j,t}/L_{j,t}}{\overline{K}_{j,t-1}/\overline{L}_{j,t-1}}\right), \qquad (6)$$

and where $V_{j,t}/L_{j,t}$ = labour productivity, $K_{j,t}/L_{j,t}$ = capital intensity and $S_{j,t}$ = one minus the labour-cost share of value added. The upper bar superscript indicates the respective values for the average firm benchmark. The index has the advantage that it is based on a translog production function, thus being a second-order approximation of the true but unknown production function. The index is exact if the true production function is translog.

3. Data and estimation of human capital

The labour data used for this study are from the Confederation of Finnish Employers, where 75% of firms are in the manufacturing sector. The original data with 3.09 million observations cover the years 1996-2002 and include both blue- and white-collar employees. The data include a rich set of variables covering compensation, education and profession. The white-collar employees receive salaries and the blue-collar workers are remunerated on an hourly basis. Employee data are linked to financial statistics data from the Balance of Consulting and Suomen Asiakastieto, mainly to include information on value added and capital intensity (fixed assets). The manipulation of the linked employer-employee data is further described in Appendix A. After checks for real creations and dissolutions of firms the original data included 2,359 firms and the firm-effect could be identified for 1,421 firms based on job transferees. The sample, including all observations for employees with one or more job transferees in the time period under consideration (286,000), accounts for 13% of all observations in the 1,421 firms with at least 30 job transferees. At the same time, these firms cover most of the employee-year observations – 2.09 million out of 2.76 million.

We are interested in estimating both individual and firm heterogeneity in wage formation. Individual heterogeneity, as captured by the person-specific fixed effect, can be subsequently used to assess the returns to education. The remaining part of the person-specific fixed effect is the proportion of wages that cannot be explained by observed characteristics (to the econometrician). We refer to this as the unobserved human capital of the individual.

Abowd, Creecy & Kramarz (2002) have developed a numerical solution to deal with the large set of firm dummies in the Least Squares Dummy Variables Estimator. We use the two-step method suggested by Andrews, Schank & Upward (2004). We include dummy variables for the firm heterogeneity that are estimated at the first step in data covering only individuals that move from one firm to another and sweep out the worker heterogeneity by taking deviations from individual means. The dependent variable is the natural log of the hourly wage $\ln(y_{\mathrm{ijt}})$ of an individual *i* working in firm *j* at time *t* measured as a deviation from the individual mean wage over the time period. This is expressed as a function of individual heterogeneity, firm heterogeneity and measured time-varying characteristics for movers as a deviation from individual means.

$$\ln(y_{\mathrm{ijt}})-\mu_{yi} = \beta(x_{it}-\mu_{xi})+\gamma(w_{it}-\mu_{wi})+\sum_{j=1}^{J}\psi_j(D_{it}^{j}-\mu_{Di}^{j}) + e_{ijt} \quad . \tag{7}$$

$\beta(x_{it}-\mu_{xi})$ shows the compensation for time-varying human capital stated as a deviation from the individual mean human capital: hence it contains time dummies and experience expressed up to the fourth power. $\gamma(w_{it}-\mu_{wi})$ shows the respective time-demeaning for all firm-specific variables: occupations, seniority, R&D work and performance-related pay. ψ_j captures the effect of unmeasured employer heterogeneity. $D_{it}^{j}-\mu_{Di}^{j}$ is the firm dummy as a deviation from individual mean μ_{Di}, while e_{ijt} represents a statistical error term. It should be noted that $D_{it}^{j}-\mu_{Di}^{j}$ will be zero for any worker *i* who does not change firms.

The firm effect is measured within a group of firms where there is movement of workers between the firms. (In a firm group, two firms are linked by a job transferee and these two firms are linked to a third firm by a job transferee, and so forth.) In each group of firms the firm effect is defined with respect to a reference (omitted) firm when firm dummies are used. Following Abowd, Creecy & Kramarz (2002), we assume that the average effect is the same across groups and take the firm effect $\hat{\psi}_j$ as a deviation from the grand mean in each group. Almost all of them, 99.8%, belong to the largest pool, where firms are linked to each other through job transferees across firms. Estimates of firm heterogeneity are obtained by computing $\hat{\psi}_{j(i,t)} = \sum_{j=1}^{J} \hat{\psi}_j D_{it}^j$, where *j(i,t)* indicates the worker's job at employer *j* at date *t*. In the second step, $\delta \hat{\psi}_{j(i,t)}$, where δ is a scalar, the following equation is placed:

$$\ln(y_{j(i,i)}) - \mu_{wi} = \beta(x_{it} - \mu_{xi}) + \gamma(w_{it} - \mu_{wi}) + \delta(\hat{\psi}_{j(i,t)} - \mu_{\psi i}) + e_{ijt} , \qquad (8)$$

where $\mu_{\psi i}$ is the individual mean of the firm effect. The second-step estimation covers all workers in the sample of firms for which the firm effects were identifiable.

Given the data dimension with 1,421 firm dummies, it was not possible to solve even the reduced two-step method suggested by Andrews, Schank & Upward (2004) using the Stata econometrical package in the Windows environment. Instead, we adopted an analogous estimation procedure using the SAS system for Windows. The estimation of the first-stage wage equation (7) is shown in column 1 in Table A.1 in the appendix. Time-varying human capital includes experience up to the fourth potency. Time-varying firm characteristics include seniority, performance-related pay, the share of R&D employees and job mobility across occupations (blue-collar and white-collar work in 17 categories as listed in Table A.1).

Results from the second-stage estimation (8) are reported in column 2 in Table A.1 in the appendix. The coefficients for the first-stage estimation for the sample with job transferees do not largely differ from the coefficients for the larger sample also covering non-movers (see columns 1 and 2 in Table A.1). The table also reports the Chow test for the breaking estimation between movers and non-movers. It indicates that coefficients are not statistically different from each other. The 17 occupations are available in white-collar work. It can be observed that earnings are on average higher in the blue-collar than in the white-collar occupations in the data covering mainly manufacturing.

The person-specific fixed effect is the person average using the second-step estimation results: $\theta_i = \mu_{yi} - \hat{\beta}\mu_{xi} - \hat{\gamma}\mu_{wi} - \mu_{\psi i}$, where $\hat{\beta}$ and $\hat{\gamma}$ are the estimated values of the coefficients. The person effect θ_i can now be regressed against all time-invariant variables. The decomposition of the person effect θ_i uses the estimates of

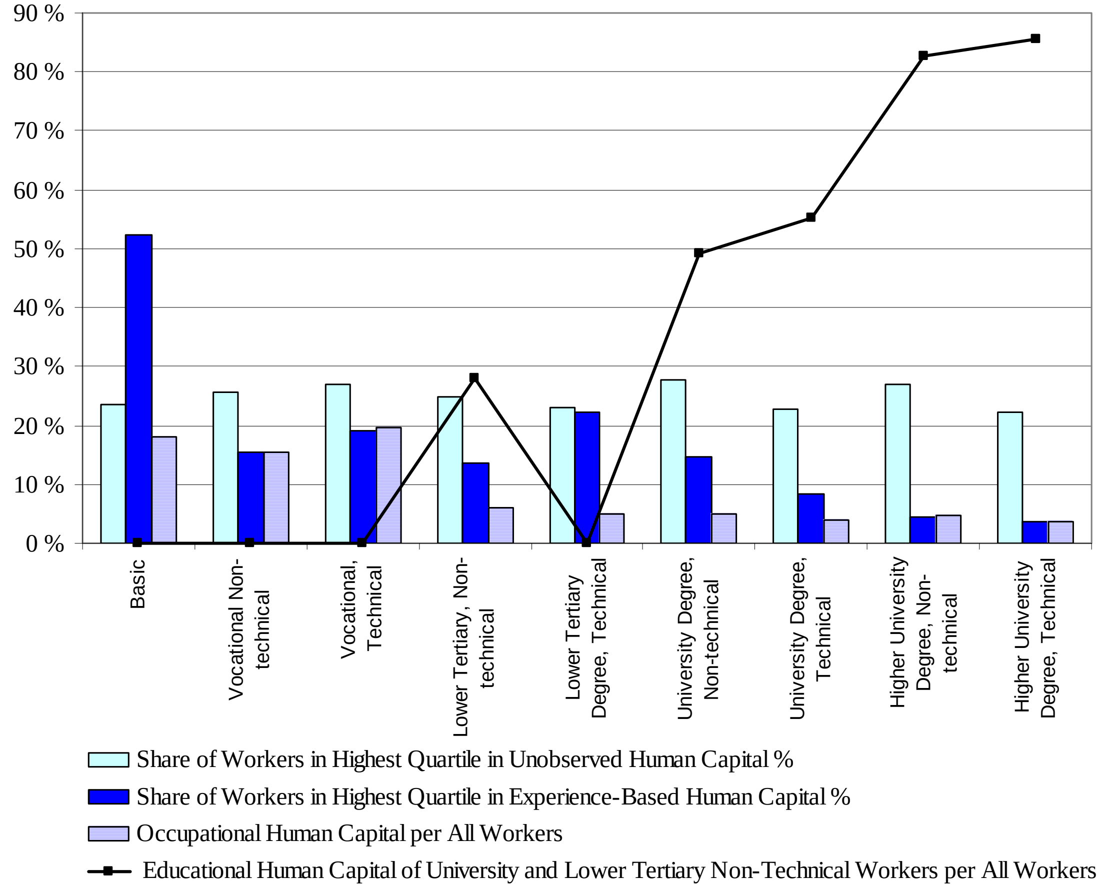
$$\theta_i = Int + z_{i\in e} u_e \eta_e + u_2 Gen_i + \varepsilon_i , \qquad (9)$$

where Int is the intercept, η_e is the education level (from $e = 1, ..., E$), u_e is the respective coefficient, $z_{i\in e}$ indicates the worker belonging to this education group (zero otherwise), Gen_i indicates gender and ε_i is the statistical error. Five educational levels are identified for five fields. Unobserved human capital is the person effect that cannot be explained by education or gender $\alpha_i = \theta_i - z_{i\in e}\hat{u}_e\eta_e - \hat{u}_2 Gen_i$. Unbiased estimates of returns to education rely on the assumption that $\operatorname{cov}(\alpha_i, \eta_e)$=0 and $\operatorname{cov}(\alpha_i, Gen_i)$=0. In other words, unobserved individual heterogeneity is assumed to be uncorrelated with the education level (and gender). A positive bias in the estimate of returns to education will be generated if a missing variable such as talent or excess demand for skilled workers explains both higher levels of education-based and unobserved human capital.

Table A.2 in the appendix shows the estimation results. (In what follows we only use data for 1,421 firms with an estimable firm effect covering 2.10 million employees.) As can be seen, returns to education increase monotonously with the educational level, at least within the education-related fields. All workers with higher university education, except those in the health and service sector, belong to the highest quartile for overall human capital. As a measure of education-based human capital we take into account both the share of the highly educated and the relative rate of return in each highly educated group. Thus, the difference to a compensation-weighted average measure is that the denominator is not the number of highly educated workers, but all the workers in the firm (see Appendix A for further details).

Figure 2 shows the breakdown of experience-based and unobservable human capital into nine educational categories, using five educational degrees (basic, vocational, lower tertiary degree, university degree and higher university degree) that have been divided, with the exception of the first category, into technical and non-technical fields.

Figure 2. Education- and occupation-based human capital and the share of workers over the 75th percentile of the overall unobserved or experience-based human capital



It can be noted that the share of individuals belonging to the highest quartile of experience-based human capital generally decreases with the educational level, although variation in average ages causes some heterogeneity at the vocational and lower tertiary levels. Unobserved human capital is fairly evenly distributed, as is expected by the design of the model. Occupation-based human capital decreases with the educational level.

4. Results

This section uses the constructed human-capital variables to explain firm-level and regional productivity growth. Table 1 summarises the variables and correlations between the individual- and firm-specific human capital variables. The variables as described above are also listed in Appendix A.

Table 1. Summary and correlation table

Person-Average Variable	Person Effect	Human Capital	$u\eta$	α	Exper. H.C.	Gender H.C.	ψ	Occupat. H.C.	Seniority H.C.*10	PRP	R&D H.C.
Mean	1.179	2.723	0.239	1.187	1.297	-0.247	0.030	0.142	0.034	0.009	-0.002
Std	0.491	0.382	0.230	0.422	0.394	0.087	0.283	0.101	0.003	0.009	0.004
Mean Blue-Collar	1.144	2.665	0.147	1.234	1.284	-0.237	0.038	0.230	0.033	0.007	0.000
Mean White-Collar	1.220	2.790	0.347	1.132	1.311	-0.259	0.021	0.038	0.035	0.011	-0.003
Person Effect	**1**	0.59	0.47	0.86	-0.63	0.21	-0.43	-0.08	-0.37	0.06	-0.21
Human Capital	0.59	**1**	0.22	0.57	0.23	0.01	-0.59	-0.19	0.17	0.14	-0.11
Education $u\eta$	0.47	0.22	**1**	0.00	-0.37	0.02	0.05	-0.42	-0.27	0.15	-0.42
Unobserved α	0.86	0.57	0.00	**1**	-0.52	0.02	-0.53	0.11	-0.29	-0.02	0.00
Experience H.C.	-0.63	0.23	-0.37	-0.52	**1**	-0.03	-0.03	-0.05	0.63	0.07	0.14
Gender H.C.	0.21	0.01	0.02	0.02	-0.03	**1**	0.01	0.13	0.02	0.04	-0.07
Firm Effect ψ	-0.43	-0.59	0.05	-0.53	-0.03	0.01	**1**	0.02	0.00	0.08	-0.06
Occupational H.C.	-0.08	-0.19	-0.42	0.11	-0.05	0.13	0.02	**1**	-0.05	-0.23	0.36
Blue-Collar	-0.03	-0.01	-0.06	-0.02	0.03	0.018	0.105	**1**	0.015	0.058	0.305
White-Collar	-0.03	-0.17	-0.03	-0.03	-0.12	0.02	-0.10	-0.10	-0.06	0.12	-0.12
Seniority H.C. *10	-0.37	0.17	-0.27	-0.29	0.63	0.02	0.00	-0.05	**1**	0.10	0.11
Blue-Collar	-0.31	0.29	-0.30	-0.25	0.63	0.062	0.042	0.015	**1**	0.202	0.038
White-Collar	-0.45	0.02	-0.35	-0.33	0.64	-0.007	-0.065	-0.101	**1**	-0.029	0.197
PRP	0.06	0.14	0.15	-0.02	0.07	0.04	0.08	-0.23	0.10	**1**	-0.18
R&D H.C.	-0.21	-0.11	-0.42	0.00	0.14	-0.07	-0.06	0.36	0.11	-0.18	**1**

Firm-Average Variable	Educat. H.C.	Educat. H.C. of Highly Educated	Unobser. H.C.	ψ	Occup. H.C.	Seniority H.C.*10	Share of R&D Workers	Highly Educat. Spillover	R&D Worker Share Spillover	Log TFP Growth	Log TFP Catching Up
Mean	0.210	0.094	1.137	0.018	0.156	0.028	0.092	0.007	0.012	-0.017	4.533
Std	0.092	0.103	0.382	0.383	0.067	0.015	0.142	0.015	0.038	0.574	1.644
Number of Obs	7532	7532	7532	5698	7532	7532	7532	7532	7532	5490	7532

Table includes 1,13 million blue-collar and 0.96 million white-collar workers and related means and respective correlations of occupational and seniority human capital. Human capital is the sum of educational uη, unobserved α and experience human capital. Educational human capital at firm level is the per capita value of the sum of educational human capital uη. Correlations for blue and white-collar workers are withing the respective group.

Source: Author’s calculations based on data from the Confederation of Finnish Employers.

Abowd et al. (2001) find that the firm effect is positively related to the level of human capital (the person effect), while in Table 1 the correlation is negative in accordance with most of the empirical literature. (See, for example, Gruetter & Lalive, 2003, Barth & Dale-Olsen, 2003 and Andrews, Schank & Upward, 2004.) The firm effect, ψ_i has a negative correlation in particular with the unobserved human capital (correlation of -0.53). All other individual-based components of log wages *ln(y)* are not correlated strongly with the firm effect. The exception is the positive relation of experience-based human capital to that related to average seniority.

It can be observed that in the mainly manufacturing firms that have been considered white-collar workers have more human capital, which is here the sum of unobserved, education- and experience-based human capital. This is primarily explained by higher returns to education. The difference is small because blue-collar workers have more unobserved and occupation-based human capital. Table 1 also shows that returns to education are negatively correlated with returns to experience (-0.37) and to occupation-based human capital (-0.42).

It is also clear that blue-collar workers with high wages owing to seniority are also endowed with human capital. This gives support to the idea that long experience in the firm is especially important for the accumulation of human capital by blue-collar workers. On the other hand, the human capital of white-collar workers is unrelated to seniority or to occupation-based capital. Note also that the negative relation exists only between returns to education of white-collar workers and the occupation-based capital of blue-collar workers. Within the two groups the correlation between education- and occupation-based human capital is close to zero. Apart from seniority and occupation-based capital (which is insufficiently recorded in statistics for blue-collar workers) all other correlations are fairly similar for white-collar and blue-collar workers and are not reported.

Table 2 shows the estimation results of (5) in explaining firm-level growth. We use the average employment as a weight, thus placing greater emphasis on large firms (except in column 4). Explanatory variables include individual human capital (education- and experience-based as well as unobserved human capital) and firm-level human capital (occupation-based, firm effect, performance-related pay and returns to R&D work). We use average seniority rather than seniority-related payments. A high value of it is a sign of a mature firm. Spillovers from the agglomeration of education-based human capital are included, while those from the agglomeration of R&D workers turned out to be insignificant.

The OLS estimations in columns 2 and 3 are the preferred models, while the first column excludes interaction terms. Column 4 uses no weights. We also evaluate the human capital that is important for firms close to or far from a frontier firm, where firms are split by the mean value of the productivity gap (columns 5 and 6).

Column 1 in Table 2 shows that firms with more education-based capital generate stronger growth. In columns 2-3 education- and occupation-based human capital are interacted, which has a strong positive effect on growth. The coefficient for education-based human capital is no longer significant. We find the *growth* of education-based capital to be negatively related to TFP growth. These findings are similar to those of Benhabib & Spiegel (1994), who explain, using more aggregated measures of education-based human capital, productivity growth in 61 countries. The importance of education-based human capital cannot be interpreted in terms of pure, labour productivity-augmenting technology, since it is the level and not the rate of change in education- and occupation-based human capital that is important.

Table 2 reveals that low-productivity firms appear to catch up with the top-productivity firm in the industry. This shows some variation as indicated by the standard deviation of catching-up in Table 1 of 1.64 with a positive mean value of 4.53. The interaction of the catching-up term with education-based human-capital spillover is positive in column 3. Column 6 also shows that catching-up and agglomerated education-based human capital is especially important for firms close to the productivity level of the frontier firm. Thus the catching-up process takes place especially in human-capital abundant, high-productivity areas.

A natural consequence of the Benhabib & Spiegel model is that imitation is more important for firms that are far from the level of the frontier firm, whereas highly productive firms have to invest more in innovation in order for their growth to continue. From columns 5 and 6 it can be seen that the engines for growth are fairly similar in firms that close and far from the frontier firm. One difference is that the firm effect and the share of the workforce belonging to the highest quartile in unobserved human capital are important in firms that are far from the frontier firm.

Table 2. TFP growth

				No Firm Weights	Far from Frontier	Close to Frontier
Constant	-1.662***	-1.417***	-1.424***	-1.728***	-1.966***	-1.440***
	[3.3]	[3.5]	[3.5]	[15.8]	[5.2]	[3.2]
Catching Up Frontier Firm	0.184**	0.172**	0.169**	0.229***	0.218***	0.181*
	[2.0]	[2.0]	[2.0]	[20.1]	[5.8]	[1.9]
Catching Up,Education H.C. Spillover			0.179***	0.091	-0.292	0.381**
			[2.6]	[0.9]	[1.4]	[2.0]
Education Human Capital	1.037**	0.771	0.775	0.533***	0.559	0.996
	[2.1]	[1.4]	[1.4]	[2.8]	[1.0]	[1.5]
Difference Education Human Capital	-0.539	-0.423	-0.423	-0.336*	-0.814**	-0.395
	[1.3]	[1.1]	[1.1]	[1.9]	[2.6]	[0.7]
Education H.C. Agglomeration	-0.555***	-0.447**	-0.771**	-0.475	1.817	-1.036**
	[2.6]	[2.3]	[2.6]	[1.0]	[1.5]	[2.6]
Workers Above 75% for Unobserved H.C.	0.109	0.044	0.045	0	0.535***	-0.11
	[0.9]	[0.3]	[0.3]	[0.0]	[3.9]	[0.6]
Workers below 25% for Experience H.C.	-0.219	-0.796	-0.782	-0.306**	-0.411	-0.724
	[0.8]	[1.1]	[1.1]	[2.4]	[1.3]	[1.1]
Workers Above 75% for Experience H.C.	0.186	-0.487	-0.462	-0.193	-0.266	-0.368
	[0.6]	[0.6]	[0.5]	[1.4]	[0.8]	[0.4]
Workers below 25%, Above 75% for Experience H.C.		4.902	4.814	1.492***	-0.012	5.488
		[1.3]	[1.3]	[2.8]	[0.0]	[1.4]
Firm Effect	0.109	0.048	0.045	0.047	0.333***	-0.076
	[1.2]	[0.5]	[0.5]	[1.2]	[3.7]	[0.5]
Occupation Human Capital	1.202***	0.733	0.715	1.365***	1.095*	0.881
	[2.6]	[1.6]	[1.6]	[5.8]	[1.7]	[1.5]
Education H.C., Occupation H.C.		7.426*	7.226*	1.574	6.886*	7.804
		[1.8]	[1.8]	[0.9]	[1.8]	[1.5]
Returns to PRP	-6.255*	-5.883*	-5.804*	-0.802	-5.770**	-6.278*
	[1.8]	[1.9]	[1.9]	[0.6]	[2.4]	[1.7]
Returns to R&D Research	20.876	12.313	13.433	12.241	-5.156	20.476
	[0.6]	[0.5]	[0.5]	[1.6]	[0.2]	[0.7]
Seniority /100	-1.074*	-1.640**	-1.628**	-0.381*	-0.326	-2.662*
	[1.8]	[2.1]	[2.1]	[1.9]	[0.6]	[1.9]
Seniority Squared/1000	0.054	0.257	0.268	0.166**	0.105	0.577
	[0.2]	[0.6]	[0.7]	[2.1]	[0.4]	[0.8]
Firm Size	0.077***	0.069***	0.070***	0.054***	0.067***	0.072***
	[3.6]	[3.4]	[3.5]	[7.3]	[4.2]	[3.3]
Observations	4411	4411	4411	4411	1982	2429
R-squared	0.187	0.199	0.2	0.135	0.168	0.238

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Estimation includes female share (insignificant), 5 area, 19 industry and year dummies.

Source: Author's calculations based on data from the Confederation of Finnish Employers.

The firm effect can also be considered as a proxy for the unobserved components of technology (intangible capital and managerial ability) that is also captured by other firm-level characteristics: occupation-based human capital, R&D work and performance-related pay. The human resource practices in a firm as explained by performance-related pay or returns to R&D work do not play a very important role in the growth process. We can conclude that firms with high levels of productivity growth are not only characterised by a high share of educated workers but also by highly paid professions, by workers with unobserved human capital and by intangible capital. These characteristics are vital for growth to continue in firms that are not close to the frontier in terms of productivity.

It can be seen from Table 2 that firms are very heterogeneous when assessing the importance of the work or job experience. The share of workers belonging to the highest quartile in experience-based human capital has an insignificant effect on growth in columns 1-6. Nevertheless, the coefficient for the interaction between the share of employees belonging to the highest and lowest quartile of overall experience-based capital is positive in column 4. We find that average experience is likely to fail to capture productivity effects since it ignores the importance of having a heterogeneous workforce with younger and older workers. We also note that seniority has a non-linear effect, so that firms with a very stable workforce and a high average level of seniority tend to grow more slowly.

The catching-up process turned out to be positive with significant interactions with regional education-based human capital. We use the Monte Carlo simulation method to determine the magnitude of the productivity effects and to assess the robustness of our estimates, especially with respect to the catching-up process (see King, Tomz & Wittenberg, 2000). The simulation is based on the OLS estimation with no firm weights. Figures 3 through 6 show the simulation analysis results using the model reported in column 4 in Table 2. Figure 6 shows the catching up and seniority effects using the partial model analogous to that reported in column 1 in Table 2 with no interaction terms.

We have run 10,000 simulations, and the quantitative effects are estimated from the average of each variable. The X-axis is set to reflect a one-standard deviation increase in the explanatory variable around the mean. The Y-axis shows the fluctuation of productivity around the zero mean (standard deviation is 56.7 – see Table 1). Note that if knowledge capital purely augments the productivity of labour, which we do not believe, the labour productivity effects are two times higher than the TFP effects, as the average labour share of value added is 0.53.

Figure 3 shows that an increase in the level of education capital by one standard deviation (14 log points) raises productivity growth by around 8 log points. This effect reflects a noticeable fraction of the standard deviation in TFP growth (56.7 log points). The change in education-based human capital has a slight negative effect on productivity. Figure 4 shows that the growth effect associated with occupation-based capital is rather sizeable. It can be seen that occupation-based capital yields the same positive productivity growth in firms irrespective of whether education-based capital is set at the 2^{nd} or 8^{th} decile in the overall distribution of education-based capital.

Productivity growth does not change dramatically in the share of workers belonging to the highest quartile in work experience or in seniority in Figures 5 and 6. We can observe that the catching-up effect is twice as high when the education-based human capital interacting with the catching-up term is evaluated at its mean compared with when no interaction terms are used. The productivity effect is also potentially very strong since one standard increase in the catching-up distance (167 log points) would increase TFP growth by around 40 log points. Thus, Figure 5 shows evidence that the catching-up process is positive in line with the Nelson-Phelps type of model, i.e. s=1 in equation (4), but also depends strongly on the agglomeration of skills. We have seen that it is the other human capital that drives the growth of firms that are far from the frontier firm. These include occupation-based and unobserved human capital and intangible capital captured by the firm effect that may lead to a logistic kind of growth, i.e. s=-1 in equation (4).

Regional productivity growth may diverge when the catching-up process depends on the agglomeration of skills. We spatially allocate growth and knowledge capital embodied in the firms by using regional dummies in the growth equation. Each region dummy is given the weight of the establishment-level employment located there, relative to the total employment in the firm (regional dummies for each firm, hence, sums to unity). Some 20% of employees in establishments are located in the capital, Helsinki.

Figure 3. Education-based human capital

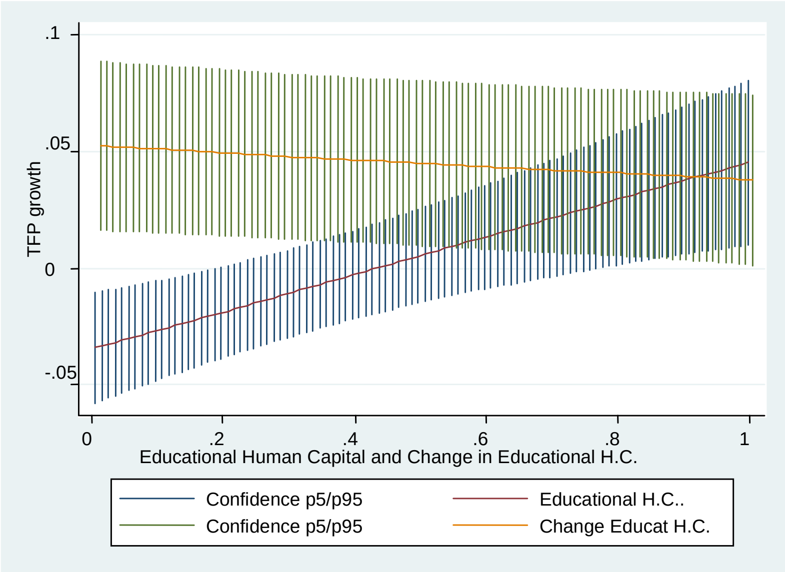


Figure 4. Occupation-based human capital

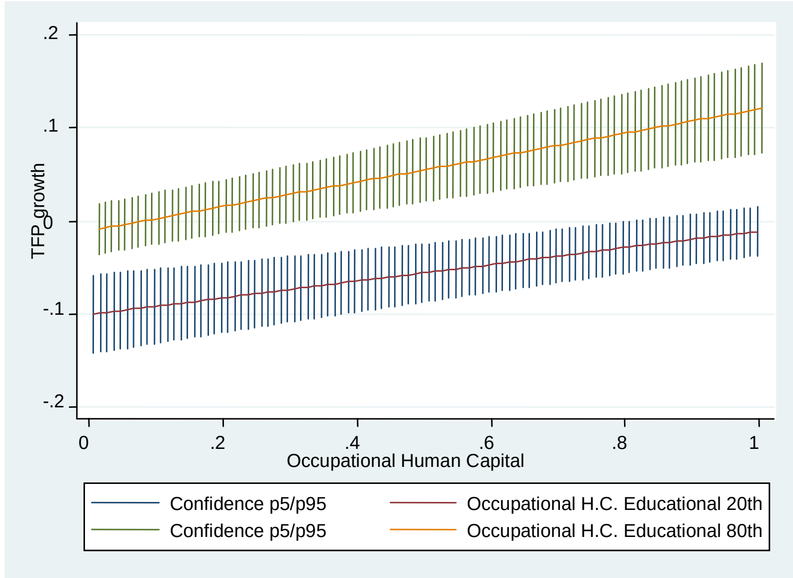


Figure 5. Catching-up and experience in the highest quartile

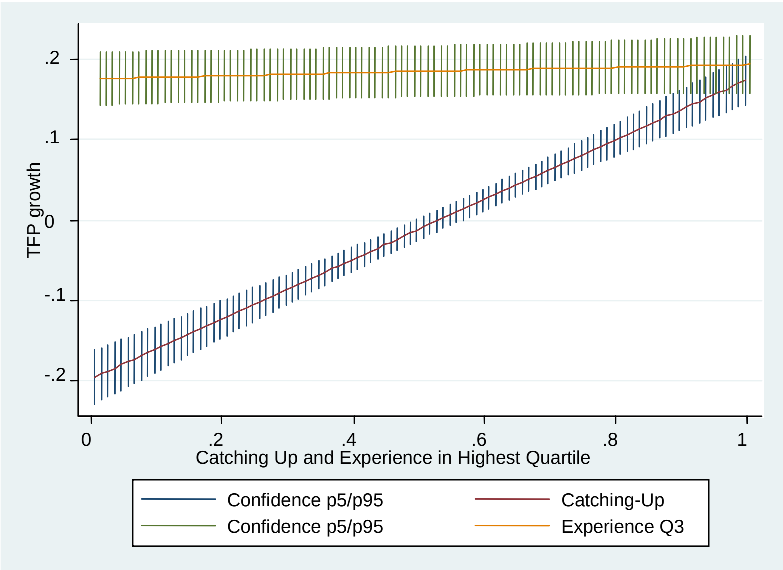
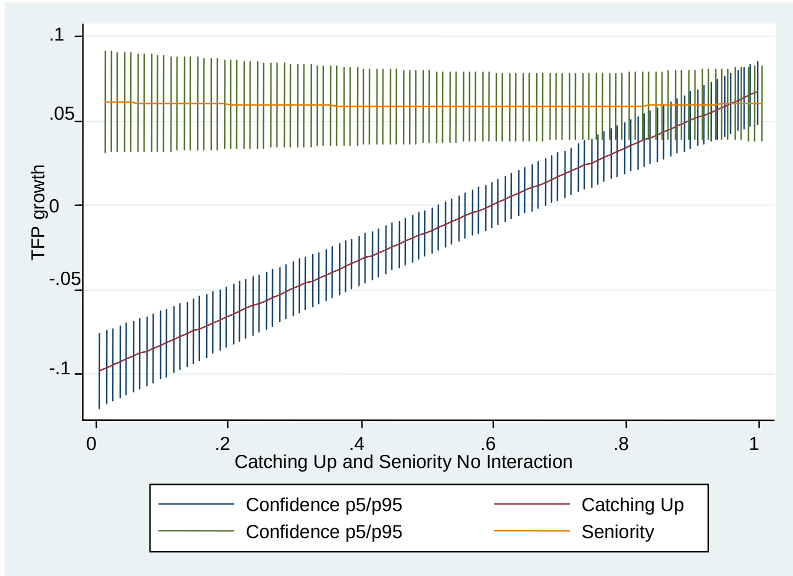


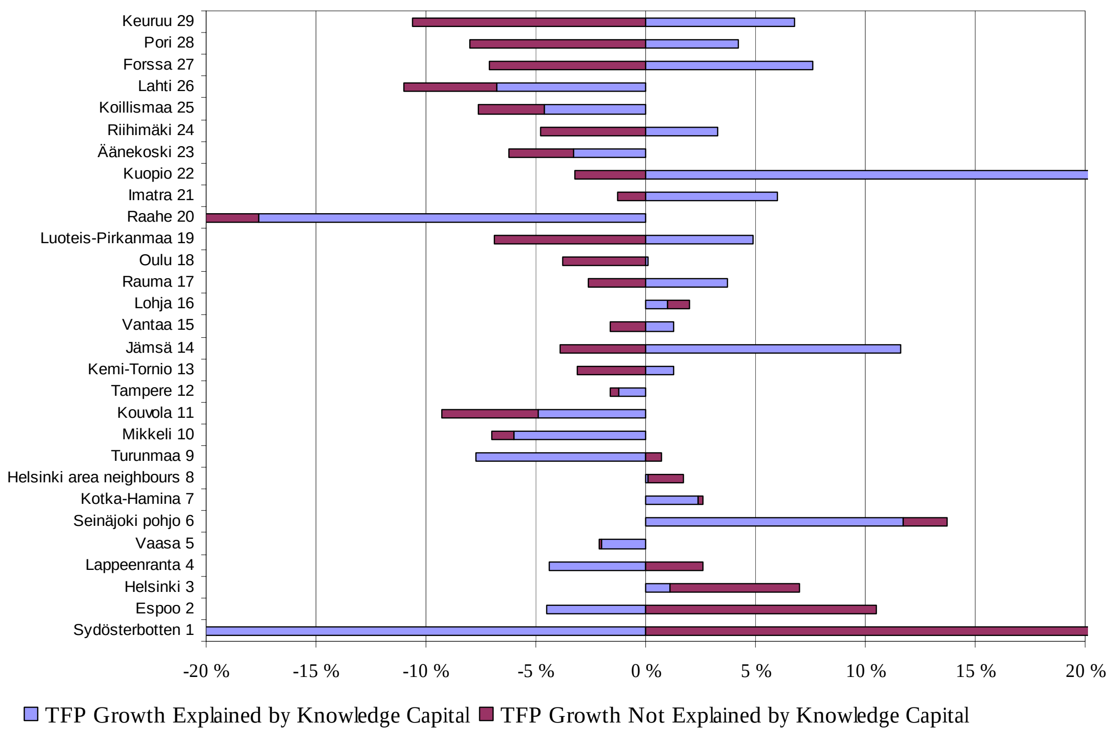
Figure 6. Catching-up and seniority, no interactions



Using the location of the head office as the reference would, instead, give a share of 50%, which is more than twice as high. In addition, we use constrained OLS regression, the purpose being that the reference is the representative employee rather than any single region. The separate constraint states that regional dummies weighted by manufacturing employment total zero. We also aggregate 85 NUTS-4 region-level dummies to 56 to combine less densely populated areas with little manufacturing.

In Figure 7 TFP growth not explained by human capital shows a coefficient for 56 regional dummies using constrained OLS estimation. The estimation simply added regional dummies to the estimation used in column 3 in Table 2 (including the interaction of industry and time dummies and dropping six regional dummies). Another estimation is similar but excludes knowledge-capital controls. Hence, all variables listed in Table 2 from catching-up to education-based capital agglomeration are dropped. The regional distribution of productivity growth, as explained by knowledge capital, is then the OLS estimate of regional dummies in the first model, including all relevant variables, subtracted by the OLS estimates of the latter. In Figure 7 the regions are arranged from 1 to 55 according to the decreasing level of TFP. (We show only every fifth region beyond the 20th most productive region.)

Figure 7. TFP growth explained – Knowledge capital and other factors in selected regions



It should be noted first that only a few of the regional dummies are significant. Nevertheless, regions in close proximity have similar characteristics. The TFP growth (the sum of that explained by knowledge capital and other factors) tends to be higher in areas where the TFP level is already high, but not always. (The correlation is 0.45.) The high-productivity, large cities of Espoo, Tampere and Oulu are not among the leaders in productivity growth. Figure 7 shows that TFP growth not explained by knowledge capital within the industry is clear in high productivity areas. (The correlation is 0.79.) In regions that are among the 25 most productive areas, factors other than knowledge capital within the industry promote productivity more than the average. This shows that the industry composition and innovative environment are also important in explaining regional growth. This is especially clear in the greater Helsinki area or within a radius of 100 kilometres from Helsinki towards Tampere. Thus, according to our results, there is a limited or even negative catching-up between the productivity levels of the different regions in Finland. This also relates to the industrial structure of a particular region and other competitiveness factors such as an innovative environment, which are examined in greater detail in Piekkola (2006).

5. Conclusions

This paper examines productivity growth driven by knowledge capital, which includes the human capital of workers and intangible capital at the firm level. Human capital is agglomerated, which explains the lack of regional convergence in productivity growth. Education- and occupation-based human capital have turned out to be the two cornerstones of productivity growth. The education-based measure of human capital used in this analysis takes into account both the share of highly educated workers and the educational premium. In line with Benhabib & Spiegel (1994 and 2005) and Brunello & Comi (2004), education provides not only an initial labour-market advantage but also a permanent advantage. The trend of firms catching up in terms of innovation is stronger and more positive for those located in geographical areas that have agglomerated human capital. The agglomeration of education-based human capital is also useful in the imitation of new technology and contributes to firms catching up, especially when they are close to the leader firm in productivity in the industry.

Education-based human capital alone plays a significant role for very advanced firms close to the leader firm at the frontier in their industry, while occupation-based human capital is important for all firms. Yet not all firms have abundant education-based human capital or highly paid professions as these are not positively correlated. Firms far from the frontier should possess unobserved human capital for their catching-up process to continue. Occupation-based, unobserved and other intangible capital in the firm can lead to a logistic-type of growth. It is also noteworthy that knowledge capital rather than the workforce employed in R&D explains the divergence in growth. This is somewhat surprising, since Kafouros (2005) finds that in the UK growth has been especially R&D-driven since 1995.

The heterogeneity of experience-based human capital explains why the overall effects on total factor productivity can be unclear. Experience-based human capital as a whole does not indicate stronger growth, while firms may find it beneficial to have both young and experienced workers. We also observe firms with high seniority levels among staff to have somewhat lower productivity growth.

In Finland, we can see that growth is concentrated in distinct regions, such as Espoo, Salo and Oulu, where the biggest mobile phone manufacturer, Nokia Corporation, has important facilities. Finland has experienced agglomeration and divergence in productivity growth at the regional level since 1995. One reason is that the catching-up process is faster for low-productivity firms in high-productivity areas with abundant education-based capital. It is evident that it is important for specific clusters of regions to have access to a regional pool of education-based human capital. It can also be argued that substantial labour mobility within countries compared with that occurring between countries may explain the regional dispersion in growth (see Ottaviano & Pinelle, 2002). Nevertheless, the productivity performance explained by knowledge capital *within the same industry* only partly explains regional performance.

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Appendix A.
Description of Linked Employer-Employee Data

Data with 3,096,771 observations cover all workers (excluding top management) who have worked for at least one year during 1996-2002 in firms that belong to the Confederation of Finnish Employers. The estimation for observations with a firm code totals 2,755,716 (181,048 were dropped for missing hourly wages, 118,243 were omitted for log wages deviating more than five standard deviations from the predicted value using experience up to the fourth potency, gender and 22 education classes, and some 40,000 observations were discarded for having no education, seniority or firm codes). This number reduces to 2,096,523 when only employees with an estimable firm-effect are included.

Variables

Total factor productivity (TFP) is the multilateral total factor productivity index, where productivity is compared with the benchmark plant in 22 industries (see text and Caves et al., 1982).

Catching-up is the difference between the TFP and the most productive firm in 22 industries.

Education-based human capital (HC) uses the relative rate of return of each educational degree in explaining the person effect and measures the share of the highly educated using these relative returns as weights

$$Educational\ HC_{j,t} = \sum_{i_t=1}^{I_t} z_{i_t \in H} u_H \eta_H \Big/ \sum_{i_t=1}^{I_t} i \quad , \tag{A.1}$$

where $z_{i \in H}$ indicates that the worker belongs to the highly educated group H (where the rates of return are indicated by the solid line in Figure 2). The difference from a pure, weighted average measure is thus that the denominator is not the number of highly educated workers, but all the workers in the firm. We also include non-technical lower-level tertiary degrees in the highly educated group. The exclusion of workers with technical lower-level tertiary degrees can be justified by the lower wages in the technology section. The selected workers closely form the share of workers belonging to the highest quartile of education-based human capital.

Education-based HC agglomeration consists of the spillover from education-based human capital defined above in region *r* and the influence of other regions. Spatial weights are based on a negative exponential function. The half-decay distance that reduces the spatial interaction by one-half is set, on average, at 122 kilometres.

Regional education-based HC in the interaction term uses the employment-weighted average of education-based HC in the region.

Unobserved HC is a person-specific fixed effect in wage estimations that cannot be explained by education or gender and is hence unobserved to the econometrician. The share above 75% is the proportion of workers in the firm above 75% in the distribution of overall unobserved human capital.

Experience-based HC shows returns to work experience, which is age, having subtracted years in education (from 7 to 14 according to the educational degree attained) and minus 6 years. Shares below 25% and above 75% are defined as for unobserved HC.

Gender HC refers to the relative log wages of men.

The firm effect is obtained from coefficients for firm dummies and assessed as a deviation from the grand mean in each firm group (e.g. in a firm group, two firms are linked by a job transferee and these two firms are linked to a third firm by a job transferee). The worker-level firm effect is the deviation from the individual mean.

Occupation-based HC is based on occupational movement that may also include job transferees.

Seniority is the job duration in the firm. Firm creations and dissolutions are considered as a mere transfer of the firm, in instances where persons employed either at the old firm at date t-1 or at the new firm at date t constitute more than 40% of all employees in these firms at dates t-1 and t. These unnatural states account for about 3% of all firm creations and dissolutions. Many of the old or new firms are large, and hence, recoding will affect 9% of the employees.

Table A.1 Estimates of the effects of experience, year, individuals and firms on the log of wages for 1996 to 2002 with plant dummies and person-effects

	First-Stage Eqn (8)		Second-Stage Eqn (9)	
Variable	Coefficient	t-value	Coefficient	t-value
Experience/10	1.239	(67.7)***	1.272	(195.4)***
$\text{Experience}^2/100$	-0.438	(40.9)	-0.457	(116)***
Experience^3 / 1000	0.081	(23.2)***	0.088	(72.8)***
Experience^4 / 10000	-0.006	(15.2)	-0.006	(50.9)***
Seniority/1000	0.361	(5.2)***	0.214	(5.4)***
Seniority/10000	0.052	(6.6)***	0.028	(6)***
Performance Related Pay	0.023	(21.9)***	0.026	(70.9)***
R&D Work	-0.063	(2.6)	-0.016	(4.3)***
Blue-Collar Work	0.213	(27)***	0.233	(84)***
Other White-Collar Work	0.028	(3.6)***	0.036	(13.5)***
Management Accountancy	-0.008	(1.2)	-0.012	(4.9)***
Invoicing	-0.028	(3.8)	-0.019	(6.7)***
Secreterial	-0.016	(2.9)	-0.014	(6.8)***
Construction	0.072	(2.8)**	0.035	(8.1)***
Planning	-0.010	(1.6)	0.009	(3.8)***
Logistic	0.012	(3)**	0.008	(6.7)***
Customer Service	0.003	(1.4)	-0.006	(2.8)**
Marketing	0.004	(0.4)	0.013	(4.2)***
Information, data processing	-0.014	(1.7)	-0.003	(1.2)
Legislation 1	0.017	(3.6)***	0.025	(17.9)***
Legislation 2	-0.008	(0.9)	0.002	(0.6)
Office work 1	-0.005	(0.6)	0.009	(3)**
Office work 2	0.003	(0.3)	0.015	(4.9)***
Office work 3	-0.001	(0.2)	0.008	(2.7)**
Personnel Policy Work	-0.016	(1.6)	-0.006	(1.9)
Buyer	0.013	(1.3)	0.024	(6.9)***
Psihat			0.045	(27.2)***
Observations	285,730		2,096,523	
Chow test between (289,031 obs) movers and non-movers (1,919,171 obs) in Eqn (9)			F-value 12.180	Pr > F <0.0001
R squared	0.157		0.136	

Estimation includes 1,421 firm dummies and time dummies. * Significant at 95% level, ** Significant at 99% level, *** Significant at 99.9% level.

Source: Author's calculations based on data from the Confederation of Finnish Employers.

Table A.2 Education effects

Variable	Coefficient	Std
Intercep	-47.289	(69)***
Upper Secondary Level		
General	0.474	(183.2)***
Teacher	0.099	(20.1)***
Humanities, Arts	0.100	(21.9)***
Natural Science	0.196	(9.6)***
Technology	0.194	(106.6)***
Health, Services, Agriculture	0.211	(62.6)***
Lowest Level Tertiary	0.075	(8)***
General, Teacher		
Humanities, Arts	0.294	(100.1)***
Natural Science	0.585	(44.7)***
Technology	0.207	(69.1)***
Health, Services, Agriculture	0.332	(38.1)***
Lowest-Degree, University	0.265	(30.5)***
General, Teacher		
Humanities, Arts	0.621	(95.8)***
Natural Science	0.414	(18.1)***
Technology	0.554	(184.9)***
Health, Services, Agriculture	0.608	(30.8)***
Highest-Degree, University	0.651	(80)***
General, Teacher		
Humanities, Arts	0.907	(163.2)***
Natural Science	0.772	(90.6)***
Technology	0.867	(231)***
Health, Services, Agriculture	0.893	(36.1)***
Doctoral Level	0.872	(78.2)***
Gender Effect	-0.191	(119.3)***
Number of Observations	142,810	
R-Squared	0.35	

* Significant at 95% level, ** Significant at 99% level, *** Significant at 99.9% level.

Source: Author’s calculations based on data from the Confederation of Finnish Employers.

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PRAXIS	Center for Policy Studies, Tallinn, Estonia
RCEP	Romanian Centre for Economic Policies, Bucharest, Romania
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ENEPRI publications are partially funded by the European Commission under its Fifth Framework Programme - contract no. HPSE-CT-1999-00004.

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