INNODRIVE WORKING PAPER SERIES

Intangible investment in people and productivity

Pekka Ilmakunnas and Hannu Piekkola

December 2010

INNODRIVE Working Paper No 8.

The research leading to these results has received funding from the European Community's Seventh Framework Programme under grant agreement n° 214576

Intangible investment in people and productivity[♣]

Pekka Ilmakunnas* and Hannu Piekkola**

* Department of Economics, Aalto University School of Economics, Finland
E-mail: pekka.ilmakunnas@hse.fi
Tel. 358-9-47038746
Fax. 358-9 47038738

** Department of Economics, University of Vaasa, Finland
E-mail: hannu.piekkola@uwasa.fi (corresponding author)
Tel. 358-44-0244349
Fax. 358-6-3248171

Abstract

Organizational work, ICT activity, and R&D work can be classified as work that creates intangible capital. We measure productivity of organizational type work (defined as management and marketing activity), along with productivity of all other intangible capital type work, by accounting for differences in productivity compared with other work. We find some upskilling of intangible capital type work in the 2000s including increasing relative productivity of organizational work. The productivity effects of organizational work are pervasive and related to globalization. Outsourcing is positively related to the productivity impact of organization work but not to that of R&D work.

JEL classification: M40, J30, O30, M12, J62

Keywords: Intangible capital, R&D, market valuation, linked employer–employee data.

[♣]This paper is part of the Innodrive project financed by the EU 7th Framework Program No. 214576.

November 3, 2010

1. Introduction

Intangible capital is often understood to explain a substantial part of the difference between the market value (stock market value plus liabilities) and the balance sheet value of tangible assets (for recent studies, see Brynjolfsson and Hitt, 2000 and Brynjolfsson, Hitt, and Yang 2002). For example, using Australian data, Webster (2000) found that the ratio of intangible to all enterprise capital rose by 1.25% annually over 50 years to 1998. The World Bank (2006) applied this analogy to the difference between total wealth (measured as the net present value of future sustainable consumption) on the one hand and natural and produced capital on the other hand in 120 countries. The rest is referred to as intangible capital: human capital, trust, and the value of institutions. They constitute the largest share of wealth in virtually all countries, i.e., an average of 77% of total wealth. This puts Nordic countries at the top of the list of richest countries aside from Switzerland, the United States and Germany in terms of intangible capital.

The approaches to assessing intangible capital have recently been extended to disaggregated expenditure-based measures and other performance-based measures (Sichel, 2008). Corrado, Hulten, and Sichel (2005, 2006) used the expenditure-based approach and defined intangible capital in a broad sense to cover all intangible investments that are expected to yield positive returns in the long run. Nearly half of the total is economic competence, which includes new intangibles: brand equity, firm-specific human capital (training provided by employers), and organizational structure.

The ‘other performance-based approach’ (taken here) values intangibles by their productivity or profit effects. Cummins (2005) used the discounted value of profit forecasts as a key to evaluating the intangible capital inherent in the firm. He also included the adjustment costs in the estimated return on each type of capital (tangible and intangible) from US firm-level panel data. He found R&D and advertising insignificant, whereas sizable intangibles were created by information, communications, and technology (ICT). McGrattan and Prescott (2008) used as the performance measure profits with the assumption of equal after-tax returns to tangible and intangible assets. They calculated the range for the value of intangible capital to be from 31 to 76% of US GDP.

Lev and Radhakrishnan (2005) measured the contribution of intangible capital as the difference in sales growth with and without intangible capital in a production function estimation in US firms. Piekkola (2009) found their instrument for organizational capital, “selling, general and administrative expenses” to be rather sensitive to economic cycles using Finnish data. In any case, both Lev and Radhakrishnan (2005) and Piekkola (2009) found that not all intangible capital is appropriately valued in the analysts’ forecasts. Thus, intangibles have significant predictive power for the future performance and market value of corporations.

Our analysis relies on four premises. 1) Intangibles are related to the core of a firm’s operations, i.e., organizational, R&D, and ICT work. The organizational structure is linked to the creation of brand capital, which, according to Lev and Radhakrishnan (2005), aims to provide a positive image to the firm in the market and helps it to secure future orders. Management and marketing are considered as same kind of intangible capital type work. Marketing is difficult to disentangle from organizational capabilities in terms of the business processes, management structures and organizational systems specifically designed to maximize the value of output. Marketing work is also highly valued, and it is second in compensation only to management in European labor force surveys[1]. The distinction between R&D work and marketing can also be indeterminate. In services, a marketing occupation is often a promotion from R&D work and separate R&D

[1] Similar results have been obtained using linked employer–employee data from six countries in the Innodrive project.

facilities do not even exist. As such, R&D is most clearly a longer-term investment in the future and thus deserves a category of its own.

Our third category of intangibles is ICT investment. Ito and Krueger (1996) and Bresnahan and Greenstein (1999) suggest that organization capital complements ICT and that it typically exceeds the direct financial costs of the ICT investments. Brynjolfsson, Hitt, and Yang (2002) argue that their reported large returns on ICT investments are largely explained by a relationship between the utilization of IT and skilled workers on the one hand and human resource management on the other (with a greater decentralization of certain decision rights and team-oriented production). Brynjolfsson, Hitt, and Yang (2002) also refer to case studies indicating that computers and software are just the tip of the iceberg of the implementation costs of ICT.

2) All technology is labor-augmenting. There are good reasons to believe that a major part of intangible investment occurs in people. For example, it is well known that some 70-80% of R&D investment consists of compensation for employees. Similarly, organizational capital type work drives much of the organizational investments.[2] Following the 'other performance-based approach', we then explain the productivity of intangible capital type work relative to other work. We use the method introduced by Griliches (1967) and more recently popularized by Hellerstein, Neumark, and Troske (1999) to measure the value of three kinds of labor engaged in intangible-capital work. Specific attention is given to using the Olley–Pakes/Levinsoh-Petrin approach to account for the possibility that the measures of intangibles are correlated with productivity

[2] Bernd Görzig in Piekkola, Görzig and Riley (2010) show using the Eukleed database that capital costs in ICT and organizational capital do not seem to have much influence on the production of intangible capital type goods. Intermediate inputs are also used less in Nace73 (a R&D intensive industry) than in Nace74 (an organizational capital intensive industry) in Germany although the situation differs in other countries.

shocks. For example,, ICT workers are recruited extensively in years of positive productivity growth (expectations) and sparsely in years with negative productivity growth.

3) The share of intangible-capital related work considered as long-term investment or the depreciation rates used in the expenditure-based approach are to a large extent not based on empirically valid estimates over all datasets, which also makes comparability across countries very difficult. In Piekkola, Görzig and Riley (2010) the resources engaged in the production of organizational goods are a certain fraction of total expenditures on these types of workers. Furthermore, input-output data from other business activities (Nace 72) are used to evaluate the amount of intermediate and capital expenditures needed to produce intangible goods. Taking all this into account the investment share from managerial and marketing wage costs was 30%, which exceeds the 20% share of managerial labour costs considered as investment in Corrado, Hulten, and Sichel CHS (2005). CHS measured brand value by the predetermined 40% share of advertising expenditures and the true average share of management expenditure share can be closer to this share.[3] The literature also offers only vague estimations of the depreciation rates. CHS used estimates of 20% for R&D, 36% for databases and software, and 40% for management expenditures. In our approach, we do not need a separate assessment of the depreciation rates or share of labour costs producing intangible goods that are assumed to be consumed within a year.

4) Finally, intangibles should be clearly separated from general human capital, for which ownership does not satisfy the traditional definition of assets used in the SNA. To be precise, we aim at measuring the labor input that generates firm-specific intangible assets that are valuable to the firm. This follows the well-known division of annual compensation between general human capital and firm-specific human capital by Becker (1962). Intangible-capital work that is valuable

[3] Haskel and Marrano (2007) use private data sources from media companies in equivalent calculations for Europe.

to the firm and not (necessarily) to the employee is synonymous with firm-specific human capital. The general human capital is controlled by the firm averages of person effects from individual-level wage equations. Iranzo, Schvandi, and Tosetti (2007) argued that this cleans some of the institutional constraints stemming from the union wage determination as firm fixed effect is separately estimated encompassing these institutional elements, too. The human capital measure also includes abilities not reflected in education and work experience and thus evidently provides a more valid measure for the abilities of production workers (40% of all employees in our data). By separating intangible capital from human capital, the ownership is well defined, which is one of the underlying definitions of assets used in the SNA.

Our results show that intangible-capital work, whether it be organizational, R&D, or ICT, explains an important share of variation in total factor productivity (TFP). We come to this conclusion after eliminating two biases: (i) a downward bias due to firm differences in productivity explained by an unobserved, serially correlated productivity shock, which is a determinant of both survival probabilities and input choices; and (ii) an upward bias in the estimates of the productivity effects of intangible-capital work when not controlling for the human capital of workers.

Section 2 of this paper presents the model, the econometric approach, and the composition of intangible capital, along with the data. The estimation of the production function and calculation of the contribution of intangible capital is done in section 3. Section 4 analyzes the productivity growth induced by intangibles over time and relates this growth to the market restructuring and globalization process. Section 5 concludes the paper.

2. Model and Econometric Approach

2.1 Production Function

We assume a constant-returns-to-scale production function, where labor input is quality-adjusted:

$$VA_{it} = b_{0it}(Q_{it}L_{it})^{b1}K_{it}^{b2}\exp(e_{it}), \qquad (1)$$

where VA_{it} is the value added by firm *i* in year *t*, $Q_{it}L_{it}$ is the quality-adjusted labor input (L is the total number of employees), K_{it} is the net plant, property, and equipment, and e_{it} is an error term. Labor L_{it} is here measured by units and not by total hours, which would include overtime hours for production workers. The regular weekly working hours for non-production workers have a low variation, while the overtime hours of production workers would increase the sensitivity of our measurements to productivity shocks. We separate the labor input of organizational (OC), R&D, and ICT workers, and the others serve as the reference group. Following the approach used by Griliches (1967) and Hellerstein, Neumark, and Troske (1999) in another setting, the quality-adjusted labor input is written as

$$\begin{aligned} Q_{it}L_{it} &= a_{OC}OC_{it} + a_{RND}RND_{it} + a_{ICT}ICT_{it} + (L_{it} - OC_{it} - RND_{it} - ICT_{it}) \\ &= L_{it}\left[1 + (a_{OC}-1)\frac{OC_{it}}{L_{it}} + (a_{RND}-1)\frac{RND_{it}}{L_{it}} + (a_{ICT}-1)\frac{ICT_{it}}{L_{it}}\right], \end{aligned} \qquad (2)$$

where OC_{it}, RND_{it}, and ICT_{it} are the total number of organizational, R&D, and ICT workers, respectively, in the firm. OC_{it} relates to management and marketing. Here, we allow the productivity of organizational, R&D, and ICT workers to differ from that of the other workers by the factors a_{OC}, a_{RND}, a_{ICT}, respectively. In log form, we can approximately write

$$\ln\left[1+(a_{OC}-1)\frac{OC_{it}}{L_{it}}+(a_{RND}-1)\frac{RND_{it}}{L_{it}}+(a_{ICT}-1)\frac{ICT_{it}}{L_{it}}\right] \approx (a_{OC}-1)\frac{OC_{it}}{L_{it}}+(a_{RND}-1)\frac{RND_{it}}{L_{it}}+(a_{ICT}-1)\frac{ICT_{it}}{L_{it}}, \quad (3)$$

as the second, third, and fourth terms in the squared brackets are not too far from zero. Therefore, the production function can be written in log form as

$$\ln VA_{it} = b_{0it} + c_{OC}\frac{OC_{it}}{L_{it}} + c_{RND}\frac{RND_{it}}{L_{it}} + c_{ICT}\frac{ICT_{it}}{L_{it}} + b_1 \ln L_{it} + b_2 \ln K_{it} + e_{it}, \quad (4)$$

where $c_{OC} = b_1(a_{OC}-1)$, $c_{RND} = b_1(a_{RND}-1)$ and $c_{ICT} = b_1(a_{ICT}-1)$. The productivity equation (4) can now be expressed in terms of TFP as

$$\ln TFP_{it} = b_{0it} + c_k X_{it} + e_{it}, \quad \text{where} \quad (5)$$

$$\ln TFP_{it} = \ln VA_{it} - b_1 \ln L_{it} - b_2 \ln K_{it}, \quad (6)$$

$X_i = OC_i / L_i, RND_i / L_i, ICT_i / L_i$ is a vector of employment shares, and c_k is a vector of respective productivity parameters (later to be estimated). Equation (5) differs from a conventional, aggregate productivity-growth measurement, where the evolution of the productivity of all inputs is left in the term b_{0it}. Our formula allows us to analyze the technical efficiency improvement explained by intangibles. The productivity-growth impact of each factor input in intangible-capital work can be expressed as

$$c_k dX_{it} = b_1(a_k - 1)\, dX_{it}. \quad (7)$$

We have two unknown parameters, b_1 and a_k, for each intangible-capital work *k (k=OC, R&D, ICT)*. We assume constant returns to scale with respect to quality-adjusted labor input and capital. Therefore, $b_1 = \partial \ln VA / \partial \ln QL$ is equivalent to the income share of labor. In addition to the production contribution from changes in factor shares given in equation (7), we allow the input productivities themselves to change over time. We thus also evaluate

$$X_{it} dc_{k,jt} \quad , \tag{8}$$

where productivity change takes place in industries *j=1,…,8*. The productivity shifts that are due to changes in the proportions of intangible-capital work and the productivities are referred to as intangible capital type upskilling.

To be consistent with our definitions, the human capital and the firm-specific intangible capital that is inherent in labor should be separated. We therefore need a measure of human capital, ln*HC*, as a control variable. As explained below, this is based on the firm average of the person effects obtained from the estimation of wage models for individuals with separate person and firm effects. We further add controls, *Z*, that include indicators for industries and years along with their interactions (to account for the deflation of the nominal variables), firm age, a multiplant dummy, and firm size categories. The final model is

$$\ln TFP_{it} = c_0 + c_{OC} \frac{OC_{it}}{L_{it}} + c_{RND} \frac{RND_{it}}{L_{it}} + c_{ICT} \frac{ICT_{it}}{L_{it}} + c_1 \ln HC_t + c_2 X_{it} + c_3 Z_{jt} + e_{it} \quad . \tag{9}$$

Rather than estimating a production function with three inputs and labor quality variables, we first directly calculate the TFP using observed, two-digit industry factor shares and then explain this measure of TFP with the other variables. This approach follows Foster, Haltiwanger, and

Syverson (2008), among others. In this way, we avoid some of the common problems with panel production function estimation, such as unreasonably low estimates of the capital input coefficient (Griliches and Mairesse, 1998).

However, we still have to take into account the possibility that there are unobserved firm-specific variations correlated with the intangibles. If these effects are time-invariant, they could be taken into account with fixed-effects estimation. Because they may be time-varying, we resort to the kind of estimation approach suggested by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Assume that the error term of the model is decomposed into two parts, $e_{it} = u_{it} + v_{it}$, where u_{it} is a productivity shock that is correlated with the variables measuring intangible-capital work. For example, during positive shocks, the firm may be more inclined to invest in intangibles. The intangibles are treated as state variables that can only be adjusted slowly. The way the firm adjusts its intangibles is through hiring new employees for tasks related to OC, ICT, and R&D. We can therefore treat hiring (i.e., the hiring rate) as a proxy variable for the productivity shocks in the same way as Olley and Pakes use investments. If hiring depends on the shocks and the intangible variables, inverting this relationship gives the shock as a function of hiring and the state variables.

In the first step, ln*TFP* is regressed on the controls and polynomials of the proxy and the state variables and their interactions to approximate the true, unknown relationship between the variables. In our setup, there are no variable inputs (beyond the controls) to be estimated in the first stage. Nevertheless, the first step gives an expression of the firm-specific shocks in terms of the estimated polynomial and the intangible variables. In the second step, assuming a Markov process for the productivity shock, ln*TFP* minus the contribution of the controls is regressed on the intangible variables and a polynomial of the shocks. As an alternative, we assume that the shocks follow a second-order Markov process. In this case, we need two proxy variables (see Ackerberg et al., 2007). We use materials as the second proxy variable. The use of materials as a proxy has been suggested by Levinsohn and Petrin (2003). We also control for the selectivity caused by the exit of firms. Following Olley and Pakes (1996), the likelihood of exit is modeled with a probit model, and the predicted probability is used as an additional variable in the second step.[4]

The equation includes private human capital as a control variable. An estimate for private human capital is obtained from a wage equation to be estimated with individual-level data. The wage regression includes only time-varying characteristics as deviations from their means. The dependent variable is the log of the wage $\ln(w_{\mathrm{ijt}})$ of a person *i* working in firm *j* at time *t,* measured as a deviation from the individual mean, μ_{wi}. This is expressed as a function of individual heterogeneity, firm heterogeneity, and measured time-varying characteristics in

$$\ln(w_{\mathrm{ijt}}) - \mu_{wi} \;=\; \theta_i + \psi_{J(i,t)} \;+ \beta(x_{it} - \mu_{xi}) + e_{ijt}\,. \qquad (10)$$

where θ_i is the time-invariant compensation for human capital (individual fixed effect). $\psi_{J(i,t)}$ captures the effect of unmeasured employer heterogeneity, where $J(i,t)$ indicates the employer of *i* at date *t*. $\beta(x_{it} - \mu_x)$ shows compensation for time-varying human capital, stated as a deviation from the individual mean, and e_{ijt} represents a statistical error term. The time-variant variables are experience and seniority. Experience is measured by age minus years of education minus age when school started, and seniority is duration in the job measured in years. Individual heterogeneity, as captured by the person-specific fixed effect in the wage equation, includes the

[4] The estimation procedure is adapted from Yasar, Raciborski, and Poi (2008).

returns to education, and the remaining part of the person-specific fixed effect is the proportion of wages that cannot be explained by observed characteristics (to the econometrician).[5]

2.2 Data

We use linked employer–employee data, which have been extensively utilized in the study of human capital formation starting with Abowd, Kramarz, and Margolis (1999). These data are convenient in an analysis relying on the operation of different tasks and occupations that have emerged in the new wave of globalization. The labor data are from the Confederation of Finnish Industry and Employers, with 7.9 million person–year and 87,972 firm–year observations for the years 1996–2008. The data include a rich set of variables covering compensation, education, and occupation. The occupational classification is specific to the data from the Confederation of Finnish Employers and is available for all employees in the firms considered. The occupational codes can be transformed into ISCO-88 with the help of additional information on education level (for qualifications) and industrial codes. Most importantly, the occupations in manufacturing and services are separated. We end up with 41 non-production worker occupations, which are listed in Appendix A. Occupations classified as relating to organization capital are management and marketing.

The employee data are linked to financial statistics data provided by Suomen Asiakastieto[6] to include information on profits, value added, and capital intensity (fixed assets). To eliminate firms with unreliable balance sheets, we include in the analysis only those firms that have on average at

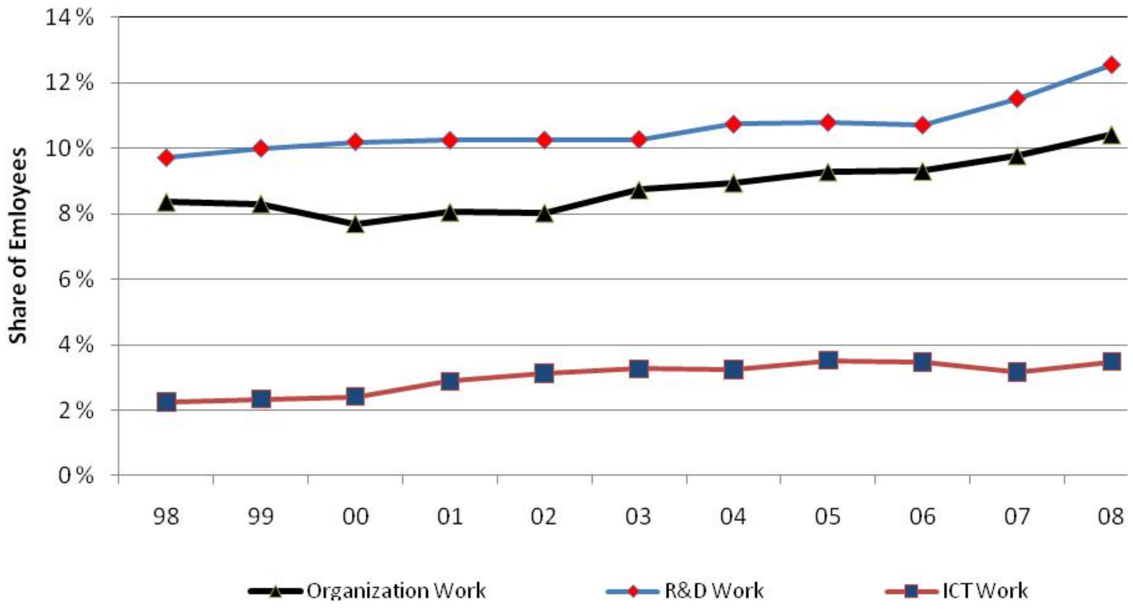
---

5 Abowd, Creecy, and Kramarz (2002) develop a numerical solution to deal with the large set of firm dummies when evaluating both individual and firm fixed effects at the same time. We use their method as applied to Stata by Ouazad (2008).

6 Suomen Asiakastieto is the leading business and credit information company in Finland.

least 30 employees and real sales exceeding €2 million (in 2000 consumer prices). The final, linked employer–employee data cover 1,729 firms with 10,624 firm–year observations after dropping the years 1998–99 used for calculating the proxies in the preferred model. The employee data in the sample cover 384,000 employees annually on average and the original employee data cover 588,000 employees or 40% of the entire workforce in the respective private sector. The average sales of these firms are €152 million. Appendix B shows the summary of the variables in the estimation sample. Figure 1 shows the share of workers in work related to production and intangible capital in the original data in 1998-2007 (year 2008 is omitted because of partly incomplete data).

Figure 1. Shares of intangible-capital workers



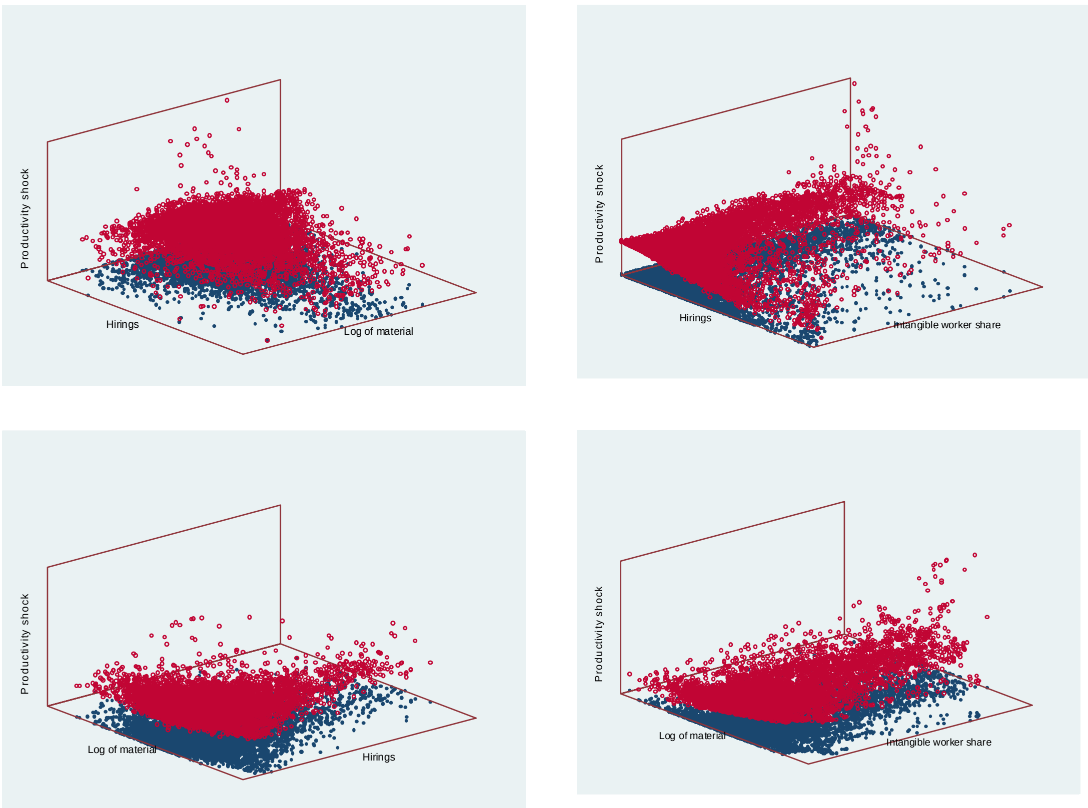
Since the start of the period, the share of organizational workers has been around 8%, while the share of R&D workers has been around 10%. The share of ICT workers has been on average only 3% and unevenly distributed, with a 13% share in business equipment, finance and healthcare (including computers, software, and electronic equipment; finance; private healthcare, medical equipment, and pharmaceuticals). The share of workers in intangible capital type of work has increased over the years.

2.3 Validity of the Proxies

The proxy variable (Olley–Pakes/Levinsoh-Petrin) estimation requires monotonicity between the state variables: organizational, R&D, and ICT shares, and the proxies for productivity shocks. Hiring and materials are non-zero in around 98% of firms, i.e., virtually all firms have non-zero materials and hire at least one worker per year. We are therefore able to avoid the problem of a large share of zero observations often encountered with other proxy variables, like investment. The zeroes may reflect kinks in the factor demand curves arising from adjustment costs, for example. Ackerberg et al. (2007) suggest that productivity shocks can be divided into those related to a firm's own productivity increase and the general shocks covering the entire industry. We believe that materials better capture productivity increments from a firm's own research activity. Hiring may instead reflect general productivity shocks. It is well known that labor markets become stagnant in periods of economic downturn (for Finnish evidence from the early 1990s recession, see, e.g., Böckerman and Piekkola, 2001, and Ilmakunnas and Maliranta, 2003). The separations decrease dramatically as new job opportunities disappear. Hiring follows this trend.

Levinsohn and Petrin (2003) graphically examined the monotonicity between proxies and productivity shocks. Figure 2 shows in the left panels the relationship between the estimated productivity shock (the vertical axis) and the log of materials and hiring (the axes to the left and right). The figures in the right panels show the relationship between the estimated productivity shock (the vertical axis) and one of the two proxy variables (hiring or the log of materials – the axis to the left) at various levels for the shares of intangible-capital workers (the sum of the worker shares engaged in organizational, R&D, and ICT work – the axis to the right).

Figure 2. Monotonicity of the proxy variables



It can be seen from the upper-left panel that hiring is evenly spread across the entire range of the log of materials and monotonously related to productivity shocks in a weakly positive manner.

The lower-left panel shows that materials are less monotonously related to productivity shocks. Furthermore, some firms with a high hiring rate do not use materials extensively. The log of materials alone is therefore not a good proxy for productivity shocks in firms where worker reallocation is high. The upper-right panel shows that hiring has a positive relationship with productivity shocks at various levels for the shares of intangible-capital related workers. The lower-right panel shows that materials are non-linearly related to productivity shocks. Therefore, the log of materials may not work as a good proxy when it is used alone. Overall, this graphical overview suggests that hiring is fairly evenly distributed in all firms and reflects general productivity shocks, while the log of materials can be more tied to a firm's own productivity evolution. In the next section, we experiment using both of these alternative proxies.

3. Estimation Results

As argued by Levinsohn and Petrin (2003), it is to be expected that the productivity shocks are positively correlated with variable inputs. To the extent that the variable inputs and the state variables are positively correlated, this will cause a downward bias in the OLS estimates of the coefficients of the state variables. Our setting is slightly different because we use TFP as the dependent variable. We have also controlled for unbalanced data, i.e., for the exit of firms. Later, we see evidence that firms with intangible capital are profitable: productivity increases, but employment compensation does not necessarily increase. Firms with intangible capital are thus less likely to exit. Not controlling for the exit of firms with negative realizations owing to less intangible capital would bias our estimates downwards. Finally, it has also been important in the probit estimates for exits to control for human capital due to frequent mergers and acquisitions in sectors that use a skilled workforce. In these cases, there is an exit of the acquired firm that is not explained by low profitability.

Table 1 reports the OLS and proxy variable estimates in explaining TFP. All estimations include the average person effect as a control variable for human capital. Our proxy for a productivity shock is hiring in column 2 and the log of materials in column 3. We use both proxies in column 4, where the shocks are assumed to follow a second-order Markov process. All state and proxy variables are included in the first-step estimation up to the fourth power, and the estimations also include interactions between all state and proxy variables. The standard errors are obtained with bootstrapping. For the sake of comparison we also present the estimates obtained using GMM-SYS (system-GMM ; see e.g. Bond, 2002) in column 5.

Table 1. Total factor productivity and intangible capital

	OLS	Hiring proxy	Materials proxy	Hiring and materials proxies	GMM-SYS
Human capital	0.859***	0.885***	0.827***	0.876***	0.514*
	(15.24)	(19.97)	(19.67)	(19.66)	(2.13)
Organization worker share	0.481***	0.331*	0.293*	0.299*	0.431**
	(9.44)	(2.55)	(1.96)	(2.17)	(3.11)
R&D worker share	-0.0499	-0.303	-0.268	-0.404*	-0.315*
	(0.81)	(1.6)	(1.36)	(1.99)	(1.97)
ICT worker share	0.322*	0.014	-0.00361	-0.0555	0.0325
	(2.44)	(0.03)	(0.01)	(0.11)	(0.2)
Firm age/10	-0.0758***	-0.0700***	-0.0644***	-0.0742***	0.193
	(3.48)	(4.38)	(4.28)	(4.62)	(1.36)
Firm age/1000	0.122***	0.111***	0.106***	0.117***	-0.39
	(3.67)	(4.33)	(4.37)	(4.55)	(1.78)
2-3 plants	-0.132***	-0.126***	-0.127***	-0.124***	0.057
	(6.93)	(7.97)	(8.45)	(7.82)	(1.29)
4 or more plants	-0.117***	-0.123***	-0.129***	-0.121***	-0.206
	(4.88)	(6.22)	(6.73)	(6.08)	(1.88)
Firm size 20-49	-0.0604**	-0.0229	-0.0215	-0.0254	-0.123
	(3.24)	(1.46)	(1.36)	(1.56)	(0.68)
Firm size 50-149	-0.0709***	-0.043***	-0.0456***	-0.0457***	-0.0616
	(4.9)	(3.61)	(3.72)	(3.65)	(0.41)
Firm size >499	0.0192	-0.00445	-0.00705		0.612**
	(0.98)	(0.27)	(0.41)		(2.61)
Sample size (OLS, first step OLS of OP, and GMM)	6407	9862	10515	9862	11977
Sample size (last step of OP)		7210	7210	6407	
Number of firms					1720
R-squared adjusted	0.419	0.422	0.414	0.423	
Arrelano-Bond test AR(1) first difference p-value					0.000
Sargan test of overidentifying restrictions p-value					0.000
Hansen test of overidentifying restrictions p-value					0.346

Notes: All variables except for dummies and organizational, R&D, and ICT worker shares are in log form. The OLS estimation is done for the sample used in the non-linear estimation with hiring and log of materials as proxies. The OP observations and R Squared are for the first step estimation. In proxy variables estimation (OP), the state variables are organizational, R&D, and ICT worker shares, and the proxy variable is as indicated. In GMM-SYS, GMM-type instruments include state variables and log of fixed assets with lag. The number of replications in the bootstrap is 50. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

With a few exceptions, the results are relatively stable across different estimations. A substantial degree of the variation in the TFP is explained by the human capital-intensity of the firms. Organizational workers constitute a very important part of intangible capital, as they have management and marketing abilities beyond those explained by general skill levels (human capital). The organizational worker share has a significant positive coefficient, which is approximately 0.3 in the proxy variable estimations and around 0.45 in the OLS and GMM-SYS estimations.[7] As the results from the proxy variable estimations are below the OLS estimate, the latter is biased upwards. Generally, a 10 percentage point rise in the organizational worker share increases TFP by around 3 percent. The choice of proxy does not have a very large effect on our estimates. The estimates with hiring as a proxy are close to the estimates with the materials proxy, or with both hiring and materials as proxies for productivity shocks. Recall that a positive coefficient indicates that productivity in organizational work exceeds that in the non-intangible work.

Some of the positive returns to organization capital also stem from higher returns in R&D-intensive firms. Cummins (2005) found that the accumulation of organization capital is positively associated with investment in R&D assets (and with marketing assets). It is well known that the

[7] We should treat the GMM results with some caution, as the Sargan test rejects the overidentifying restrictions. According to the Hansen test, they are accepted, although the relatively high value of the test statistic may be an indication of overfitting with too many instruments.

estimates of returns to R&D suffer from numerous omitted variable problems, many of which are controlled here. Klette and Kortum (2004) summarize the main finding in the literature, which is that productivity level and R&D across firms are positively related, while the effect of R&D on productivity growth is unclear. Here, the coefficient of R&D worker share is insignificant or even negative in the proxy variable estimates with hiring and material proxies and in GMM-SYS. The low productivity of R&D may be related to the fact that we are measuring short-run productivity. The gains from R&D likely come with a lag.

Finally, the ICT worker share has a positive coefficient in OLS estimation. Taken at face value, the insignificant coefficient in the other estimations implies that ICT work is not more productive than non-intangible work. One explanation is the strongly negative coefficient of the interaction between the organizational worker and ICT worker shares in the first-step estimation. Below, we find it relevant to evaluate the return on ICT work only in ICT-intensive industries.

More than two thirds of the firms in our sample are from manufacturing or construction. Therefore, it is not surprising that the estimates would be largely the same when including only these industries. It is of greater interest to analyze the service sector. Service-sector firms rely less on tangible capital investments. The share of workers with tertiary education is also much higher than in manufacturing. Therefore, intangible capital can potentially play a significant role. We also estimate the model separately for high-productivity and low-productivity firms. We know that firms with a TFP above the industry average are close to the productivity frontier. These firms are expected to invest more in innovation and to do less catching up with the most productive firms. The estimation results for the service sector, the high-productivity firms, and the low-productivity ones are shown in Table 2.

Table 2. Intangible capital and TFP in the services sector and in high- and low-productivity firms

	OLS	Hiring proxy	Material proxy	Hiring and materials proxies	GMM-SYS
		Services			
Human Capital	0.820***	0.756***	0.668***	0.792***	0.837***
	(6.64)	(8.3)	(7.97)	(8.65)	(12.57)
Organizational worker share	0.980***	1.104*	1.193*	1.336*	0.958***
	(5.44)	(2.33)	(2.41)	(2.5)	(19.73)
R&D worker share	0.324**	-0.0732	-0.515	-0.52	0.618***
	(3.02)	(0.14)	(0.81)	(0.59)	(23.97)
ICT worker share	0.584**	-0.0333	-0.109	-0.0238	0.727***
	(3.19)	(0.1)	(0.29)	(0.06)	(26.29)
Sample size (OLS, first step OLS of OP, and GMM)	1136	1859	2121	1859	2701
Sample size (last step of OP)		1367	1367	1136	
		High-productivity firms			
Human Capital	0.657***	0.623***	0.586***	0.612***	0.541*
	(8.1)	(10.12)	(10.11)	(9.89)	(1.96)
Organizational worker share	0.522***	0.326	0.326	0.432**	0.551***
	(7.97)	(1.85)	(1.95)	(2.62)	(3.74)
R&D worker share	-0.182*	-0.235	-0.222	-0.281	0.0413
	(2.37)	(1.21)	(1.18)	(1.13)	(0.27)
ICT worker share	-0.188	0.353	0.313	0.365	0.0812
	(1.14)	(0.5)	(0.41)	(0.38)	(0.45)
Sample size (OLS, first step OLS of OP, and GMM)	2915	4622	3320	4622	5843
Sample size (last step of OP)		3320	3320	2915	
		Low-productivity firms			
Human Capital	0.105*	0.133**	0.128**	0.143***	0.0386
	(2.01)	(3.09)	(3.13)	(3.32)	(0.26)
Organizational worker share	0.104*	0.178	0.146	0.156	0.0747
	(1.99)	(1.62)	(1.13)	(1.37)	(0.75)

R&D worker share	-0.033	-0.158	-0.104	-0.214	-0.00619
	(0.51)	(1.05)	(0.63)	(0.96)	(0.06)
ICT worker share	0.0581	-0.217	-0.172	-0.319	0.0176
	(0.38)	(0.88)	(0.52)	(0.71)	(0.17)
Sample size (OLS, first step OLS of OP, and GMM)	3459	5240	5540	5240	6134
Sample size (last step of OP)		2610	2610	2316	

Notes: See the footnotes in Table 1. In the GMM-SYS, the p-value in Sargan test of overidentifying restrictions is 0.00 in all estimations. The p-value of the Hansen test of overidentifying restrictions is 0.88 in services, 0.99 in high-productivity and 0.96 in low-productivity firms. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the service sector, the coefficient of the organizational worker share is significantly positive in all estimations. In services, R&D work is often more integrated with management and organization capital compared to manufacturing, which is consistent with the results that the return to R&D work does not differ significantly from the average in OP. Overall, we find evidence that organizational capital is at least equally important in the service sector than in manufacturing. However, we later find the returns do strongly differ according to the type of services.[8]

The returns for organizational work are highest in high-productivity firms. It seems that the results of all firms are driven by those that have high productivity. In contrast, in low-productivity firms, the coefficients of the intangible variables are not significant. Firms far from the productivity frontier also rely less on the use of human capital in improving productivity.

Our next step is to analyze whether intangible capital increases the profitability of the firm. To this end, the labor productivity and wage effects of intangible labor are compared again using the

[8] Again, the GMM results should be treated with caution, as the Sargan test rejects the overidentifying restrictions.

methodology envisaged by Hellerstein, Neumark, and Troske (1999).[9] We use both hiring and materials as proxies. We thus allow two sources of productivity shocks. Models are estimated for productivity and average wage, and the coefficients of the variables for the intangible work share in the models are compared. Because of the linear approximation, the coefficients from the productivity model have to be divided by the labor share in the value added before comparison with the coefficients from the wage model. More precisely, from equations (1) to (4), we see that $\partial \ln VA / \partial (OC/L) \approx c_1 = b_1(a_1 - 1)$, and from equation (6), we also see that $\partial \ln TFP / \partial (OC/L) \approx c_1$, so we can analyze the productivity effect from the *TFP* equation. Because we should compare (a_1-1) to the coefficient of *OC/L* in the wage model, we have to first divide the productivity model coefficient by the labor share, b_1. The difference between the coefficient of *OC/L* in the productivity equation, divided by b_1, and the coefficient of *OC/L* in the wage equation is defined as the productivity–wage gap of organizational work (see Ilmakunnas and Maliranta, 2005). The same argument applies to the other intangible labor categories. In the wage regression we explain log annual earnings using the same explanatory variables as in the productivity model above.

Work related to intangibles improves productivity while having a dampening effect on wages (Table 3). We can thus see that intangibles improve the profitability. Intangible-capital work can therefore be used to increase the market value of the firm. It is of interest to compare the productivity–wage gap explained by the model over the years. Figure 3 shows the aggregate productivity–wage gap. This is evaluated as the sum of the shares for intangible-capital workers multiplied by the corresponding productivity–wage gaps, where productivity is now divided by the labor share.

---

[9] In contrast to that study, however, we use a linear approximations rather than a nonlinear estimation.

Table 3. TFP versus wages in the proxy variable estimation

			High TFP firm		Low TFP firm	
	TFP	Wages	TFP	Wages	TFP	Wages
Human capital	0.876***	0.933***	0.612***	1.030***	0.143***	0.561***
	(19.66)	(18.28)	(9.89)	(12.86)	(3.32)	(8.35)
Organization worker share	0.299*	-1.532***	0.432**	-1.336***	0.156	-1.615***
	(2.17)	(9.1)	(2.62)	(6.66)	(1.37)	(7.38)
R&D worker share	-0.404*	-1.444***	-0.281	-0.798	-0.214	-1.961***
	(1.99)	(4.77)	(1.13)	(1.75)	(0.96)	(4.62)
ICT worker share	-0.0555	-1.101	0.365	-1.643	-0.319	-0.713
	(0.11)	(1.32)	(0.38)	(1.92)	(0.71)	(0.93)
Observations	9862	9913	4622	4651	5240	5262
R-squared	0.445	0.852	0.478	0.871	0.646	0.858
R-squared adjusted	0.423	0.846	0.434	0.86	0.619	0.848

All variables except dummies and the organizational, R&D, and ICT worker shares are in log form. In Olley–Pakes, the state variables are the organizational, R&D, and ICT worker shares and the proxy variables are hiring and materials. The number of replications in bootstrap is 50. * < 0.05, ** < 0.01, *** < 0.001

Figure 3. Productivity–wage gap in intangible-capital work at the firm level

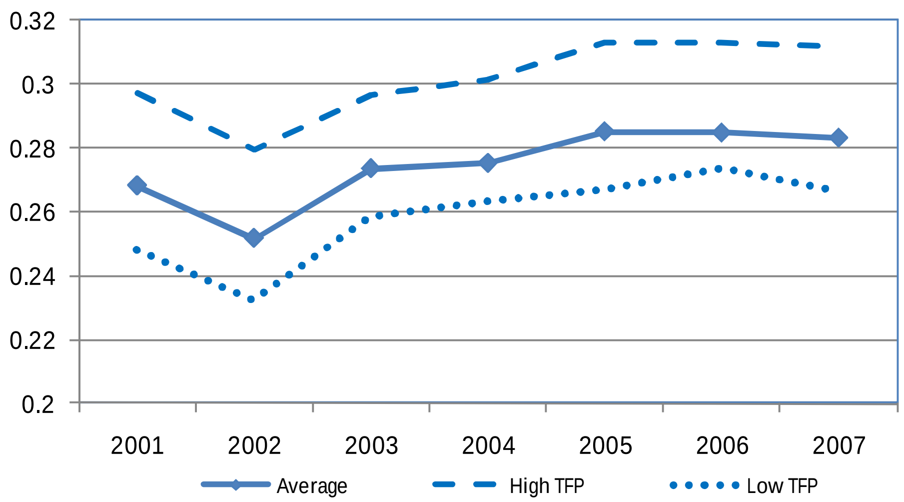


Figure 3 shows that the productivity–wage gap is on average 0.28. In firms with a high level of TFP, the gap is higher than the average, while the gap is lowest among the low-productivity firms. Changes in the gaps are due to changing shares of intangible-type workers over the years, as the parameters are from proxy variable estimation for the whole period. On average there is some widening of the gaps over time.

4. Productivity Induced by Intangible-capital Work over Time, Market Restructuring and Globalization

We estimate the returns to intangibles over time by pooling data over three-year periods and using an Olley–Pakes estimation with the two proxies, hiring and materials. In other words, returns to intangible capital for the year 2002 and onward are estimated using the data over three-year periods (2000–02, 2001–03, etc.). The years 1998–99 are lost because we assumed the second-order Markov process in the productivity shock.

Appendix C shows the adapted industry classifications, which follow Fama and French (1988, 1997) with some modifications.[10] The estimation is done separately for eight industries. However, the average share of R&D workers is below 0.4% in wholesale and retail, and the average share of ICT workers is around 1% or less in all other industries except in business equipment, finance and healthcare (where the share was 12.9%). As the coefficients would be imprecisely estimated, we do not evaluate the productivity of R&D work in wholesale and retail, and evaluate the productivity of ICT work only in business equipment, finance and healthcare.[11] We report in

---

[10] The manufacturing of non-durables (mostly the manufacturing of electronic products and also food, textiles, and leather) is separated from and merged with some services, as firms in these industries may more easily adapt their organizational capital to the business cycle.

[11] In the other industries, R&D or ICT work is included as part of 'other' work.

Table 4 the average coefficients and mean t-statistics from separate proxy variable estimations for the 42 industry–year categories (with 36 industry-year categories in R&D work and 6 industry-year categories in ICT work). Fama and MacBeth's "t-statistics" $t(\overline{\beta}_k) = \overline{\beta}_k / \left(s(\beta_k) / \sqrt{z} \right)$, where z is the number of industry-years, are shown for each of the coefficients (Fama and MacBeth, 1973). We also report the average coefficients and the "t-statistics" when the tails of the industry-year coefficient distribution are constrained to values at 5% and 95% deciles in organizational and R&D work. This means that organizational worker share coefficients below -2.1 receive the value -2.1 and coefficients exceeding 4.2 receive the value 4.2 (the respective figures for R&D work are -2.0 and 1.2). We also report the weighted average coefficients with the inverse of each variable's within-industry variance as the weight.

Table 4. Average TFP contribution of organizational, R&D, and ICT work from proxy variable estimates in four-year periods by industry

Panel Mean Estimate	Average	After eliminating outliers	Weighted
OC share	0.702	0.754	0.514
"t-value"	(2.65)	(3.55)	
R&D share	-0.400	-0.411	-0.293
"t-value"	(1.5)	(1.83)	
ICT share	0.177	0.176	0.117
"t-value"	(.68)	(.68)	

The estimation spans 7 industries for OC share, 6 industries for R&D share and 1 industry for ICT share. The table shows the average coefficient, Fama and MacBeth's "t-statistics", and the weighted average coefficient for the industries and years, with inverse of variance as the weight.

Table 5. Industry-specific returns to intangibles

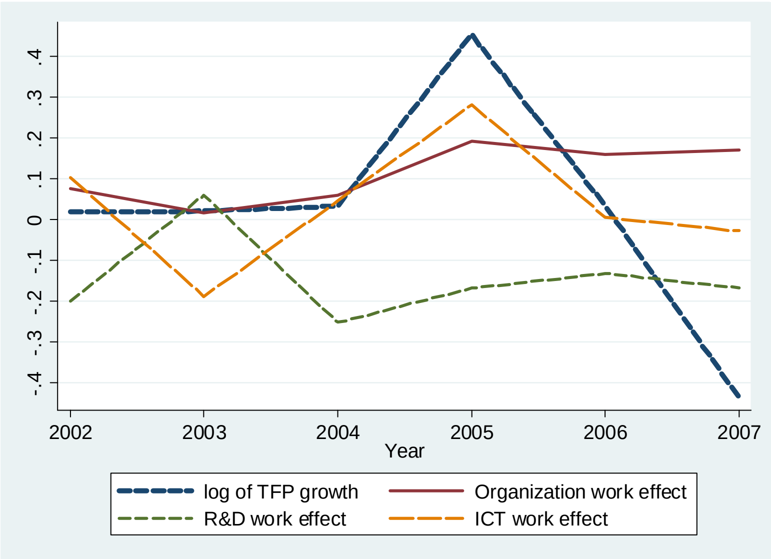
Industry	OC share	R&D share	ICT share
Service, consumer non-durables production: food, tobacco, textiles, leather, non-office furniture, publishing, hotels, and restaurants	0.49	-0.17	–
Consumer durables production (cars, TVs, furniture, household appliances; transportation, toys, and sports)	-0.56	0.26	–
Other manufacturing: machinery, metal, trucks, planes, office furniture, and paper	-0.12	0.62	–
Chemicals and allied products, energy, oil, gas, and coal extraction and products	0.97	-0.84	–
Business equipment (computers, software, and electronic equipment), money, finance, healthcare, medical equipment, and pharmaceuticals	1.66	-0.80	0.18
Wholesale, retail, and some services (laundries, repair shops)	1.70	–	–
Other (construction, transportation, building materials, and mining)	0.59	-0.82	–

The average relative productivity of organizational work over the industries is positive and significantly different from zero. The average is about the same when eliminating the outliers and somewhat smaller when using the weighted average. In R&D work, the returns are more volatile. The share of ICT work has the largest variation over the years and on average it is positively related to ICT share. In the following analysis, we use the estimates obtained after eliminating the outliers.

Table 5 shows the average estimates by industry. Organizational work has its highest returns in services and especially in business services and in wholesale, retail and some other services. The returns are instead negative in manufacturing other than consumer non-durable production. There is also large heterogeneity in R&D work, which has positive returns in manufacturing, while the productivity effects are negative in other industries.

Figure 4 shows cyclical productivity growth. Aggregate productivity growth is measured as the sales-weighted average of the firm-level log of TFP growth deflated by producer prices (the mean is 2.8). The figure also shows the part of log of TFP explained by the relative productivities of organizational, R&D and ICT work over time. Productivity growth reaches a peak in 2005 after which productivity growth has been strongly negative. Organizational work has been by far the the only type of intangibles contributing to productivity in all of the years, as the relative productivity has exceeded that of the rest of workers.

Figure 4. Development of productivity growth and contribution by different types of intangible related work to productivity



Next, we analyze productivity growth and decompose the growth effects into within- and between-effects across the firms. We first follow the decompositions suggested by Diewert (2005) and Maliranta (2010) in the division of TFP (below we denote $P_i \equiv \ln TFP_i$) into its parts:

$$\Delta P = \sum_i \overline{s}_{it,t-1} \Delta P_i + \sum_i \overline{P}_{it,t-1} \Delta s_i + \sum_i s_{it}^{Entry} \left(P_{it}^{Entry} - \overline{P}_{it} \right) + \sum_i s_{it-1}^{Exit} \left(P_{it-1}^{Exit} - \overline{P}_{t-1} \right). \tag{11}$$

The first component $\sum \overline{s}_{it,t-1} \Delta P_i$ represents the within-firms component of the change in productivity $\Delta P_i = P_{it} - P_{it-1}$, using the average output shares in periods *t* and *t*-1 as weights, $\overline{s}_{it,t-1} = 0.5(s_{it} + s_{it-1})$. In addition, we have measured the between component of productivity growth, $\sum \overline{P}_{it,t-1} \Delta s_i$. This second component represents the change in productivity due to changes in output shares $\Delta s_i = s_{it} - s_{it-1}$ using the average firm-level productivities as weights, $\overline{P}_{it,t-1} = 0.5(P_{it} + P_{it-1})$. The entry and exit effects measure the deviation of entering or exiting firms from the average productivity in the same periods (period *t* for entry and period *t*-1 for exit). The treatment of stayers differs in many papers analyzing micro-level restructuring, starting with Bailey, Hulten, and Campbell (1992).

The intangible capital type upskilling is more complex, as it includes the changes in the proportions of intangible-capital- work and in their productivities as given by equations (7) and (8). We again rely entirely on the more straightforward Diewert (2005) and Maliranta (2010) approaches in the decompositions, using weighted averages over the two periods as weights in

$$\Delta \left(c_{x,j} X_i \right) = \sum_i \overline{c}_{x,jt,t-1} \Delta X_i + \sum_i \overline{X}_{it,t-1} \Delta c_{x,j} \quad , \tag{12}$$

where $X_i = OC_i / L_i, R\&D_i / L_i, ICT_i / L_i$, and $c_{x,j}$ = the estimated respective productivity parameter for intangible-capital work of type *x* in industry *j*. The first component, $\sum \overline{c}_{x,jt,t-1} \Delta X_i$, represents the change in productivity owing to changes in the proportions of intangible-capital workers

$\Delta X_i = X_{it} - X_{it-1}$ using the estimated average, industry-level productivity parameters in periods *t* and *t*-1 as weights, $\overline{c}_{x,jt,t-1} = 0.5(c_{x,jt} + c_{x,jt-1})$. In addition, we have measured the productivity evolution of intangible-capital workers, $\sum \overline{X}_{it,t-1} \Delta c_{x,j}$. This second component represents the change in productivity due to changes in the industry and intangible capital-specific productivities $\Delta c_{x,j} = c_{x,jt} - c_{x,jt-1}$ using the average, firm-level, respective shares of intangible workers in periods *t* and *t*-1 as weights, $\overline{X}_{it,t-1} = 0.5(X_{it} + X_{it-1})$. Changes in intangible capital related worker shares and in industry-specific productivities can be further decomposed as before, and entry and exit effects can be included so that

$$\begin{aligned}\Delta\left(c_{x,j} X_i\right) = \sum_i \overline{c}_{x,jt,t-1} \Big\{ & \overline{s}_{it,t-1} \Delta X_i + \overline{X}_{it,t-1} \Delta s_i + \\ & s_{it}^{Entry}\left(X_{it}^{Entry} - \overline{X}_{it}\right) + s_{it-1}^{Exit}\left(X_{it-1}^{Exit} - \overline{X}_{it-1}\right)\Big\} \\ + \sum_i \overline{X}_{it,t-1} \Big\{ & \overline{s}_{it,t-1} \Delta c_{x,j} + \overline{c}_{x,jt,t-1} \Delta s_i + \\ & s_{it}^{Entry}\left(c_{x,jt}^{Entry} - \overline{c}_{x,jt}\right) + s_{it-1}^{Exit}\left(c_{x,jt-1}^{Exit} - \overline{c}_{x,jt-1}\right)\Big\} .\end{aligned} \tag{13}$$

The first term in the right-hand side of (13) depends on intangible-capital worker shares and the second term on changes in related productivities, all decomposed into within, between, entry and exit effects. Because productivity is measured at the industry level, in the latter part, the between effects $\sum \overline{X}_{it,t-1} \overline{c}_{x,jt,t-1} \Delta s_i$ are expected to be relatively small relative to the within effect $\sum \overline{X}_{it,t-1} \overline{s}_{it,t-1} \Delta c_{x,j}$, i.e., to changes in productivity over time within any industry. The entry and exit effects affect productivity depending on whether the entry and exit of firms are more or less productive than the average.

We next show the decompositions for ln*TFP* growth from equation (12). We use our estimates for the three-year periods to calculate the growth effects in Table 6.

Table 6. Decomposition of TFP growth

Change in logTFP		Log TFP
Aggregate		6.5 %
Within	$\sum \bar{s}\,\Delta P$	5.8 %
Between	$\sum \bar{P}\Delta s$	0.7 %
Entry		0.1 %
Exit		-0.1 %

TFP growth was positive 6.5% on average (note however the large cyclical variation in Figure 4). The within effect dominates the growth but also the between effect is positive so that firms that have been on average more productive have increased in size. Firms that have entered into the market or exited it have been on of average productivity. The relative weight of the within effect would be lower if a plant rather than a firm were chosen as the observation unit. This is because a greater turnover share of the observation unit leads to a greater within-unit effect. The results differ from the US, where the reallocation related to the between, entry and exit effects accounts for a greater share, equivalent to about half of manufacturing TFP growth (Foster, Haltiwanger, and Krizan, 2001, 2006). It should, however, be noted that the reallocation terms are most likely biased downwards by mismeasured prices (Foster, Haltiwanger, and Syverson, 2008).

Table 7 uses equation (13) to show the decomposition of productivity growth induced by intangible capital related to organizational, R&D, and ICT work relative to that of other kinds of work. The overall relative productivity growth induced by organizational work (0.6%) and R&D work (0.9%) is positive, while that generated by ICT is negative (-2.9%) (see the line of Table 7 combining changes in worker shares and productivity). Most of the productivity improvement generated by organizational work is due to higher returns, while the changes in the organization worker shares have had moderate overall effects. In contrast with organizational work, the relative productivity of R&D work has not improved over time. Changes in the share of R&D workers have instead contributed to the productivity growth on average. The R&D work intensity has increased over time (within effect is positive) but relatively less in firms and sectors that are on average more productive (between effect is negative).

Table 7. Decomposition of TFP growth as explained by intangibles

Change in worker shares	$\sum \bar{c}\Delta X$	Organ. work	R&D work	ICT work	Change in producti-vity	$\sum \bar{X}\Delta c$	Organ. work	R&D work	ICT work
Aggregate		-0.6 %	1.1 %	-3.0 %			1.2 %	-0.3 %	0.1 %
Within	$\sum \bar{c}\,\bar{s}\Delta X$	-0.3 %	1.7 %	-3.5 %		$\sum \bar{X}\,\bar{s}\Delta c$	0.4 %	0.1 %	0.0 %
Between	$\sum \bar{c}\,\bar{X}\Delta s$	-0.4 %	-0.3 %	0.0 %		$\sum \bar{X}\,\bar{c}\Delta s$	-0.1 %	-0.2 %	0.1 %
Entry		0.1 %	-0.1 %	0.0 %			0.8 %	-0.1 %	0.0 %
Exit		-0.1 %	-0.1 %	0.6 %			0.1 %	-0.1 %	0.0 %

Change in worker shares and productivity		Organ. work	R&D work	ICT work	Aggregate All Intangibles
Aggregate		0.6 %	0.9 %	-2.9 %	-1.5 %
Within	$\sum \bar{s}\Delta(cX)$	0.1 %	1.8 %	-3.5 %	-1.6 %
Between	$\sum (cX)\Delta s$	-0.5 %	-0.5 %	0.0 %	-1.0 %
Entry	$\sum (cX)\Delta s$	0.9 %	-0.1 %	0.0 %	0.8 %
Exit		0.0 %	-0.2 %	0.7 %	0.4 %

The share of ICT workers may adjust quickly to productivity expectations. The jumps in the share of these workers and productivity thus go hand in hand. Overall, the relative productivity of ICT workers has decreased by a large magnitude, as the sales share of business equipment, finance and private healthcare is around 7% of all industries, and the overall contribution to growth is close to -2.9%.

Table 6 indicated that a notable share of productivity growth is explained by the within effect and to less degree by restructuring. The situation is similar for organizational and R&D work in Table 7, where almost all of the improvement in relative productivity takes place within industries.

It appears to take time for new firms to build an efficient organization or to use R&D work for new production as the market reallocation is relatively unimportant in growth generated by intangibles. At the same time, globalization has been prominent and multinational firms have expanded their activities and employment abroad. Employment at domestic plants has remained at about half a million in our data, while employment abroad has expanded from 137,000 in 1996 to nearly 400,000 by 2006 according to data from the Bank of Finland on foreign direct investment.[12] It can be argued that organizational capital is needed to maintain the network of tasks spread over the plants across the countries. We therefore examine the connection of globalization and intangibles. A panel estimation will be used to analyze how the overall productivity improvement is related to background characteristics. Productivity growth related to organizational, R&D, and ICT work are interchangeably explained by globalization proxies and other firm characteristics, and, in comparison, we also do the same for total lnTFP. The model that we estimate is

---

[12] Data collected by *Talouselämä* magazine from the 500 largest firms in Finland give roughly the same figures. For large firms with employees abroad, the average domestic employment is 4,400 and employment abroad is 2,200.

$$
\begin{aligned}
dP_{xit} = {} & a_1 P_{xit-1} + a_1 GLOB_{it} + a_2 PRP_{it} + a_3 Y_{it} \\
& + m_0 + IND_{IT} + m_1[Year] + m_1[Year]*IND_{IT} + e_{it}
\end{aligned}, \qquad (14)
$$

where P_{xit} is either ln*TFP* or $c_{x,i}X_i$, indicating the additional productivity of organizational, R&D, or ICT work given by equation (5), $GLOB_{it}$ includes measures of globalization, PRP_{it} is a performance-related pay dummy and Y_{it} refers to the controls. Globalization is measured by employment abroad, by the number of plants (1, 2-3, and 3<) and by whether the firm is listed on the stock market. PRP_{it} is equal to one if the firm has implemented a PRP scheme.[13] The control factors Y_{it} include market share $MKS_{imt} = SALES_{imt} / \sum_{j=1}^{n} SALES_{jmt}$ at the two-digit industry level, along with firm age and its square. Furthermore, there are indicators for industries, years, and their interactions. Since many of the explanatory variables are not time-varying, we report the random-effect estimates with robust standard errors.

Productivity growth slows as the initial productivity level increases (column 1 of Table 8). The negative relationship between growth and the initial level also holds for the relative productivity of intangible work relative to other kinds of work (columns 2-4). Similar to the overall productivity growth, the positive growth explained by organizational work is more concentrated in globalizing firms with increasing employment abroad. The estimates thus show that increasing foreign employment is positively related to the part of productivity explained by organizational work but is negatively related to that explained by R&D work. The causal relationship can go either way, such that outsourcing of low-skilled production work is related to positive productivity growth stimulation by organizational work in the parent country. Outsourcing firms

[13] PRP remunerations are paid afterwards based on the set targets. PRP schemes are a relatively recent form of compensation, covering less than 10% of firms in 1995 and extending to over 60% of firms among those with more than 30 employees by 2006. The average pay is less than 5% of annual salaries (Confederation of Finnish Employers).

may have been less inclined to go on with R&D activity in the parent country. Production work abroad is accompanied by also foreign R&D activity.

Table 8. Explanation of TFP growth generated by intangible capital

	lnTFP	Growth in lnTFP Organizational	lnTFP R&D	lnTFP ICT
Lagged level	-0.192***	-0.780***	-0.779***	-1.086***
	(8.75)	(22.21)	(15.69)	(21.26)
Foreign employment	0.0152**	0.00661**	-0.00631*	-0.000676
	(2.79)	(3.01)	(2.45)	(0.21)
2-3 plants	-0.138***	0.0104	0.0144	-0.00676
	(7.68)	(0.82)	(1.39)	(0.58)
4 or more plants	-0.112***	-0.0109	0.0128	-0.0293
	(5.26)	(0.87)	(1.05)	(1.33)
Listed Firm	-0.0810*	-0.0856***	0.0942***	-0.0144
	(2.15)	(3.78)	(7.45)	(1.03)
Performance-related-pay	0.007	0.00457	-0.00975	0.011
	(0.67)	(0.61)	(1.34)	(0.96)
Firm age/10	-0.0106*	0.0102***	0.00578	0.00165
	(2.56)	(4.07)	(1.67)	(0.35)
Market share	0.000528	0.0000956	0.000805	0.000137
	(0.45)	(0.21)	(1.53)	(0.13)
Observations	5847	5032	4436	591
Number of firms	1305	1276	1112	156
R Squared within	0.32	0.698	0.636	0.702
R Squared between	0.0136	0.186	0.097	0.789
R Squared total	0.0872	0.585	0.453	0.703

Random effect log growth estimates with robust t-statistics in parentheses. All variables except dummies and market share are in log form. Four firm size dummies, industry and year effects and their interactions included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

It is noteworthy that the use of performance-related-pay is not positively related to productivity growth, not even to that generated by organization work. Firm age has a positive relationship with the kind of organizational work that improves productivity. The firm age may, however, be imprecisely measured, as it is derived from the longest length of service among non-production workers (or among all workers in the absence of non-production workers).

We can conclude that global firms have more intangible capital and that their organization work is more productive than that of non-globalized firms. R&D activity is more bound to the closeness of production activity, and the greater share of production of global firms takes place abroad. Including only R&D investment in intangibles thus underestimates the agglomeration of intangible-related work in the parent country of a multinational firm.

5. Conclusions

Our analysis shows the need for a broad view of intangible capital that includes managerial and marketing work. This concept is much broader than the product/process innovation questions on R&D surveys. The share of R&D work incorporates largely physical, mathematical, and engineering science professions, while management and marketing staff are at least equally important. A significant omitted-variable problem could arise if only the shares of R&D or ICT workers were used and organizational work ignored. Our estimation method is also robust to productivity shocks and does not necessitate ad hoc assumptions regarding the shares of work considered to produce goods that can be considered as long-term investment.

Overall, we find important intangible capital type upskilling in the 2000s that explains a large part of the total factor productivity growth. However, organizational work has been the only type of intangible-capital related work that has clearly improved TFP. Its productivity has exceeded that of other types of work almost throughout the years. Other intangibles have had an insignificant effect or even negative effect for productivity growth.

Organizational work is the dominant intangible capital type of work in services. Bloom, Sadun, and Van Reenen (2007) have emphasized the importance of organizational capital for productivity growth in services, which are more domestically oriented. Although the service sector is heterogeneous, organizational work clearly has a positive overall effect on productivity. The analysis shows that the productivity of organizational capital is highest in business services and in wholesale, retail, and some other services that typically lack other type of capital.

Workers engaged in intangible capital type of work are also not a burden to the firms. We show that intangible-capital work clearly improves the profitability of firms by moderating rather than increasing wages. This is especially true in high-productivity firms and is due to both organizational and R&D work. In the Finnish case, both centralized bargaining and the low taxation of earnings from capital investment play a role. Bargaining leads to low wage dispersion and taxation gives incentives to take earnings as capital income instead of salary. Finally, the productivity effects of changing shares of intangible-related workers stem fairly little from the total reallocation effects associated with the between firms effect of productivity growth and the entry and exit of firms. Market restructuring is thus not the origin of the productivity growth stimulated by changing shares in organization and R&D work. Intangibles are firm-specific and may require years of accumulation and productivity growth also takes place predominantly in high-productivity firms. Especially organizational work has more positive effect on productivity in more mature firms.

Firms having long-term investment in intangibles have a global perspective. We find that the productivity improvement of organizational work is clearly related to an increase in foreign employment or operations abroad and that global firms also have more intangible capital. R&D work instead appears more tied to production activity, which has been intensively off-shored in recent years.

An area for future research is to go more deeply into the measurement of intangibles by industry, which is essential for any performance-based measurement. In intangible-capital related work the share of labour costs that can be considered to produce long-term investment and not consumed within a year is indeed expected to change both by type of industry and by type of work.

Bibliography

Abowd, J.M., R.H. Creecy, and F. Kramarz (2002), "Computing Person and Firm Effects Using Linked Longitudinal Employer–Employee Data", Unpublished manuscript.

Abowd, J.M., F. Kramarz, and D.N. Margolis (1999), "High Wage Workers and High Wage Firms", *Econometrica*, Vol. 67, No. 2, pp. 251-333.

Ackerberg, D., C.L. Benkard, S. Berry, and A. Pakes (2007), "Econometric Tools for Analyzing Market Outcomes", in J.J. Heckman and E.E. Leamer (eds), *Handbook of Econometrics*, Vol. 6, Amsterdam: Elsevier, pp. 4171-4276.

Bailey, M., C. Hulten, and D. Campbell (1992), "Productivity Dynamics in Manufacturing Plants", in *Brookings Papers on Economic Activity: Microeconomics*, Vol. 4, Brookings Institution, Washington, D.C., pp. 187-267.

Becker, G.S. (1962), "Investment in Human Capital: A Theoretical Analysis", *Journal of Political Economy*, Vol. 70, No. 5, pp. 9-49.

Bloom, N., R. Sadun, and J. Van Reenen (2007), *Americans Do I.T. Better: US Multinationals and the Productivity Miracle*, CEPR Discussion Paper No. 6291, Centre for Economic Policy Research, London.

Bond, S. (2002), "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice", *Portuguese Economic Journal*, Vol. 1, pp. 141-162.

Bresnahan, T.F. and S. Greenstein (1999), "Technological Competition and the Structure of the Computer Industry", *Journal of Industrial Economics*, Vol. 47, No. 1, pp. 1-40.

Brynjolfsson, E. and L.M. Hitt (2000), "Beyond Computation: Information Technology, Organizational Transformation and Business Performance", *Journal of Economic Perspectives*, Vol. 14, No. 4, pp. 23-48.

Brynjolfsson, E., L.M. Hitt, and S. Yang (2002), "Intangible Assets: Computers and Organizational Capital", in *Brookings Papers on Economic Activity*, No. 2002-1, Brookings Institution, Washington, D.C., pp. 137-181.

Böckerman, P. and H. Piekkola (2001), "On Whom Falls the Burden of Restructuring?", in P. Jensen and A. Holm (eds), *Nordic Labor Market Research in Register Data*, TemaNord, 2001:593.

Corrado, C.A., Hulten, C.R. and Sichel, D.E. (2005), "Measuring Capital and Technology: An Expanded Framework", in C. Corrado, J. Haltiwanger and D. Sichel (eds.), *Measuring Capital in the New Economy, National Bureau of Economic Research, Studies in Income and Wealth* Vol. 65, Chicago and London: University of Chicago Press.

Corrado, C., C. Hulten, and D. Sichel (2006), *Intangible Capital and Economic Growth*, Finance and Economics Discussion Series No. 24, Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington, D.C.

Cummins, J. (2005), "A New Approach to the Valuation of Intangible Capital", in C. Corrado, J. Haltiwanger, and D. Sichel (eds), *Measuring Capital in the New Economy, National Bureau of Economic Research, Studies in Income and Wealth*, Vol. 65, Chicago and London: University of Chicago Press, pp. 47-72.

Diewert W.E. (2005), "Index Number Theory using Differences rather than Ratios", *American Journal of Economics and Sociology*, Vol. 64, No. 1, pp. 347-395.

Fama, E.F. and J.D. MacBeth (1973), "Risk, Return, and Equilibrium: Empirical Tests", *Journal of Political Economy*, Vol. 81, No. 3, pp. 607-636.

Fama, E.F. and K.R. French (1988), "Permanent and Temporary Components of Stock Prices", *Journal of Political Economy*, Vol. 96, No. 2, pp. 246-273.

———— (1997), "Industry Costs of Equity", *Journal of Financial Economics*, Vol. 43, No. 2, pp. 153-193.

Foster, L., J. Haltiwanger, and C.J. Krizan (2001), "Aggregate Productivity Growth: Lessons from Microeconomic Evidence", in *New Developments in Productivity Analysis*, Chicago and London: University Chicago Press.

———— (2006), "Market Selection, Reallocation, and Restructuring in US Retail Trade Sector in the 1990s", *Review of Economics and Statistics*, Vol. 88, No. 4, pp. 748-758.

Foster, L., J. Haltiwanger, and C. Syverson (2008), "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?", *American Economic Review*, Vol. 98, No. 1, pp. 394-425.

Griliches, Z. (1967), "Production Functions in Manufacturing: Some Preliminary Results", in M. Brown (ed.), *The Theory and Empirical Analysis of Production*, New York: Columbia University Press.

Griliches, Z. and J. Mairesse (1998), "Production Functions: The Search for Identification", in S. Strom (ed.), *Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium*, Cambridge, MA: Cambridge University Press, pp. 169-203.

Haskel J. and G. Marrano (2007), *How much Does the UK Invest in Intangible Assets?*, CEPR Discussion Papers No. 6287 .

Hellerstein, J.K., D. Neumark, and K.R. Troske (1999), "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations", *Journal of Labor Economics*, Vol. 17, No. 3, pp. 409-446.

Ilmakunnas, P. and M. Maliranta (2003), "The Turnover of Jobs and Workers in a Deep Recession: Evidence from the Finnish Business Sector", *International Journal of Manpower*, Vol. 24, No. 3, pp. 216-246.

————— (2005), "Technology, Worker Characteristics, and Wage–Productivity Gaps", *Oxford Bulletin of Economics and Statistics*, Vol. 67, No. 5, pp. 623-645.

Iranzo, S., F. Schivardi, and E. Tosetti (2007), "Skill Dispersion and Productivity: An Analysis with Matched Data", *Journal of Labor Economics*, Vol. 26, No. 1, pp. 247-285.

Ito, T. and A.O.E. Krueger (1996), "Financial Deregulation and Integration in East Asia", in *NBER-East Asia Seminar on Economics*, Vol. 5, Chicago and London: University of Chicago Press.

Klette, T. and J. Kortum (2004), "Innovating Firms and Aggregate Innovation", *Journal of Political Economy*, Vol. 112, No. 5, pp. 986-1018.

————— (2005), "The Valuation of Organizational Capital", in C. Corrado, J. Haltiwanger, and D. Sichel (eds), *Measuring Capital in the New Economy*, *NBER Studies in Income and Wealth*, Vol. 65, Chicago and London: University Chicago Press, pp. 73-99.

Levinsohn, J. and A. Petrin (2003), "Estimating Production Functions using Inputs to Control for Unobservables", *Review of Economic Studies*, Vol. 70, No. 2, pp. 317-342.

Maliranta, M. (2010), "In Search of an Ideal Method for Analyzing Micro-Level Dynamics of a Great Productivity Leap", Unpublished manuscript.

McGrattan, E.R. and E.C. Prescott (2008), *Technology Capital and the U.S. Current Account*, NBER Working Paper No. 13983, National Bureau of Economic Research, Cambridge, MA.

Olley, G.S. and A. Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, Vol. 64, No. 6, pp. 1263-1298.

Ouazad, A. (2008), "A2REG: Stata module to estimate models with two fixed effects", Statistical Software Components S456942, Boston College Department of Economics.

Piekkola, H. (2009), *Intangible Capital: Can It Explain the Unexplained?*, University of Vaasa Department of Economics Working Paper No. 13, University of Vaasa.

Piekkola H., Görzig B. and R. Riley (2010), "Production of own account intangible investment and growth: Methodology in Innodrive project", Innodrive working paper No 1. Unpublished.

Sichel, D. (2008), "Intangible Capital", in S.N. Durlauf and L.E. Blume (eds), *The New Palgrave Dictionary of Economics*, 2nd edition, Basingstoke: Palgrave Macmillan (retrieved from http://www.dictionaryofeconomics.com/article?id=pde2008_I000299).

Webster, E. M. (2000), "The growth of intangible enterprise investment in Australia", Information Economics and Policy, Vol 12, No. (1), pp. 1-25,

World Bank (2006) *Where is the Wealth of Nations? Measuring Capital for the 21st Century*. Washington D.C., World Bank.

Yasar, M., R. Raciborski, and B. Poi (2008), "Production Function Estimation in Stata using the Olley and Pakes Method", *Stata Journal*, Vol. 8, No. 2, pp. 221-231.

Appendix A. Occupational classification of non-production workers

Table A.1 Occupational classifications

	Occupation of Non-Production Worker	Organization Worker	R&D Worker	IT Worker
Manufacturing	Management	Management		
	R&D		x	
	R&D superior		x	
	Supply transport non-prod			
	Supply transport non-prod superior			
	Computer			x
	Computer superior			x
	Safety quality maintenance non-prod			
	Marketing purchases non-prod	Marketing		
	Marketing purchases non-prod superior	Management		
	Administration non-prod	Administration		
	Administration non-prod superior	Administration		
	Finance admin non-prod			
	Finance admin non-prod superior	Management		
	Personnel management non-prod	Administration		
	Cleaner garbage collectors messengers			
Services	Media			
	Computer processing services			x
	Computer processing services superior			x
	Salesperson contract work services			
	Warehouse transport services			
	Maintenance gardening forest services			
	Teacher counceling social science professionals			
	Hotel restaurants			
	Hotel restaurants superior			
	Social and personal care			
	Health sector			
	Forwarder services			
	Purchases and sales services			
	Insurance worker			
	Insurance worker superior			
	Small business manager			
	Finance services			
	Finance services superior	Management		
	Marketing services			
	Marketing services superior	Marketing		
	R&D worker services		x	
	Personnel project manag services	Administration		
	Personnel project manag services superior	Management		
	Administration services			
	Administration services superior	Management		

Source: Own calculations applying unique occupational classification of employee data by the Confederation of Finnish Industry and Employers to satisfy ISCO classification but separating service and non-service occupations.

Appendix B. Summary of Variables

Table B.1 Summary of variables

Variable	Mean	Std	Median	Obs
TFP ln(Y/L)-(1-a)*ln(K/L)	3.2	0.58	3.1	6407
Sales	148508	1E+06	22115	6407
Employees	363	1018	122	6407
Human Capital	-0.004	0.14	-0.007	6407
Organ. worker share	0.11	0.13	0.065	6407
R&D share	0.064	0.12	0.027	6407
ICT worker share	0.019	0.06	0.0016	6407
Net Plant, Property, Equipment	33217	192153	3239	6407
Firm age	38	14	41	6407
Hirings	0.18	0.14	0.15	6396
Material	12527	48980	2213	6407
Equity ratio	0.37	0.25	0.36	6154
Performance-Related-Pay	0.58	0.49	1	6407
2-3 plants	0.54	0.5	1	6407
4 or more plants	0.18	0.38	0	6407
Firm size 20-49	0.17	0.38	0	6407
Firm size 50-149	0.38	0.49	0	6407
Firm size >499	0.14	0.35	0	6407

Table B.2 Correlations

	HC	Org worker share	R&D worker share	ICT worker share	Hiring
Human capital	1.000				
Organizational worker share	0.189	1.000			
R&D worker share	0.264	0.167	1.000		
ICT worker share	0.185	0.197	0.080	1.000	
Hiring	0.199	-0.113	-0.071	-0.039	1.000
Log of materials	0.090	-0.002	0.083	-0.068	-0.060

Appendix C. Industry classifications

Table C.1 Industry classifications

	Industry	NACE Rev. 1	Main industry
1	Service, consumer non-durables: food, tobacco, textiles, apparel, leather, non-office furniture, publishing, hotels, restaurants, entertainment, and utilities	DA, DB, DC, DL (335), DM (354), E, H	Services, production of non-durables
2	Consumer durables: Cars, TVs, furniture, household appliances, transportation, toys, and sporting goods	DM (excl. 354) DL (322-323) DN (excl. 3611-3612) I (excl. 642)	Manufacturing
3	Other manufacturing: machinery, metal, trucks, planes, office furniture, and paper	DM (351-353) DD, DE, DK, DN (3611-3612), DJ, DN	Manufacturing
4	Chemicals and allied products, energy, oil, gas, and coal extraction and products	DG (excl. 244), DH, DI, DF	Manufacturing
5	Business equipment: computers, software, and electronic equipment; Finance Healthcare, medical equipment, and pharmaceuticals	DL (300, 311-316, 332-335) K (721-724) J, K (incl. 721-724) N (private), DG (244)	Services, production of non-durables
6	Telecoms, telephone and TV transmission	I (642)	Services, production of non-durables
7	Wholesale, retail, and some services (laundries and repair shops)	J, K (excl. 721-724)	Services, production of non-durables
8	Other: construction, transportation, building materials, and mining	CA, CB, F	Construction, others

Source: Classification adjusted from Fama and French (1988, 1997)