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ELINKEINOELÄMÄN TUTKIMUSLAITOS
THE RESEARCH INSTITUTE OF THE FINNISH ECONOMY
Lönnrotinkatu 4 B 00120 Helsinki Finland Tel. 358-9-609 900
Telefax 358-9-601 753 World Wide Web: http://www.etla.fi/

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Hannu Piekkola*

KNOWLEDGE CAPITAL

AS THE SOURCE OF GROWTH

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* The Research Institute of the Finnish Economy ETLA, Lönnrotinkatu 4B, 00120 Helsinki, Finland, E-mail: hannu.piekkola@etla.fi

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ABSTRACT: This paper uses micro-level linked employer-employee data for Finland to assess knowledge capital in firms and the growth driven by it. The high-productivity firms utilise education human capital and especially in imitative growth. Low-productivity firms – far from frontier firms in the industry – need high-ability workforce and other kinds of intangibles for productivity growth. We thus find a qualitative shift away from unobserved human capital and intangibles towards the use of education human capital as the growth of productivity continues and the firm bridges the gap to the frontier firms.

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1. Introduction

This paper examines the role of knowledge capital for productivity growth in Finnish companies. Growth is concentrated in the Greater Helsinki region, which is 12%-13.5% more competitive than other areas; see Piekkola (2005c). The more IT-intensive regions of Oulu and Salo are also among the most competitive locations in Finland. It can be argued that the concentration of growth in the urban centres is related to the increasing role of knowledge in economic growth from the beginning of 1990s. This is particularly true for Finland, which is ranked as one of the most competitive countries in the world, see Global Competitiveness Report 2004-2005 (www.weforum.org/gcr). One attribution of this is high tertiary enrolment, as Finland exhibits a distinct increase in the attainment levels for higher educational as compared to the rest of Europe (see, for example, comparisons across countries at the NUTS-2 level in Badinger and Tondl, (2002)). Finland can also be said to be an R&D-driven economy and innovative activities are thus an important source of growth; see Lehto (2000).

This study uses for Finland linked employer-employee data which, starting with Abowd, Kramarz and Margolis (1999), have been used extensively to study human capital formation. Linked employer-employee data allow the analysis of knowledge capital composition that includes returns from individual- and firm-specific experience and occupational careers. Human capital specific for the workers includes education, experience, unobserved and occupation human capital. Similarly to Abowd et al. (2003), human capital of workers can also be used to categorize companies according to the share of workers below the 25th and above the 75th percentile for overall human capital.

Intangible capital specific for the company includes R&D and specific type of work organisation such as performance-related pay.

The growth of productivity within Finnish companies is explained by two basic hypotheses: (i) the most important constituents of knowledge capital are education human capital – measured in efficiency units for various educational degrees and different fields – and returns to occupational careers and their strong interlinkage, (ii) agglomeration of human capital should support growth. We also analyse separately growth in IT sector and in firms close to technology frontier. This relies less on physical capital investment and more on innovation-based strategy analogously to Acemoglu, Aghion and Zilibotti (2006). In their study innovative firms use short-term relationships, younger firms, less investment, and better selection of firms and managers. Our focus is here the knowledge embedded in employees, where only part is shown to be important in innovative growth.

The rest of the paper is structured as follows: Section 2 presents the data and estimation strategy. Section 3 presents the results of the estimation. Section 4 concludes.

2. Estimation of Knowledge and Productivity

We are interested in evaluation the growth effects of knowledge capital. Individual heterogeneity in wage formation is used to assess the returns to education, experience, occupation including R&D work. We also use information of those individuals who move from one firm to another to get information of knowledge capital embedded in firms. After assessing the returns to various ingredients of knowledge capital, we use the knowledge capital structure of firms to explain total factor productivity growth. In the first-stage estimation sufficient data to get information on knowledge capital in firms is to include only job switchers in the analysis. Firm dummies capture the intangible capital in the firms when we eliminate worker heterogeneity by taking the deviations from individual means. In second-stage, we use estimation of all the workers and include in this firm-effects estimated at first stage. We thus use the two-step method suggested by Andrews *et al.* (2004).[1] The dependent variable is the natural log of the hourly wage $\ln(y_{ijt})$ of an individual *i* working in firm *j* at time *t* measured as a deviation from the individual mean wage μ_{yi} over the time period. This is expressed as a function of individual heterogeneity, firm heterogeneity and measured time-varying characteristics as a deviation from the individual mean.

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

$\beta(x_{it} - \mu_{xi})$ shows the compensation for time-varying human capital stated as a deviation from the individual mean human capital, $\gamma(w_{it} - \mu_{wi})$ shows the respective time-demeaning for all firm-specific variables and 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}. e_{ijt} represents a statistical error term. It should be noted that $D_{it}^j - \mu_{Di}^j$ would have been zero for any worker i who did not change firms. Time-varying human capital includes work experience up to the fourth potency and 18 occupational categories where the fixed effect estimation uses the returns when switching from one occupation to another. Work

[1] Alternatively, Abowd *et al.* (2002) develop a numerical solution to deal with the large set of firm dummies in the Least Squares Dummy Variables Estimator.

experience is increasing in age, while time spent on education is deducted from this. Time-varying firm characteristics include seniority, performance-related pay and the share of R&D employees, see Appendix A for the definition of the variables.

The firm effect is thus measured at first stage estimation within a group of firms where there is worker movement between firms. (In the group, two firms are linked by a job transferee and these two are linked to a third firm by another job transferee etc.) In each group of firms, if firm dummies are used, the firm effect is defined with respect to a reference (omitted) firm. Following Abowd *et al.* (2002), we assume that the average effect is similar across groups and take the firm effect $\hat{\psi}_j$ as a deviation from the overall mean of each group. Almost all, 99.8%, belong to the largest pool, where firms are linked to each other via job transferees. 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, is placed in the following equation

$$\ln(y_{\mathrm{ijt}}) - \mu_{wi} \;=\; \beta(x_{it} - \mu_{xi}) + \gamma(w_{it} - \mu_{wi}) + \delta(\hat{\psi}_{j(i,t)} - \mu_{\psi i}) \; + e_{ijt} \;, \qquad (2)$$

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. The estimation of the first-stage wage equation (1) is shown in column 1 in table A.1 in the appendix.[2]

2 Given the data dimension of 1,421 firm dummies with worker mobility, it was not possible to solve even the reduced two-step method suggested by Andrews *et al.* (2004) with the STATA econometrical package in the Windows environment. Instead, we adopted an analogous estimation procedure using the SAS system.

Results from the second-stage estimation (2) 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 differ much from the coefficients for the larger sample that also included non-movers (see columns 1 and 2 in table A.1). The table also reports the Chow test for the estimation distinguishing between movers and non-movers, indicating that the coefficients are not statistically different from each other. 17 of the 18 occupations are for white-collar workers. In the data covering mainly manufacturing, it is seen that earnings on average are higher in the blue-collar occupation than in the white-collar occupations. Much of the difference would vanish in level estimation. Major part of the 95,000 person-year observations for mobile blue-collar workers is in fact job mobility from or to white-collar work very similar to blue-collar work. Half of the mobility also takes place in postal traffic and graphic industry. It is also seen that in white-collar work, maintenance of estate and machine and production task jobs are also well-paid. Finally, the returns to R&D work are fairly low.

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

$$\theta_i = Int + z_{i\in e} u_e \eta_e + u_2 Gen_i + \varepsilon_i \ , \qquad (3)$$

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 educational group (zero otherwise),

Gen_i indicates gender and ε_i is the statistical error. Five education levels are identified for five fields. Unobserved human capital is the person effect that cannot be explained by education and 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 $\mathrm{cov}(\alpha_i, \eta_e)$ =0 and $\mathrm{cov}(\alpha_i, Gen_i)$ =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 and unobserved human capital.

In measuring productivity we apply the multilateral total factor productivity index (TFP) 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

$$d \ln A_{j,t} = \ln(A_{j,t}) - \ln(A_{j,t-1}) \text{ , where} \tag{4}$$

$$\ln(A_{j,t}) = \ln(\frac{V_{j,t}/L_{j,t}}{\bar{V}_{j,t-1}/\bar{L}_{j,t-1}}) + \frac{S_{j,t}+\bar{S}_{j,t-1}}{2}\ln(\frac{K_{j,t}/L_{j,t}}{\bar{K}_{j,t-1}/\bar{L}_{j,t-1}}), \tag{5}$$

and where $V_{j,t}/L_{j,t}$ = labour productivity, $K_{j,t}/L_{j,t}$ = capital intensity and $S_{j,t}$ = one minus labour cost share of value added. 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 gives a second-order approximation of the true but unknown production function. The index is exact if the true production function is translog. The TFP index is measured relative to a company representative of the industry and should not depend on the cyclical variation in the utilisation rate of inputs. The TFP measure also gives a lower weight to catching-up, since productivity is measured within industries, i.e. individually for industries with low and high productivity. Governmental policy to stimulate catching-up and replication only can be a disincentive to successful innovations by making them more short-lived and less profitable. Davidson and Segerstrom (1998) argue that only innovative R&D subsidies lead to faster economic growth. Leading technology is assessed for 19 industries.

Firms included in the data are members of the Confederation of Finnish Industries and 75% of these are from the manufacturing sector. Kangasharju and Pekkala find that an analysis of the manufacturing industries can also provide the key for explaining the regional disparities in growth in Finland. The original data with 3.09 million observations cover nearly one-fourth of private sector employment over the years 1996-2002. Nearly all of the manufacturing sector firms with more than 30 employees as well as some of the major service sector companies are covered. The data include a rich set of variables covering compensation, education and profession. White-collar employees receive salaries and blue-collar workers are remunerated on an hourly basis. Employee data are linked to the financial statistics data from the Balance of Consulting and Suomen Asiakastieto, to include mainly information on value added and capital intensity (fixed assets), see Appendix A for more detailed data description.

Table A.2 in the appendix shows the estimation results. As is seen, returns to education increase monotonously with the educational level, at least within the educational fields. All workers with higher university education, except those in the health and service sector, belong to the highest quartile in the distribution of education human capital for all workers.

3. Explaining Growth by Knowledge Capital

The most commonly used measure of human capital is education human capital. It is interesting to see how other human capital is distributed by education level. It is natural that experience-based human capital decreases with the education level. Unobserved human capital, by the design of the model, is fairly evenly distributed among the education classes. Table 1 summarizes the human capital in Finnish firms and related correlations (data for 1,421 firms with an estimable firm effect covering 2.10 million employees.) Variables as described above are also listed in Appendix A.

Table 1. Human Capital in Finnish Firms and Correlations

Variable	Person Effect	α	ψ	Education Human Capital	Occupat. H.C.	R&D Work
Mean	1.176	1.187	0.039	0.114	0.147	-0.001
Firm Average Mean	1.110	1.135	0.105	0.150	-0.001	0.000
Std	0.491	0.425	0.276	0.106	0.101	0.004
Firm Average Std	0.397	0.375	0.118	0.070	0.002	0.000
Mean Blue-Collar	1.153	1.240	0.076	0.231	0.000	0.000
Mean White-Collar	1.207	1.118	0.163	0.037	-0.003	0.000
Person Effect	**1**	0.87	-0.46	0.19	-0.06	-0.19
Unobserved Human Capital α	0.87	**1**	-0.55	0.01	0.13	0.01
Firm Effect ψ	-0.46	-0.55	**1**	0.11	-0.01	-0.06
Education Human Capital	0.19	0.01	0.11	**1**	-0.40	-0.50
Occupational Human Capital	-0.06	0.13	-0.01	-0.40	**1**	0.36
R&D Work	-0.19	0.01	-0.06	-0.50	0.36	**1**
TFP	0.11	0.06	0.18	0.31	0.10	-0.11
TFP Close to Frontier	0.17	0.08	0.18	0.48	-0.16	-0.26
TFP Far from Frontier	0.02	0.03	0.15	0.00	0.38	0.17
TFP Growth	-0.02	0.00	0.06	-0.08	0.12	0.09
Hirings	0.05	0.03	-0.07	0.09	-0.08	-0.08
Separations	0.00	-0.01	0.02	0.04	0.02	-0.02

Table includes 0,96 million blue-collar and 0.74 million white-collar workers. Firm-average is for 1,110 firms.

Abowd *et al.* (2001) find that the firm effect, ψ_i, a measure of intangible capital, is positively related to the level of human capital (and to the person effect), but here the correlation is negative in accordance with most of the empirical literature. (See, for example, Gruetter and Lalive (2003), Barth and Dale-Olsen (2003) and Andrews, Schank and Upward (2004).) The firm effect has negative correlation in particular with the unobserved human capital (correlation of -0.55). However, the firm effect is positively correlated with the education human capital. One expects that high-wage firms are forerunners of the industry and these firms have large share of highly educated. It can also be seen that highly educated are generally located in firms that have high level of hirings and separations.

It is seen that all human capital components are positively related to total factor productivity. Firms with large share of their white-collar workers in R&D related work also have large share of blue-collar workers. R&D related work is positively correlated with occupational human capital, which is highest for blue-collar workers. The combination of R&D intensive manufacturing firms and highly-paid blue-collar workers is unambiguously related to total factor productivity level. As total factor productivity is measured within an industry, it is not surprising that most blue-collar worker intensive firms within the particular industry are not among the most productive.

An important distinction here is firms that are close to the frontier firm and far from it (see following section). We do this separation by dividing firms by the median value of the productivity gap between top firm and the catching-up firm in the industry. This gives a larger selection of innovative firms from industries, where productivity differences are narrower. This can relate either to homogeneity of the industry or to greater competitive pressure. The innovative firm is thus not defined in respect of productivity in the industry but also in respect of the firm being located in an industry with narrow productivity band. We can see that firms that are close to the top in productivity measured this way have education human capital and other firms use occupation human capital. This also roughly follows a division to white-collar abundant and blue-collar abundant firms as occupational human capital decreases with the education level. It should be also noted that within the blue- and white-collar groups, the correlation between education and occupational human capital is, in contrast, close to zero (not reported).

IT industry - the most innovative part of manufacturing - has played an important role in the new economic growth. Nokia Ltd., the biggest company in Finland, is responsible for 61% of the total value added of the IT industry worldwide and 29% of overall employment. Nokia Ltd. has the biggest plants in six locations: Espoo, Helsinki, Tampere, Oulu, Jyväskylä and Salo. Table 2 summarizes the human capital in IT firms and its related correlations. The firms given in Table 2 account for 30% of the value added and 19.5% of overall employment of the companies that are members of the manufacturing section of Confederation of Finnish Employers (included in these figures are foreign activities which on the part of Nokia implies that 50% of its total employment is foreign-based).

Table 2. Human Capital in Finnish IT Firms and Correlations

Variable		Person Effect	α	ψ	Education Human Capital	Occupat. H.C.	R&D Work
Mean		1.301	1.208	0.041	0.229	0.079	-0.005
		1.218	1.146	0.005	0.218	0.097	-0.004
Std		0.458	0.353	0.199	0.154	0.087	0.007
		0.313	0.297	0.291	0.167	0.069	0.004
Mean Blue-Collar		1.199	1.296	-0.005	0.156	0.229	0.000
Mean White-Collar		1.330	1.184	0.054	0.250	0.036	-0.006
Person Effect		**1**	0.76	-0.10	0.32	-0.09	-0.32
Unobserved Human Capital	α	0.76	**1**	-0.32	0.03	0.14	-0.01
Firm Effect ψ		-0.10	-0.32	**1**	0.50	-0.15	-0.27
Education Human Capital		0.32	0.03	0.50	**1**	-0.25	-0.52
Occupational Human Capital		-0.09	0.14	-0.15	-0.25	**1**	0.32
R&D Work		-0.32	-0.01	-0.27	-0.52	0.32	**1**
TFP		0.33	0.18	0.41	0.65	0.18	-0.28
TFP Close to Frontier		0.28	0.15	0.21	0.51	-0.14	-0.28
TFP Far from Frontier		0.16	0.08	0.18	0.48	0.53	-0.07
TFP Growth		0.03	0.01	0.10	0.08	0.13	0.00
Hirings		0.08	0.07	-0.02	0.06	-0.05	-0.05
Separations		0.08	0.05	0.14	0.14	0.01	-0.08

Table includes 63,000 blue-collar and 221,000 white-collar workers. Firm-average is for 141 firms (685 year observations). ICT sector includes in NACE2002: Manufacture of insulated wire and cable 313, Manufacture of electrical equipment n.e.c. 321,322, 323, Manufacture of medical, precision and optical instruments 331,332,333, Telecommunications 642, Computer and related services 72, Research and development 73, Service in business activities 742,743 744,748.

It can be noted that IT workers have more human capital and a higher level of education. It also more clearly relates to total factor productivity and to its growth than for all firms on average. In IT firms, blue-collar workers constitute the minority and therefore occupational human capital level is lower in these firms than in non-IT firms. It is also seen that unobserved human capital and firm-effect are less negatively correlated (-0.32), and education human capital and firm-effect much more positively correlated (0.50) than in all firms on average. Both the education human capital and firm-effect correlates positively with total factor productivity and its growth. High productivity IT firms can be said to be characterised by highly-educated workers located in high-wage firms. It is seen that the puzzle of having negative correlation with firm-effect and person-effect applies only to the use of unobserved human capital.

We now turn to econometric estimation of the determinants of productivity growth at firm level. The explanatory variables include those reported above such as individual human capital (education, unobserved, experience, occupation) and firm-level human capital (firm effect, performance-related pay PRP, returns to R&D). The empirical testable specification may be written following Nelson and Phelps (1966), Griffith et al. (2003) and Benhabib and Spiegel (2005) as

$$\begin{aligned} d\ln A_{j,t} &= b + \beta_1 \ln H_{j,t} + s\beta_2 \ln H_{j,t} \left(\ln\left(\frac{A_{M,t}}{A_{j,t}}\right)^s - 1 \right) \\ &\quad + \beta_3 \ln F_{j,t} + \beta_4 Agglo_{r,t} + \mu_T + \mu_I + \varepsilon_j \\ &= b + (\beta_1 - s\beta_2)\ln H_{j,t} + s\beta_2 \ln H_{j,t} \ln\left(\frac{A_{M,t}}{A_{j,t}}\right)^s \\ &\quad + \beta_3 \ln F_{j,t} + \beta_4 Agglo_{r,t} + \mu_T + \mu_I + \varepsilon_j \quad , \end{aligned} \tag{6}$$

where β_1, β_2 are the coefficients for the component of TFP that depends on the level of knowledge capital $H_{j,t}$ in firm *j* at period *t* with catching-up depending on $s\beta_2$, β_3 is the coefficient for the component of TFP that depends on the level of knowledge capital with no catching-up $F_{j,t}$, β_4 is the coefficient for agglomeration of knowledge capital in region *r*, μ_I is industry specific effects and μ_T is time specific effects. $\ln(A_{Mt} / A_{jt}) - 1$ shows the productivity gap to frontier firm, which is the leader firm M in the industry in productivity. We expect the coefficient $s\beta_2$ to be positive in a Nelson-Phelps type model of technology diffusion; *s* thus equals one.

Benhabib and Spiegel (2005) also present alternate catch-up of a logistic model of technology, where s equals -1. In the logistic specification the relative importance of the catching-up process is similarly decreasing at knowledge capital level. The distance to the frontier firms, however, creates a non-linear relationship between technological capital and catching-up. At a sufficiently high enough catch-up rate ($-s\beta_2$ high enough), the leader will pull other market entrants towards the same technological level and productivity differences will converge. If the catch-up rate is slow enough, 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.

Knowledge capital with catching-up $H_{j,t}$ is assumed to be a function of the education, the occupation human capital and a function of the fraction of workers above the 75th percentile for unobserved and experience human capital across firms over the period. Knowledge capital with limited catching-up process $F_{j,t}$ is assumed here to include the firm effect $\psi_{j,t}$ in addition to the time-specific firm-level human capital explained by seniority, performance-related pay and R&D work. These capture intangible human capital engaged in the human resource management and innovative capabilities, which are not transferable across firms.

In what follows, we measure education human capital for highly educated in efficiency units by taking into account the relative rate of return in each highly educated group. This differs from a compensation-weighted average figure in that the denominator is not the number of highly educated workers, but all the workers in the firm (see Appendix A for further details).We also include regional knowledge capital agglomeration, $Agglo_{r,t}$, which may also relate to the catching-up process, where subscript r indicates region r (1,…,R). This consists of the spillover from education 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 and Niebuhr (2000). The half-decay distance that reduces the spatial interaction by one-half is set, on average, at 122 kilometres for education human capital (twice as high in Northern Finland where distances are long).

Acemoglu, Aghion and Zilibotti (2006) argue that innovative firms use short-term relationships, are younger, use less investment, and have better selection of managers. We measure here average seniority rather than seniority payments. A low value for seniority is also indicative of a young firm. Otherwise, we do not measure these characteristics although expect low productivity firms rely more on physical investments than on innovations.

We use OLS estimations with the average employment as weight, thus placing greater emphasis on large firms (except in column 3). In the estimation sample, we include the 799 firms with no estimable firm effect. The inclusion of these firms was necessary in the sample of IT industry, but does not otherwise change the basic results and represent a small fraction (0.12 million) of the total 1.92 million employee-year observations. We directly control for the person- and firm-effects and therefore random or fixed effect estimations were unnecessary. Random effects estimation also yields very similar results to the OLS but with no employment weights. Table 3 shows the estimation results of (6) in explaining firm-level growth.

Table 3. Total Factor Productivity Growth

		Basic	No Firm Weights	Far from Frontier	Close to Frontier	IT Industry
Constant	-1.231**	-1.175***	-1.079***	-1.479***	-1.094**	-0.569
	[2.3]	[2.6]	[14.1]	[5.1]	[2.5]	[0.6]
Catching-Up Leading Firm	0.158**	0.159**	0.198***	0.182***	0.174*	-0.059
	[2.0]	[2.0]	[22.2]	[5.5]	[1.8]	[0.6]
Catching-Up, Education H.C. Agglomeration		0.202***	0.138*	-0.207	0.408**	21.828***
		[2.7]	[1.7]	[1.1]	[2.2]	[3.0]
Catching-Up, Region TFP		-0.018	0.004	-0.01	-0.035	-0.335***
		[1.6]	[0.9]	[1.2]	[1.2]	[2.8]
Education Human Capital	0.887**	0.37	0.125	0.561	0.51	1.508
	[2.1]	[0.9]	[0.8]	[1.0]	[1.0]	[0.4]
Education H.C., Occupational H.C.*10		0.732*	0.350**	0.577	0.906*	-0.895
		[1.9]	[2.6]	[1.5]	[1.8]	[0.4]
Education H.C., R&D Work*1000		-0.125	-0.088***	0.012	-0.13	1.215**
		[1.4]	[3.3]	[0.1]	[1.3]	[2.2]
Education H.C. Agglomeration	-0.563***	-0.937***	-0.517	1.311	-1.220***	-84.516***
	[2.9]	[2.9]	[1.3]	[1.2]	[2.8]	[3.0]
Workers Above 75% for Unobserved H.C.	-0.014	0.019	-0.013	0.372***	-0.146	0.364
	[0.1]	[0.2]	[0.3]	[3.1]	[0.8]	[0.5]
Workers Above 75% for Experience H.C.	0.211	0.267	-0.015	0.007	0.333	-1.284
	[0.9]	[1.2]	[0.2]	[0.0]	[1.1]	[1.2]
Firm Effect	-0.005	0.021	0.037	0.242***	-0.091	-0.674
	[0.1]	[0.3]	[1.2]	[2.9]	[0.7]	[1.0]
Occupational Human Capital	0.872**	0.001	0.710***	0.835	-0.116	1.72
	[2.3]	[0.0]	[3.9]	[1.4]	[0.2]	[0.4]
PRP Returns*10	-0.828*	-0.761*	-0.145	-0.571**	-0.836*	-1.189
	[1.8]	[1.9]	[1.3]	[2.6]	[1.8]	[1.0]
R&D Work Returns*1000	0.013	0.073	0.036***	-0.008	0.089	-0.443**
	[0.8]	[1.4]	[3.5]	[0.2]	[1.5]	[2.4]
Seniority/100	-0.941*	-1.116**	-0.214	-0.416	-1.633*	1.76
	[1.7]	[2.1]	[1.3]	[0.9]	[1.7]	[1.4]
Seniority Squared/1000	0.066	0.169	0.127*	0.221	0.232	-0.646
	[0.3]	[0.6]	[1.9]	[1.2]	[0.5]	[1.0]
Firm Size	0.064***	0.072***	0.033***	0.056***	0.075***	0.178**
	[3.8]	[3.4]	[5.8]	[3.9]	[3.3]	[2.5]
Observations	6557	6557	6557	3168	3389	539
R-squared	0.163	0.17	0.11	0.143	0.206	0.689

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

The basic estimation in column 2 is the preferred model, while the first column excludes interaction terms. Column 3 uses no weights. We also evaluate the human capital that is important for firms close to or far from the frontier firm, and firms are grouped according to the median value of the productivity gap (columns 4 and 5) as well as separately for the IT industry in column 6.

As can be seen from column 1 in table 3, firms with more education capital generate stronger growth. In columns 2-3 education and occupational human capital interact, having a positive effect on growth. The coefficient for education human capital is no longer significant. This shows that a high level of education is interlinked with a professional career (among the educated) and that occupational human capital is not firm-specific, but rather individual-specific. The importance of education human capital cannot be interpreted in terms of pure labour productivity augmenting technology, since it is the level of, and not the rate of change in, education and occupational human capital that is important. We find the *growth* of education capital to be insignificant or negatively related to TFP growth and is therefore excluded from the estimation. The occupation human capital is positively related to growth, which was reinforced by the positive interaction to education human capital. It is likely that the growth effect is stronger in small firms, as indicated by estimation with no firm weights (column 3).

The human resource practices in a firm, as explained by performance-related pay (PRP), do not play a very important role in the growth process. One explanation can be that in this study we do not consider the differences in the level of PRP per worker, whereas in fact the share of workers engaged in PRP. Piekkola (2005a) finds that the benefits have to be sufficiently high in order to increase productivity, which is rarely the case. Similar reasoning applies to returns to R&D, since we assume the same level of benefits per worker in all the firms. Firms with a very high share of R&D workers do not appear to grow stronger. In Piekkola (2005b), however, the relationship appears unlinear so that high-enough R&D worker share is positively related to higher growth. The exception is also smaller firms, as can be seen from the positive coefficient when no firm weights are used (column 3).

A natural consequence of the Benhabib-Spiegel model is that imitation is more important for firms lagging behind the frontier firms, whereas high-productivity firms have to invest more in innovation, as for instance investing in the education of employees, in order for the growth to continue. As is seen from table 3 (columns 1 to 5), low-productivity firms appear to be able to catch up with the top-productivity firms in the industry. However, later in Monte Carlo simulations, we find the true effects to be meagre with large confidence intervals. We can see that the human capital relevant for catching up can also differ among low and high-productivity firms. The interaction of the catching-up term with education human capital agglomeration is positive; particularly for IT firms (column 6), but not at all for firms far from frontier firms (column 4). Agglomerated education human capital in catching-up is also important for firms approaching the productivity level of the frontier firm (column 5). The use of highly educated does not especially promotes innovative growth. We rather argue that education human capital promotes *imitative* growth of *high-productivity* firms.

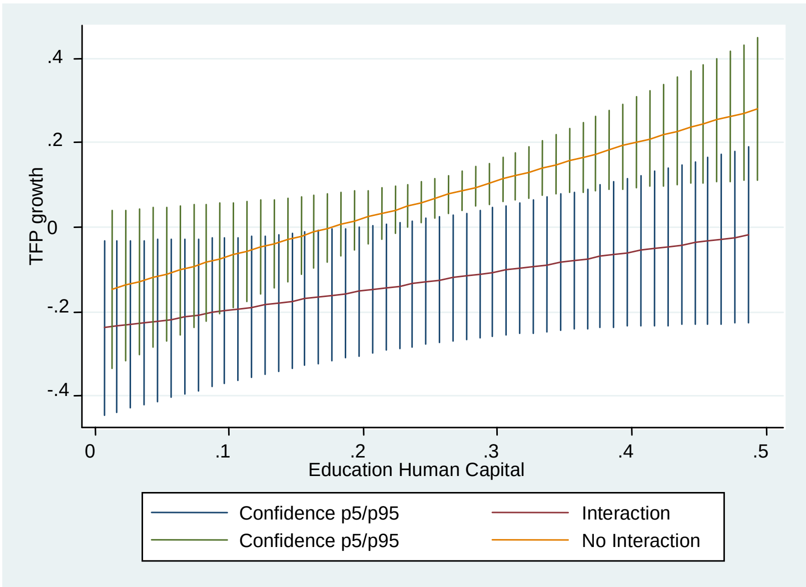
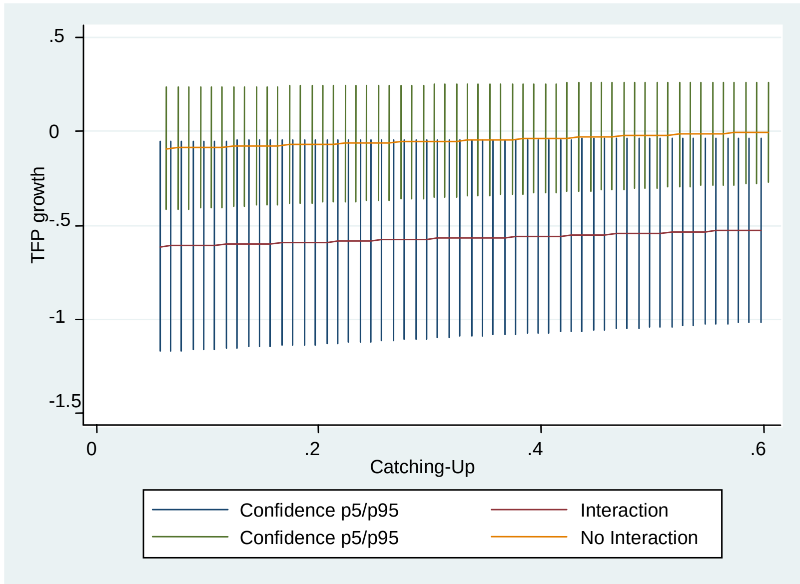
We also find a qualitative shift away from unobserved human capital and intangibles towards the use of education human capital as productivity growth continues and the firm becomes closer to the frontier firms. The unobserved components of technology (intangible capital, managerial ability) are captured by firm effects and other firm-level characteristics: R&D and performance-related pay (PRP). Firm effect and unobserved human capital appear to explain growth in firms far from frontier firms (column 4). This implies that firms have high-wage workers, where the high level of wages is not solely explained by workers having high level of education. Education human capital does not enhance catching up. All this leads to logistic type growth among the low-productivity firms.

We can conclude that high-productivity growth firms are characterised not only by a high share of educated workers but also by highly paid professions, while growing low-productivity firms in particular are characterised by workers with unobserved human capital and by intangible capital. The shortage of educated workforce is not the only bottleneck to continuing growth, and on the part of low-productivity firms it is even less so. Educated workforce is used for imitative growth in innovative firms. The relative share of a skilled workforce or extensive measures such as the coverage of employees engaged in PRP or the share of R&D workers (captured here to large extent by the returns to R&D) are not very good approximates for human capital.

Finally, it is can be seen from table 3 that the share of workers representing the highest quartile of experience-based human capital has an insignificant effect on growth in columns 1-6. We also note that seniority has a non-linear effect so that young firms with low average seniority do not reach the fast growth track immediately. A part of the logistic type of growth can indeed be explained by the high failure rates of start-up firms. We thus find little support for innovative firms being particularly young.

In the industry dummies the point of reference has been the IT industry, where Nokia takes the prominent share. Productivity growth accounted for by human capital has been even faster in the telecommunication industry (excluding Nokia), in the furniture industry and in the service sector other than business services (not reported). For the IT industry shown in the last column, representing top productivity growth industry, it is seen that the importance of education human capital spillovers is phenomenal in order for catching-up to occur. IT companies operating in areas with limited education human capital and having to resort mainly to manual manufacturing procedures may also grow but will not be the ones to catch-up rapidly with the frontier firm. This is indicated by the negative coefficient of the education human capital agglomeration and the negative interaction of catching up with regional productivity. The explanation is the global spillovers that are characteristics of IT industry. Large IT firms also have subsidiaries in remote areas, while still can enjoy the benefits of global R&D efforts in the firm.

We use Monte Carlo simulation to determine the magnitude of the productivity effects and to assess the robustness of our estimates, particularly with respect to the education and catching-up (see King *et al.* (2000)). The simulation is based on the OLS estimation with firm weights. Figures 1-2 show the simulation analysis results using the model reported in column 4 in table 3. Figures also show the partial model results analogous to that reported in column 1 in table 3 with no interaction terms.

Figure 1. Education human capital	Figure 2. Catching-up and Experience in Highest Quartile
	

We have run 10,000 simulations, and the quantitative effects are estimated around the average of each variable. The X-axis is set to reflect actual distribution of the explanatory variable from the 1st percentile to 99th percentile. Note that if knowledge capital augments the productivity of labour only, which we do not believe, the labour productivity effects are twice as high as the total factor productivity effects, as the average labour share of the value added is 0.53.

Figure 2 shows that an increase of around one standard deviation (14 log points) in the level of education human capital raises productivity growth by around 20 log points, when using the model with no interactions as in column 1 in table 3. In the model with interactions, shown in column 2 in table 3, the productivity effect is significantly lower. This is explained by the fact that coefficient for the interaction term between education and occupational human capital is positive, while these two forms of human capital are negatively related, see table 1. Recall that the education effect here is evaluated at the mean level of occupational human capital. The importance of occupational capital in enhancing the productivity effects of education human capital thus should not be ignored. In the majority of the Finnish firms occupational human capital (of educated) is not sufficient to support the efficient use of educational skills. Figure 3 shows that the productivity effects of catching-up are close to zero, or negative when catching-up is interacted with education capital spillover and regional total factor productivity. It can be seen that the confidence interval for the catching-up effect is also very high. This holds despite the finding of significant and positive coefficient for the catching-up term in all of the estimations in table 2 except for the IT industry.

4. Conclusions

This paper has examined productivity growth driven by knowledge capital, which includes human capital of workers and intangible capital at firm-level. Human capital is agglomerated, which explains no regional convergence. The relationship is complex as availability of educated workforce is directly negatively related to growth. It is clear that education human capital alone is a poor predictor of future success unless the firm has access to other human capital and to occupation human capital in particular. We also find out that education and occupation human capital are negatively related, while productivity growth is much stronger in firms abundant in both forms of human capital. We also find education human capital and availability of educated workforce important in imitative growth of high-productivity firms. We cannot thus fully agree in the findings of Aghion et al (2005) at the more aggregate state level in US that use of highly educated especially promotes innovative growth. Education human capital promotes *imitative* growth of *high-productivity* firms.

We also find a qualitative shift away from unobserved human capital and intangibles towards the use of education human capital as the growth of productivity continues and the firm bridges the gap to the frontier firms. Firms far from the frontier require unobserved human capital and intangible capital. Education human capital does not enhance catching up. All this leads to logistic type growth among the low-productivity firms.

Knowledge capital explains a major share of the growth in the IT industry, where innovative growth does not require location of the firm in area with educated workforce. One reason for the latter can be that firms have access to global R&D and possibly large IT firms can locate establishments in remote areas and make use of knowledge capital of the whole company.

Finland has experienced agglomeration and a divergence in productivity growth at the regional level since 1995. It is evident that it is important for specific clusters of regions to have access to a regional pool of human capital. Substantial labour mobility of skilled workforce within countries as compared to between countries can also be argued to explain the regional dispersion in growth, see Ottaviano and Pinelli (2002). Aghion et al (2005) find this to substantiate the growth divergence as educated workforce move to states with highest growth.

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Appendix A. Description of the Linked Employer-Employee Data

The data, with 3,096,771 observations, cover all workers (top management excluded) who have worked for at least one year during 1996-2002 in firms that are affiliated with the Confederation of Finnish Industries. Data cover manufacturing firms and a part of the service sector: the majority of these service sector firms are excluded, as they were in a separate employer's organisation until 2005. The estimation for observations with a firm code totals 2,755,716 (181,048 dropped because of missing hourly wages, 118,243 omitted because log wages deviated more than five standard deviations from the predicted value using experience up to the fourth potency, gender and 22 education classes, some 40,000 observations discarded for having no education, seniority or firm codes). This number is reduced to 2,096,523 when just the employees with an estimable firm effect are included. After checks for real births and deaths of firms, the original data included 2,359 firms and the firm-effect could be identified for 1,421 firms on the basis of 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. These firms, at the same time, cover most of the employee-year observations, 2.09 million out of 2.76 million.

Variables

Total Factor Productivity (TFP) is the multilateral total factor productivity index, where productivity is compared with a 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 each of the 19 industries.

Education Human capital is measured in efficiency units using the relative rate of return of five educational degrees for five fields (in explaining the person effect). It measures the share of the highly educated group using these relative returns as weights

$$Educational\ HC_{j,t} = \sum_{i_t=1}^{I_t} z_{i_t \in H} u_H \eta_H / \sum_{i_t=1}^{I_t} i\,, \qquad \text{(a.1)}$$

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 the total number of 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 are closely the same as those that belong to the highest quartile of education human capital.

Education H.C. agglomeration consists of the spillover from education 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 H.C. in the interaction term uses the employment-weighted average of Education H.C. in the region.

Unobserved human capital (H.C.) is a person-specific fixed effect in wage estimations that cannot be explained by education and gender and is hence unobserved to the econometrician.

Experience H.C. show returns to work experience, which is age minus years in education (from 7 to 14 according to the educational degree) minus 6 years. Shares below 25% and above 75% are defined as for unobserved human capital.

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

Occupational human capital is based on occupational mobility that may also include job transferees.

Seniority is the duration of the worker's employment in the firm. Firm births and deaths are considered as a mere transfer of the firm, in instances where people employed either at the old firm at date t-1 or at the new firm at date t constitute more than 40 per cent of all employees working in these firms at dates t-1 and t. These unnatural deaths and births account for approximately 3 per cent of all firm entrance and exits from the market. Many of the old or new firms are large and, hence, recoding will affect 9% of the employees.

Table A.1 Log Wage Estimates with Person and Firm Fixed Effects

	First-Stage Eq. (8)		Second-Stage Eq. (9)	
Variable	Coefficient	t-value	Coefficient	t-value
Experience/10	1.239	(67.7)***	1.272	(195.4)***
$Experience^2/100$	-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)***
Secretarial	-0.016	(2.9)	-0.014	(6.8)***
Maintenance: Estate, Machines	0.072	(2.8)**	0.035	(8.1)***
Planning	-0.010	(1.6)	0.009	(3.8)***
Product Planning	0.012	(3)**	0.008	(6.7)***
Logistic Planning	0.003	(1.4)	-0.006	(2.8)**
Logistic	0.004	(0.4)	0.013	(4.2)***
Marketing	-0.014	(1.7)	-0.003	(1.2)
Production Task	0.017	(3.6)***	0.025	(17.9)***
Public Relations	-0.008	(0.9)	0.002	(0.6)
Legislative	-0.005	(0.6)	0.009	(3)**
Office Work Superior	0.003	(0.3)	0.015	(4.9)***
Office work	-0.001	(0.2)	0.008	(2.7)**
Personnel Policy Work	-0.016	(1.6)	-0.006	(1.9)
Purchasing	0.013	(1.3)	0.024	(6.9)***
Firm Effect			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 Eq. (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.

Table A.2 Person-Effect Estimates: Education Effects

Variable	Coefficient	Standard Error
Intercept	-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)***
Lower 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)***
Higher 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.