CHAPTER 10

ICT AND BUSINESS PRODUCTIVITY: FINNISH MICRO-LEVEL EVIDENCE

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Abstract

Widespread use of ICT in Finnish business enterprises is quite recent. Contrary to what was believed during the new economy boom, the increasing use of ICT is primarily a phenomenon within firms; the contribution of restructuring to the observed changes in aggregate ICT-intensity is rather marginal. Decompositions of productivity growth suggest, however, that experimentation and selection are quite intense among young ICT-intensive firms. After controlling for industry and time effects as well as labour and other firm-level characteristics, the additional productivity of ICT-equipped labour ranges from 8% to 18% corresponding to roughly a 5% to 6 % elasticity of ICT capital. The effect is much higher in younger firms and in ICT-providing activities. The finding for firm age is consistent with the need for ICT-complementing organisational changes. The finding for ICT-providing activities is not driven by the communications equipment industry but rather by ICT services. Overall, the excess productivity induced by ICT seems to be somewhat higher in services than in manufacturing. Manufacturing firms benefit in particular from ICT-induced efficiency in internal communication (linked to use of local area networks or LANs) whereas service firms benefit from efficiency in external (Internet) communication. We find weak evidence for the complementarity of ICT and education.

10.1 Introduction

Koski, Rouvinen and Ylä-Anttila (2002) show that in a decade Finland has gone from being one of the least ICT-specialised industrialised countries to the most specialised. The Finnish ICT sector (see Paija, 2001; Paija and Rouvinen, 2003) is heavily specialised in communications technology production and is dominated by Nokia, although the cluster comprises several thousand firms, including over three hundred first-tier suppliers of Nokia (see, for example, Ali-Yrkkö, 2001; Ali-Yrkkö, 2003). There are indications that Finland may not be as exceptional as a user of ICT than it is as a producer. Studies at the macro level show that the overall effects of ICT are quite large in Finland, but that they are mostly linked to ICT provision (Jalava and Pohjola, 2002).

The Finnish economy has experienced a great leap in its productivity since the late 1980s, largely attributable to advances in the manufacturing sector. Analysis with plant-level data has shown that the acceleration in productivity has mostly taken place through micro-level restructuring between plants but within industries (Maliranta, 2002). These findings underline the importance of firm (and plant) demographics in the productivity evolution and are in accordance with various firm life-cycle models (Ericson and Pakes, 1995; Jovanovic, 1982). These models show that the process of incessant experimentation and selection in the markets is at the core of long-run economic development. While productivity-enhancing plant-level restructuring seems to have taken off as early as the late 1980s, it is unclear to what extent this can be attributed to ICT. Various other profound changes in the economic environment since the 1980s have probably contributed to the process and paved the road for ICT and its productivity effects in the 1990s.

In what follows, we primarily study the productivity effects of ICT at the level of a firm. We address the following questions:

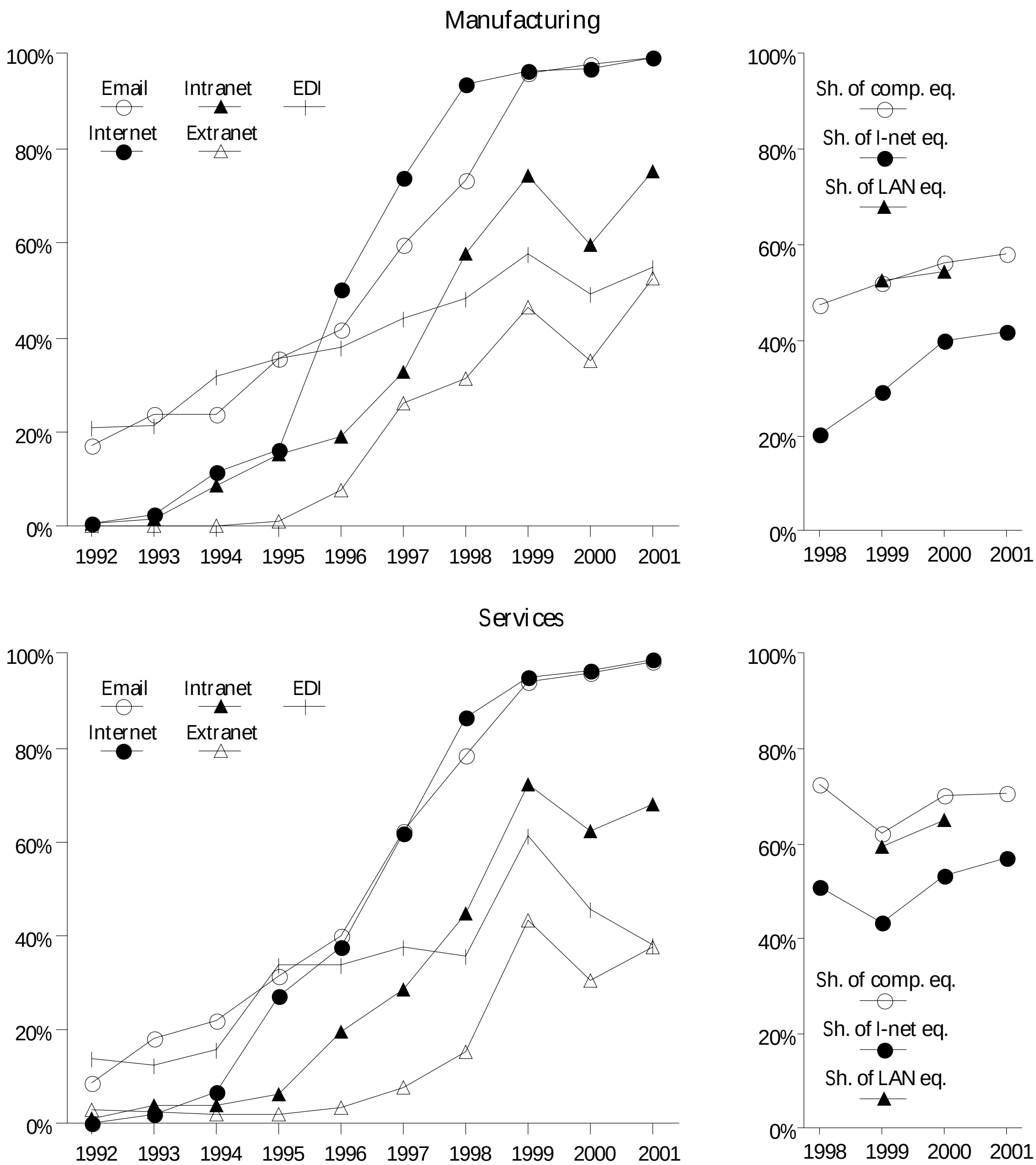
- Does ICT have measurable effects on productivity?
- If so, does the role of ICT differ between manufacturing and services and/or between ICT and non-ICT industries?
- Does the impact of ICT vary by firm age?
- Does the impact of ICT vary across time?
- Is ICT complementary to education?
- What are the effects of various technologies, *e.g.* computers, Internet, local area networks (LANs)?

This introductory part is followed by a discussion in section 10.2 of some of the developments in workers use of ICT. Section 10.3 performs a principal components and decomposition analysis. Section 10.4 provides a brief theoretical background and review of previous literature and provides the estimation results of the model. Section 10.5 concludes.

10.2 Increase in workers use of ICT

One of the key questions of the study is how much the productivity of Finnish businesses is boosted by having a greater share of ICT-equipped labour, *i.e.* workers that use a computer, Internet, and/or a local area network (LAN) at work. In order to answer this question, we first look at the increases in ICT use in recent years.

Figure 10.1. **Exposure of firms (left panels) and employment (right panels) to various forms of ICT in Finnish manufacturing and services (probability and employment weighted)**



Source: Statistics Finland's *Internet use and e-commerce in enterprises* surveys. The shares of firms and employees are calculated by using employment and probability weights. Calculations by the authors.

Figure 10.1 shows the increase in the use (or availability) of various forms of ICT. Several findings are noteworthy. First, widespread use of ICT is a recent phenomenon; as late as 1995 one third of workers had (external) email at their disposal – by 2001 this technology was nearly completely diffused. Overall it is clear that all workers and firms are exposed to at least some form(s) of ICT; discussing diffusion in *general* may therefore not be worthwhile. Some key technologies are, however, nowhere near their full penetration levels. For example, "only" three fourths of all manufacturing employment worked in a firm that had an intranet in 2001. The respective proportion for service employment is two thirds. Interestingly the role of *electronic data interchange* (EDI), in some sense the "old generation" technology for inter-organisational networking, is decreasing, especially in services.

We can also observe that the use of computers has steadily increased over time in manufacturing. 58% of manufacturing and 71% of service employment used a computer (or a terminal) at work in 2001. The figure for services in considerably higher, but has not increased in recent years. The proportions of workers that are connected to a local area network (LAN) or Internet has increased in manufacturing as well as in services.

The samples of the surveys underlying Figure 10.1 vary from year-to-year which, despite weighting, causes point estimates to be somewhat "noisy". In order to reduce the problem, we consider only firms that are included in two consecutive samples. Further, we decompose the annual changes in ICT use among continuing firms into "*within* firms" and "*between* firms" effects. The within component indicates the average change in ICT use of the firms. The between component provides us with a gauge of micro-level restructuring. It is positive when high ICT-intensity firms increase their labour share at the cost of low ICT-intensity firms.[1] The formula for the method used is as follows:

$$\Delta INT_{ICT} = \sum \Delta INT_{ICT,i}\overline{S}_i + \sum \Delta S_i \overline{INT}_{ICT,i} , \tag{1}$$

where $INT_{ICT} = L_{ICT}/L$ is the ICT intensity, *i.e.* the share of labour equipped with a computer, Internet, or LAN, $INT_{ICT,i} = L_{ICT,i}/L_i$ is the ICT intensity of the firm i, $S_i = L_i/\sum L_i$ is the employment share of the firm i in the industry, $\overline{S}_i$ and $\overline{INT}_{ICT,i}$ are the average employment share and ICT intensity of the firm i in the initial and end year, respectively.

The first term in the right-hand side of (1) is the *within* and the second the *between* component. As the decomposition method is implemented for a sample, each firm is weighted by the inverse of the sampling probability. More specifically, the average weight in the initial and end year is used. There are at least three alternative ways in analysing the year-to-year changes. One can consider:

1. Firms that are unchanged as legal entities between the two points in time (*original*).

2. Legal entities that are structurally unchanged in time, *i.e.* have not acquired or sold plants (*filtered*).

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1. We have ignored the roles of entry and exit for two reasons. More detailed investigations performed by linking ICT data with the Business Register indicated that only few firms in the ICT data are true entries and exits. Measurement of the entry and exit effects would thus be highly unreliable. Besides, true entry and exit accounts for an insignificant labour share; only a few percentages altogether (see Ilmakunnas and Maliranta, 2003). Both entry and exit should be seen as time-consuming events and therefore restructuring takes place essentially among the continuing firms (and their plants).

3. The "synthetic" firms formed by summing up the plants that the firm has continuously possessed between the two points in time (*synthetic*).

The first alternative is simple but somewhat inaccurate; the second is accurate but observations are lost quite rapidly especially if differences over longer periods are considered; the third uses available information efficiently but obscures the definition of a firm.

Table 10.1 considers the changes in the proportions of ICT-equipped employment and decomposes the changes to within and between effects using the firm definitions discussed above. Manufacturing shows a robust growth in both computer and Internet intensity, whereas the development has been more stagnant in services, as already indicated in Figure 10.1 above. The decompositions show that structural components (between effect) have a slight positive effect on diffusion, but that the growth in ICT intensity overwhelmingly takes place within firms. In other words, no evidence was found that there is a systematic re-allocation of employment towards high ICT-intensity firms within manufacturing or services.

Table 10.1. **Decomposition of the change in computer and Internet intensity (based on chained sample data on "original", "filtered" and "synthetic" firms as discussed above)**

	Original			Filtered			Synthetic		
Manufacturing, Computers	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.
1998–1999	4.7%	4.5%	0.2%	3.2%	2.8%	0.4%	4.5%	4.3%	0.1%
1999–2000	3.3%	3.4%	0.0%	3.6%	3.8%	-0.2%	3.3%	3.4%	0.0%
2000–2001	1.5%	1.5%	0.0%	5.4%	5.4%	0.0%	2.1%	2.2%	-0.1%
1998–2001	16.1%	15.9%	0.2%	14.9%	14.0%	0.9%	17.1%	16.5%	0.5%

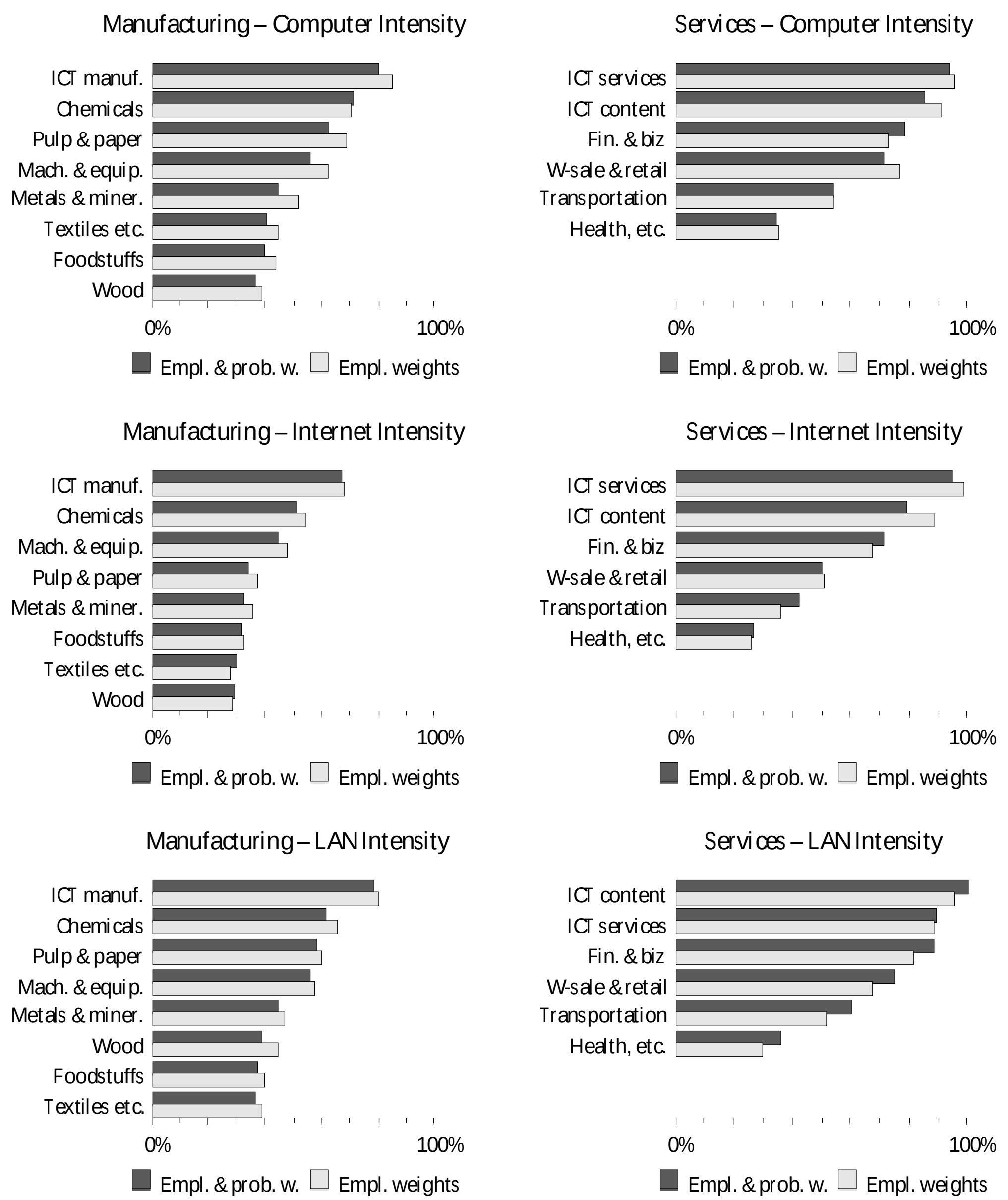
	Original			Filtered			Synthetic		
Manufacturing, Internet	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.
1998–1999	6.5%	6.6%	-0.1%	4.3%	4.1%	0.2%	6.5%	6.5%	0.1%
1999–2000	8.6%	9.0%	-0.3%	8.7%	9.0%	-0.2%	8.8%	9.0%	-0.2%
2000–2001	3.2%	3.3%	-0.1%	7.7%	7.7%	0.0%	4.1%	4.2%	-0.1%
1998–2001	22.1%	22.2%	-0.1%	21.1%	20.6%	0.4%	23.1%	22.7%	0.4%

	Original			Filtered			Synthetic		
Services, Computers	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *comp.* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.
1998–1999	1.6%	0.6%	1.0%	1.0%	0.3%	0.7%	1.5%	0.5%	1.0%
1999–2000	6.9%	7.0%	-0.1%	5.4%	4.8%	0.6%	7.0%	6.9%	0.2%
2000–2001	-2.6%	-2.3%	-0.3%	-2.3%	-2.1%	-0.2%	-2.5%	-2.3%	-0.2%
1998–2001	4.8%	5.1%	-0.3%	8.2%	6.4%	1.9%	5.3%	4.8%	0.5%

	Original			Filtered			Synthetic		
Services, Internet	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.	Ch. in the sh. of *I-net* eq. labour	*Within* effect in the ch.	*Between* effect in the ch.
1998–1999	4.2%	2.6%	1.7%	2.5%	1.6%	0.9%	4.0%	2.5%	1.5%
1999–2000	6.9%	6.4%	0.5%	7.2%	6.1%	1.0%	6.8%	6.3%	0.4%
2000–2001	1.3%	1.5%	-0.2%	0.3%	0.3%	0.0%	1.5%	1.5%	0.0%
1998–2001	16.9%	14.9%	2.0%	21.1%	17.6%	3.5%	16.5%	14.4%	2.0%

Source: Statistics Finland's Internet use and e-commerce in enterprises surveys. Calculations by the authors.

Figure 10.2. **Computer, Internet, and LAN intensity by industry (estimated by weighted OLS)**



Note: Data from Statistics Finland's *Internet Use and E-commerce in Enterprises S*urveys. Calculations by the authors. Standard errors of these estimates are 2-3 percentage points. Manufacturing industries defined as follows: Foodstuffs (15-16); Textiles etc. (17-19); Wood (20); Pulp & paper (21); Chemicals (23-25); Metals & miner. (26-28); Mach. & equip. (29, 311, 312, 314-316, 331, 334, 335, 34, 35); ICT manuf. (30, 313, 32, 332, 333). Service industries defined as follows: Wholesale & retail (50-52); Transportation (60-63); Fin. & buss (65-67, 70, 71, 741-743, 745-748); Health, etc. (55, 75, 85, 90, 91, 923, 925-927, 93); ICT services (642, 72); ICT content (221, 744, 921, 922, 924). Two-digit industries explained in Table 10.3.

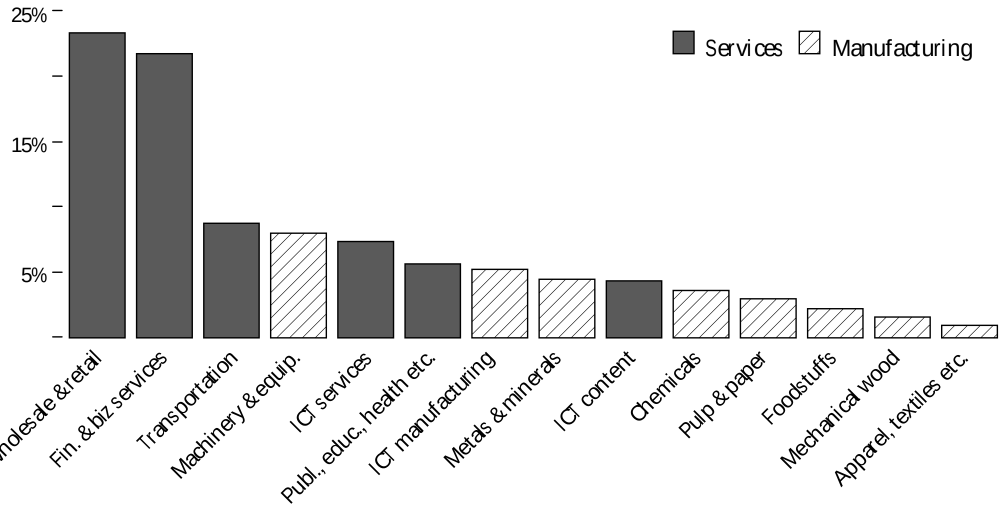
It should be pointed out that the discussion above (and in most cases also elsewhere in this paper) focused on employment-weighted results, *i.e.* they examine the situation a Finnish worker is facing and are thus appropriate when considering the broader situation. Results in this section are mainly driven by the situation in large and medium-sized firms. If one were to consider firm counts only, penetration rates would appear somewhat lower (these results have been reported in several public-cations of Statistics Finland in the *Science, Technology and Research* series).

It is quite clear that smaller firms have some disadvantages in the initial implementation of many forms of ICT. For example, the cost of establishing an extranet is not proportional to the intended scale of operation but is rather a fixed cost. Furthermore, implementing cutting-edge technologies entails risks that larger firms may be able to pool better than small firms. On the other hand, security concerns may be higher in larger firms primarily because they are more likely targets.

The analysis above ignores that there are substantial differences in ICT use between industries. These differences can be illustrated by performing a simple regression where computer, Internet, or LAN intensity is explained by a set of industry dummies. All years available for the estimation are pooled in order to have estimates that are as accurate as possible for the inter-industry differences. We therefore include dummies for different years, the reference being the last year available in the data. Estimations are performed by using employment weights and combined employment and sample weights. The results are illustrated in Figure 10.2. About 80% of all workers use computers in the ICT-producing manufacturing industries. The corresponding number in the ICT-producing services is 95%. Computer and Internet use is relatively low in foodstuffs, textiles etc., wood, and metals and minerals. The intermediate group consists of such industries as pulp and paper, chemicals, and machinery and equipment.

Based on the above intensities and overall employment, we can obtain an estimate of the sectors' shares of the ICT capital stocks in the Finnish business sector (defined here as the sum of the 14 manufacturing and service sectors above). As can be seen in Figure 10.3, although wholesale and retail trade is not among the most ICT-intensive sectors in Figure 10.2, its considerable size implies that it controls over one fifth of the overall ICT capital stock. Financial and business services also accounts for a considerable share of the overall stock. In manufacturing, machinery and equipment controls the largest share of the stock.

Figure 10.3. **Approximate shares of the ICT capital stock in the business sector (manufacturing and services as defined above) of Finland**



Note: Business sector = the sum of the 14 manufacturing and service sectors defined in Figure 10.2. ICT stocks calculated by taking the arithmetic mean of the employment and probability weighted Computer, Internet, and LAN intensities in Figure 10.2 and multiplying it by the corresponding employment.

10.3 Principal components and decomposition analysis

The preliminary analysis in this section uses plant-level (as opposed to firm-level) manufacturing (as opposed to manufacturing *and* services) data.

Principal component analysis (PCA) can be seen as a method "… to reduce the dimensionality of a data set consisting of a large number of interrelated variables…" (Jolliffe, 2002, p. 1). We perform a correlation matrix-based PCA with a sample of Finnish manufacturing plants covering roughly half of manufacturing employment in year 2000. The following variables are included: measures of ICT-intensity (the computer and Internet labour shares), measures of employees (average age of employees, average tenure in the plant, share of employees with higher technical education, and share of employees with higher non-technical education) and plant characteristics (plant age and R&D intensity).

Two principal components (PCs) with eigenvalues above one are found (results not shown but available upon request). The first PC (PC1) has an eigenvalue of nearly three and explains over one third of the variation. It has high (positive) loadings on ICT-intensities and technical education but low (negative) loadings on plant age and employee tenure. In other words, plants with a high PC1 value tend to be relatively technology-intensive new plants.

Based on the extracted PC1 values, we divide the sample into three equally sized groups. The first group consists of plants with the highest PC1 values, which we label *new*. The last group consists of plants with the lowest PC1 values, which we label *traditional*. The remaining one third belongs to the group labelled *middle*. In what follows, productivity decompositions are applied separately for these three groups. The following productivity decomposition method is applied (Foster, Haltiwanger and Krizan, 2001):

$$\Delta \ln P = \sum \overline{S}_i \cdot \Delta \ln P_i + \sum \left(\overline{\ln P_i} - \overline{\ln P} \right) \cdot \Delta S_i \, , \qquad (2)$$

where P and P_i are the productivity indicators of the total industry and plant i, respectively and S_i is the input share of the plant i. Here input is measured by a weighted geometric average of labour input and the capital stock. The weights are determined by the respective factor income shares. We limit our analysis to the continuing plants for the reasons explained in note 1.

The first term in the right-hand side of the equation is the "*within* plants" component that indicates the (weighted) average productivity growth rate of the plants. The second term is the "*between* plants" component. It gauges how much plant-level restructuring has increased aggregate productivity during the period under consideration. It is positive when there is a systematic reallocation of resources from low productivity plants to high productivity plants. It thus measures the productivity-enhancing selection among plants.

As Figure 10.4 shows, there are no major differences between the three groups in total factor productivity growth that takes place inside (within) the plants. Despite the fact that the effect of micro-structural change is eliminated from the within component, the numbers for the "representative plant" obviously hide a lot of heterogeneity in the *changes* in ICT intensity between plants.

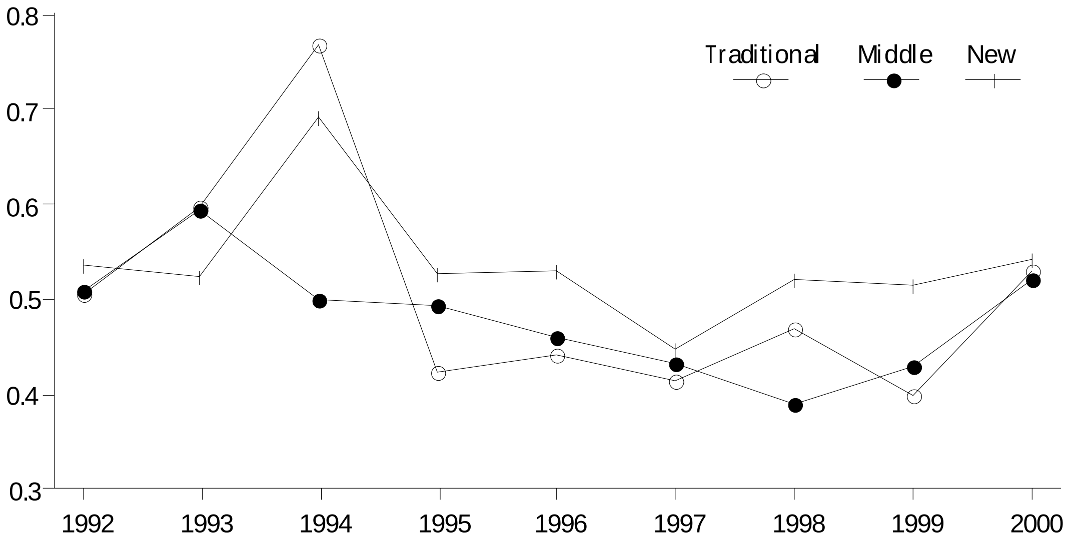
Figure 10.4. **TFP growth *within* plants – no major differences between the groups**

Figure 10.5. ***Between* plants – effect in TFP growth – "creative destruction" among new plants**

Figure 10.5 illustrates the development of the between component in the three groups of plants. The new have consistently higher between effects, indicating that productivity enhancing restructuring (selection) is the highest among them as compared to the other two groups. This is consistent with the argument that ICT-related experimentation by the new plans leads to intensive "creative destruction", *i.e.* plants with successful experimentation grow and others decline. It is worth noting that since the productivity decomposition is conducted with plant-level data these results may reflect intra-firm as well as inter-firm restructuring among the new or among the two other groups of plants. The above findings are in accordance with Maliranta (2001, pp. 37-8). His analysis indicated that a disproportionally large share of the positive between component can be attributed to plants with high R&D-intensity. However, the within component showed no significant differences between plants with high and low R&D-intensity.

Figure 10.6 shows the variation in TFP levels between the three groups. Two things immediately invite attention. *First*, the variation seems to have diminished in all three groups since the mid-1990s. This is caused by the decline of low productivity plants as a consequence of the deep recession. *Second*, after this "cutting off the lower end of the productivity distribution" had been completed by the mid-1990s, we observe higher variation in the TFP levels of new plants. This is consistent with experimentation, *i.e.* possibly equally intense but nevertheless different approaches to the implementation of ICT lead to different "draws" from the productivity distribution among the new plants. In a competitive setting we would not expect the high variation in TFP levels to persist, unless the process is not continually nourished by new innovations and further experimentation. A change in productivity dispersion suggests that the balance between experimentation (more intense experimentation increases the dispersion) and restructuring/selection (which reduces the dispersion as lower productivity plants decline) has changed in the more dynamic and competitive environment.

Figure 10.6. **Standard deviation in logged TFP levels – more variation among new plants**



10.4 Productivity effects of ICT

As section 10.2 showed, ICT penetration progressed rapidly in the late 1990s. Depending on the measure used, it grew ten to twenty percentage points in a few years. The increase was a *within* firms phenomenon; the contribution of restructuring (the *between* effect) was less than one percentage point over the four year period.

TFP decompositions in section 10.3 showed that restructuring was particularly rapid among young ICT-intensive plants ("new") even though their average TFP growth was similar to other firms. This finding is consistent with intense experimentation and selection within the new group.

10.4.1 Model

A standard Cobb-Douglas production function of firm i at time t can be presented as

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} \boldsymbol{Z}_{it}^{\beta_Z} , \qquad (3)$$

where Y is output (value added), A is *disembodied* technology, K is capital, L is labour, and $\boldsymbol{Z}$ a vector of other firm characteristics. *Embodied* technology is, by definition, included in the productive assets and/or intermediate inputs.

Assume that all workers (L) are perfect substitutes, but that they may have different marginal productivities depending on whether they use ICT (L_{ICT}) or not (L_0). This can be introduced into (3) as follows:

$$Y_{it} = A_{it} K_{it}^{\beta_K} \left(L_{it} \left(1 + \theta_{L_{ICT}} \left(\frac{L_{ICT,it}}{L_{it}} \right) \right) \right)^{\beta_L} \boldsymbol{Z}_{it}^{\beta_Z} , \qquad (4)$$

where $\theta_{L_{ICT}}$ is a parameter capturing the possible *additional* productivity effect associated with the use of ICT. Slight manipulation yields the labour productivity specification

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \ln A_{it} + \beta_K \ln\left(\frac{K_{it}}{L_{it}}\right) + \beta_L \ln\left(1 + \theta_{L_{ICT}} \left(\frac{L_{ICT,it}}{L_{it}}\right)\right) + \left(\beta_K + \beta_L - 1\right) \ln L_{it} + \boldsymbol{\beta}_Z \ln \boldsymbol{Z}_{it} , \qquad (5)$$

where $\left(\beta_K + \beta_L - 1\right) \ln L_{it}$ controls for deviations from constant returns to scale (Griliches and Ringstad, 1971). Approximating $\ln\left(1 + \theta_{L_{ICT}} \left(L_{ICT,it} / L_{it}\right)\right)$ with $\left(L_{ICT,it} / L_{it}\right)$ yields

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) \approx \ln A_{it} + \beta_K \ln\left(\frac{K_{it}}{L_{it}}\right) + \beta_L \theta_{L_{ICT}} \left(\frac{L_{ICT,it}}{L_{it}}\right) + \left(\beta_K + \beta_L - 1\right) \ln L_{it} + \boldsymbol{\beta}_Z \ln \boldsymbol{Z}_{it} . \qquad (6)$$

An increase in A will make all factors proportionately more productive. Lehr and Lichtenberg (1999) propose that this might be the case with ICT if its primary function is to improve communication. Atrostic and Nguyen (2002), for example, incorporate a computer network dummy into A.

This leads us to consider alternative ways of introducing ICT into (3). ICT efficiency E can be defined as follows ($s_{L_{ICT}}$ indicates the share of ICT ($L_{ICT,it} / L_{it}$) and s_{L_0} the share of non-ICT ($L_{0,it} / L_{it}$) labour):

$$E_{it} = e^{s_{L_0,it} + \left(1 + \theta_{L_{ICT,it}}\right) s_{L_{ICT,it}} - 1} \qquad (7)$$

If the role of ICT is merely to augment labour, (3) becomes

$$Y_{it} = A_{it} K_{it}^{\beta_K} \left(e^{s_{L_0,it} + \left(1 + \theta_{L_{ICT,it}}\right) s_{L_{ICT,it}} - 1} L_{it} \right)^{\beta_L} \boldsymbol{Z}_{it}^{\beta_Z} \qquad (8)$$

leading to the specification considered in (6), where the relationship is now exact rather than approximate. If, instead, ICT augments output and/or increases efficiency of all inputs (and constant returns to scale prevails), (3) becomes

$$Y_{it} = A_{it} e^{s_{L0,it} + (1+\theta_{L_{ICT},it}) s_{L_{ICT},it} - 1} K_{it}^{\alpha} L_{it}^{1-\alpha} \mathbf{Z}_{it}^{\beta_Z} = A_{it} \left(e^{s_{L0,it} + (1+\theta_{L_{ICT},it}) s_{L_{ICT},it} - 1} K \right)_{it}^{\alpha} \left(e^{s_{L0,it} + (1+\theta_{L_{ICT},it}) s_{L_{ICT},it} - 1} L \right)_{it}^{1-\alpha} \mathbf{Z}_{it}^{\beta_Z} \quad (9)$$

leading to

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \ln A_{it} + \alpha \ln\left(\frac{K_{it}}{L_{it}}\right) + \theta_{L_{ICT}} \left(\frac{L_{ICT,it}}{L_{it}}\right) + \boldsymbol{\beta}_Z \ln \mathbf{Z}_{it} \,. \quad (10)$$

With the exception of the ICT coefficient $\beta_L \theta_{L_{ICT}}$ that appears as $\theta_{L_{ICT}}$ above, (10) is a constant returns to scale version of (6). Estimations of (6) and (10) would be identical, but the interpretation of the ICT coefficient would be somewhat different.[2]

10.4.2 Analysis

We will capture disembodied technology and industry specific shocks by defining

$$A_{it} = e^{\beta_0 + \gamma_{jt}} \quad (11)$$

where j refers to the industry of firm i. Thus, our empirical specification becomes

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \beta_0 + \gamma_{jt} + \beta_K \ln\left(\frac{K_{it}}{L_{it}}\right) + \theta_{L_{ICT}} \left(\frac{L_{ICT,it}}{L_{it}}\right) + (\beta_K + \beta_L - 1) \ln L_{it} + \boldsymbol{\beta}_Z \ln \mathbf{Z}_{it} + \varepsilon_{it} \,, \quad (12)$$

where ε is the error term. Separately and together we consider three alternative measures for $L_{ICT,it}/L_{it}$ in (12):

- Share of labour using a computer or a terminal at work (*comp.*).
- Share of labour using an Internet-connected computer or a terminal at work (*I-net*).
- Share of labour using a local area network connected computer or terminal at work (*LAN*).

Besides the ICT indicator(s), all specifications include a constant term (β_0) as well as interacted two-digit industry and annual time dummies (γ_{jt}), the (log of the) capital-labour ratio ($\ln(K_{it}/L_{it})$), and (the log of) labour ($\ln L_{it}$). Four specifications are considered:

2. A further alternative would be to specify the firm's ICT stock (proxied, *e.g.* by the number of computers in use, which could be calculated from the data at our disposal by multiplying the computer intensity by employment) as an additional factor of production in (3) or derive the ICT's share in the overall capital stock and proceed as we have done with the labour share of ICT-equipped labour.

- *Column 1*: A basic version of (12) with Z comprising two firm age dummies (control group: middle-aged firms).
- *Column 2*: As Column 1, but Z also includes the labour shares of lower, medium, and higher technical and non-technical education; two employment age dummies (control group: 35–44 year olds); and the labour share of female employees.
- *Column 3*: As Column 2, but the ICT indicator is now interacted with three firm age dummies.
- *Column 4*: As Column 1, but Z includes the average years of schooling which is also interacted with the ICT indicator.

We also estimated an variant of column 3 (not shown) with the ICT indicator interacted with time rather than with firm age dummies, but found no evidence for changes in the impact of ICT over time.[3]

All of the results are derived separately for manufacturing and services firms. Depending on the ICT indicator(s) used, the sample size varies from 949 to 1 444 observations in manufacturing and from 746 to 1 472 in services. Table 10.2 represents the basic descriptive statistics of the largest manufacturing and services samples, Table 10.3 shows the distribution of firms by industry, and Table 10.4 illustrates the time-series cross-section patterns in the data. One noteworthy point on these tables is that the panel dimension of our data is rather weak, *e.g.* only about one in ten firms is observed for all three years considered (1998–2000).

3. Note, however, that our controls include interacted two-digit industry and annual time dummies which would necessarily capture some of this effect.

Table 10.2. **Descriptive statistics of the largest (comp.) samples**

	Manufacturing					Services				
Variables	Obs.	Mean	St. dev.	Min.	Max.	Obs.	Mean	St. dev.	Min.	Max.
DEPENDENT: ln(value added / labour)	1,444	10.74	0.48	7.48	13.43	1,472	10.70	0.61	5.97	17.45
CD: ln(physical capital stock / labour)	1,444	10.59	1.37	5.07	17.66	1,472	9.79	1.54	4.12	20.61
ICT: sh. of comp. equipped labour	1,444	0.46	0.30	0.00	1.00	1,472	0.78	0.30	0.01	1.00
ICT: sh. of I-net equipped labour	1,412	0.28	0.28	0.00	1.00	1,446	0.61	0.39	0.00	1.00
ICT: sh. of LAN equipped labour	967	0.46	0.30	0.01	1.00	759	0.71	0.33	0.01	1.00
ICT: sh. of comp. × Firm: young	1,444	0.03	0.14	0.00	1.00	1,472	0.12	0.32	0.00	1.00
ICT: sh. of comp. × Firm: middle-aged	1,444	0.24	0.32	0.00	1.00	1,472	0.46	0.44	0.00	1.00
ICT: sh. of comp. × Firm: old	1,444	0.19	0.28	0.00	1.00	1,472	0.20	0.37	0.00	1.00
ICT: sh. of I-net × Firm: young	1,412	0.02	0.13	0.00	1.00	1,446	0.11	0.30	0.00	1.00
ICT: sh. of I-net × Firm: middle-aged	1,412	0.15	0.25	0.00	1.00	1,446	0.34	0.42	0.00	1.00
ICT: sh. of I-net × Firm: old	1,412	0.11	0.21	0.00	1.00	1,446	0.16	0.33	0.00	1.00
ICT: sh. of LAN × Firm: young	967	0.03	0.15	0.00	1.00	759	0.08	0.27	0.00	1.00
ICT: sh. of LAN × Firm: middle-aged	967	0.25	0.32	0.00	1.00	759	0.44	0.43	0.00	1.00
ICT: sh. of LAN × Firm: old	967	0.19	0.29	0.00	1.00	759	0.19	0.36	0.00	1.00
ICT: sh. of comp. × Labour: education	1,444	0.57	0.39	0.00	1.62	1,472	1.02	0.44	0.01	1.77
ICT: sh. of I-net × Labour: education	1,412	0.35	0.37	0.00	1.62	1,446	0.81	0.56	0.00	1.77
ICT: sh. of LAN × Labour: education	967	0.57	0.39	0.01	1.61	759	0.93	0.47	0.01	1.66
Firm: young (avg. plant age < 5)	1,444	0.06	0.23	0.00	1.00	1,472	0.14	0.35	0.00	1.00
Firm: old (avg. plant age > 15)	1,444	0.46	0.50	0.00	1.00	1,472	0.26	0.44	0.00	1.00
Educ.: sh. of technical, lower	1,444	0.36	0.16	0.00	0.85	1,472	0.17	0.18	0.00	1.00
Educ.: sh. of technical, med.	1,444	0.16	0.11	0.00	1.00	1,472	0.22	0.23	0.00	1.00
Educ.: sh. of technical, higher	1,444	0.04	0.08	0.00	0.69	1,472	0.08	0.14	0.00	1.00
Educ.: sh. of non-technical, lower	1,444	0.11	0.08	0.00	0.67	1,472	0.19	0.18	0.00	1.00
Educ.: sh. of non-technical, medium	1,444	0.04	0.07	0.00	1.00	1,472	0.13	0.17	0.00	1.00
Educ.: sh. of non-technical, higher	1,444	0.01	0.03	0.00	0.35	1,472	0.03	0.09	0.00	0.75
Labour: young (avg. age < 34)	1,444	0.31	0.15	0.00	1.00	1,472	0.36	0.21	0.00	1.00
Labour: old (avg. age > 45)	1,444	0.39	0.15	0.00	1.00	1,472	0.33	0.19	0.00	1.00
Labour: sh. of females	1,444	0.31	0.23	0.00	1.00	1,472	0.43	0.28	0.00	1.00
Labour: education (avg. years of)	1,444	1.19	0.09	0.99	1.62	1,472	1.28	0.14	0.90	1.77

Note: Internet and LAN variables do not correspond to the sets used in regressions. Education in tens of years.

Table 10.3. **Number of firms by industry (largest samples)**

Code	Obs.	Description	Code	Obs.	Description
15	126	Food products, beverages	50	99	Sale and maintenance of motor veh.
17	40	Textiles	51	304	Wholesale and commission trade
18	34	Wearing apparel, etc.	52	201	Retail trade; repair of pers. goods
19	20	Dressing of leather, etc.	55	85	Hotels and restaurants
20	93	Wood and wood products	60	24	Transport, storage and communic.
21	79	Pulp, paper, paper prod.	61	4	Water transport
22	125	Publishing, printing, etc.	63	6	Supporting transport activities, etc.
23	4	Coke, nuclear fuel, etc.	64	72	Post and telecommunications
24	70	Chemicals, etc.	70	44	Real estate, renting and business
25	73	Rubber and plastic prod.	71	10	Renting of machinery w/o operator
26	73	Other non-met. mineral prod.	72	141	Computer and related activities
27	56	Basic metals	74	481	Other business activities
28	154	Fabricated metal products	92	1	Recreational, cultural, sport act
29	185	Machinery and equipm. nec.	50–93	1,472	Services
30	4	Electrical equipment, etc.			
31	75	Electrical machinery, nec.			
32	47	Radio communic. equipm. etc.			
33	34	Medical instruments, etc.			
34	34	Motor vehicles, etc.			
35	38	Other transport equipment			
36	80	Furniture, manuf. nec.			
15–37	1,444	Manufacturing			

Note: If there are no usable observations for a given industry, it is excluded from the table.

Table 10.4. **Data patterns and their frequencies in the data for the regressions below**

Largest manufacturing sample (computers)

# of firms	# of years	Firms × years	1998	1999	2000
354	1	354		1	
162	2	324		1	1
139	1	139	1		
112	3	336	1	1	1
87	2	174	1	1	
56	2	112	1		1
5	1	5			1
915	**1–3**	**1,444**			

Largest services sample (computers)

# of firms	# of years	Firms × years	1998	1999	2000
378	1	378	1		
315	1	315		1	
97	2	194		1	1
97	2	194	1		1
80	2	160	1	1	
75	3	225	1	1	1
6	1	6			1
1,048	**1–3**	**1,472**			

Smallest manufacturing sample (LAN)

# of firms	# of years	Firms × years	1998	1999	2000
391	1	391	1		
258	2	516	1	1	
63	1	63		1	
712	**1–2**	**970**			

Smallest services sample (LAN)

# of firms	# of years	Firms × years	1998	1999	2000
343	1	343	1		
157	2	314	1	1	
103	1	103		1	
603	**1–2**	**760**			

Note: LAN is the smallest of the *single* ICT indicator samples. Data patterns of the Internet and the three ICT indicator samples are omitted. The former is similar to the largest and the latter to the smallest samples shown above.

Table 10.5 presents the results of estimating equation (12) by ordinary least squares (OLS) using *computers* as the ICT indicator. This first set of regression results is discussed in some detail; for further results we primarily concentrate on the ICT variables.

The term "fully robust" implies that we employ White (1980) heteroscedasticity consistent standard errors and also allow for the dependence (autocorrelation) of observations across t. Thus, the measurement of standard errors is robust as long as the is are independently distributed (for discussion see Stata, 2001, section 23.11). The results are *weighted*, *i.e.* they refer to employment in manufacturing or services. We do *not* impose constant returns to scale. All of the results are also derived with and without weighting as well as with and without imposing constant returns to scale and are available upon request.

In general the alternative reported below (*weighted*, constant returns to scale *not* imposed, *interacted* time and industry dummies) seems to be the least favourable to finding ICT-related results.[4] However, it is arguably the most appropriate method for the situation at hand.[5]

The first column of Table 10.5 would seem suggest that the use of a computer would increase a worker's productivity by 17% in manufacturing and by nearly 30% in services. If we control for employment characteristics (the second column), the effect becomes statistically insignificant in manufacturing and reduces to 10% in services. What is noteworthy, however, is that the effect in

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4. However, the tendency of ICT to be more productive in younger firms weakens in the unweighted results.

5. In the Table below (only the ICT indicator coefficient estimates are reported) we have re-estimated manufacturing Column 2 in Table 10.5 with all possible combinations of the following:

   - Weighted / non-weighted.
   - With / without constant returns to scale imposed.
   - Identically independently distributed (homoskedastic, no autocorrelation, non-robust) / robust / fully robust standard errors.
   - With only the constant term (No) / only industry dummies (Ind.) / only time dummies (Time) / industry and time dummies (Ind.+Time) / interacted industry and time dummies (Ind.*Time).
   - The alternative reported in the text is marked with a rectangle.

Options			Dummies				
Weighted	Constant	Robust	No	Ind.	Time	Ind.+Time	Ind.*Time
No	No	No	0.251***	0.164***	0.246***	0.154***	0.151***
No	No	Yes	0.251***	0.164***	0.246***	0.154***	0.151***
No	No	Yes, fully	0.251***	0.164***	0.246***	0.154***	0.151**
No	Yes	No	0.298***	0.208***	0.284***	0.191***	0.189***
No	Yes	Yes	0.298***	0.208***	0.284***	0.191***	0.189***
No	Yes	Yes, fully	0.298***	0.208***	0.284***	0.191***	0.189***
Yes	No	No	0.237***	0.097**	0.223***	0.076*	0.089*
Yes	No	Yes	0.237***	0,097	0.223***	0,076	0,089
Yes	No	Yes, fully	0.237***	0,097	0.223***	0,076	0,089
Yes	Yes	No	0.233***	0.088*	0.222***	0,072	0.093*
Yes	Yes	Yes	0.233***	0,088	0.222***	0,072	0,093
Yes	Yes	Yes, fully	0.233***	0,088	0.222***	0,072	0,093

As can be seen in the above table, the largest and most significant ICT coefficient estimates are reached with no or only time dummies. The smallest and least significant coefficient estimates are reached with both industry and time dummies. Weighting reduces the significance of the coefficient estimates. Robust standard errors reduces the significance of the coefficient estimates (slightly higher for fully robust than robust). Coefficient estimates are higher and more significant when constant returns to scale are imposed.

manufacturing becomes again significant if the impact of ICT is examined by firm age (the third column). The productivity effects of ICT seem to be much larger in younger than in older firms. A similar effect is not observed in services. Contrary to our findings on ICT, other studies have shown that the productivity of (primarily non-ICT) capital tends to be higher in *older* plants, which is possibly due to learning effects. While learning effects undoubtedly also exist with ICT, our finding is consistent with the argument that it may be even more important to be able to make complementary organisational adjustments. Such changes are arguably more easily implemented in younger firms and certainly in new firms, which by definition have a completely new organisational structure. We are unable to verify the complementarity of ICT and education (the fourth column).

Table 10.5. **Labour productivity ($\ln(Y_{it}/L_{it})$) regressions with the share of labour using a *computer* at work as the ICT indicator – pooled OLS with fully robust standard errors**

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ICT: sh. of comp. equipped labour	0.176**	0.089		-0.563	0.282***	0.106*		-1.165
	(0.081)	(0.072)		(1.387)	(0.073)	(0.063)		(0.869)
ICT: sh. of comp. × Firm: young			0.475**				0.118	
			(0.239)				(0.137)	
ICT: sh. of comp. × Firm: middle			0.166**				0.122*	
			(0.084)				(0.071)	
ICT: sh. of comp. × Firm: old			-0.066				-0.031	
			(0.141)				(0.143)	
ICT: sh. of comp. × Labour: education				0.527				1.120
				(1.179)				(0.735)
CD: ln(physical capital stock / labour)	0.120***	0.106***	0.104***	0.111***	0.123***	0.110***	0.109***	0.119***
	(0.035)	(0.031)	(0.030)	(0.036)	(0.026)	(0.026)	(0.026)	(0.026)
CD: ln(labour)	0.053***	0.067***	0.068***	0.049***	-0.029**	-0.026**	-0.026**	-0.017
	(0.017)	(0.016)	(0.016)	(0.016)	(0.012)	(0.012)	(0.013)	(0.012)
Firm: young (avg. plant age < 5)	0.041	0.107	-0.050	0.001	-0.188*	-0.121	-0.119	-0.139
	(0.063)	(0.086)	(0.120)	(0.074)	(0.101)	(0.103)	(0.134)	(0.107)
Firm: old (avg. plant age > 15)	0.019	0.057	0.176***	0.037	0.114**	0.123**	0.231*	0.131**
	(0.049)	(0.046)	(0.067)	(0.048)	(0.054)	(0.054)	(0.124)	(0.056)
Educ.: sh. of technical, lower		-0.061	-0.056			0.035	0.057	
		(0.319)	(0.317)			(0.214)	(0.221)	
Educ.: sh. of technical, med.		0.773**	0.783**			0.535**	0.557**	
		(0.340)	(0.336)			(0.211)	(0.225)	
Educ.: sh. of technical, higher		0.426	0.378			1.011***	1.021***	
		(0.642)	(0.640)			(0.279)	(0.287)	
Educ.: sh. of non-technical, lower		0.693*	0.689*			0.297	0.319	
		(0.397)	(0.398)			(0.224)	(0.228)	
Educ.: sh. of non-technical, medium		0.118	0.189			0.458	0.482	
		(0.383)	(0.384)			(0.315)	(0.323)	
Educ.: sh. of non-technical, higher		-1.090	-1.382			1.245***	1.267***	
		(0.856)	(0.876)			(0.313)	(0.321)	
Labour: young (avg. age < 34)		-0.241	-0.235			-0.298	-0.310	
		(0.253)	(0.253)			(0.239)	(0.237)	
Labour: old (avg. age > 45)		-0.320	-0.317			0.082	0.075	
		(0.230)	(0.231)			(0.232)	(0.231)	
Labour: sh. of females		-0.832***	-0.845***			-0.154	-0.143	
		(0.168)	(0.165)			(0.139)	(0.141)	
Labour: education (avg. years of)				0.699				0.204
				(0.717)				(0.686)
Also incl. a constant term as well as interacted industry and time dummies					Constant, industry × time			
Observations	1,444	1,444	1,444	1,444	1,472	1,472	1,472	1,472
Adjusted R-squared	0.48	0.54	0.55	0.49	0.46	0.50	0.50	0.49

Note: ***, ***, and * respectively indicate significance at 1, 5, and 10 % level. Standard errors in parentheses.

As expected, physical capital intensity has a positive and significant effect on labour productivity. The estimated coefficients may seem somewhat low, but it should be kept in mind that the interacted industry and time dummies effectively remove all variation across time and industries, which has consequences on all coefficients but especially on those with significant variation by industry such as capital intensity. There seem to be increasing returns to scale in manufacturing but decreasing returns to scale in services. Older services firms tend to be considerably more productive.

In *manufacturing*, high shares of employment with technical medium (bachelor level) and non-technical lower (post secondary but below bachelor level) levels of education seem to contribute to productivity. In our interpretation this shows that it pays to have sufficiently educated personnel on the "factory floor". In *services*, high shares of employment with technical and non-technical higher (master level or above) education as well as with technical medium level education contribute to productivity. The effect of education seems to be more straightforward in services. This may be because a more educated person is able to produce a higher value added directly, *e.g.* in professional services, whereas in manufacturing the effects are transmitted *via* the process and product innovation(s) that this type of worker may generate in the longer run.

Computer usage may be regarded as a general proxy for ICT use in the organisation in question. The next set of regressions considers Internet use, thus arguably emphasising the role of *external* electronic communication.

Table 10.6 represents the results of estimating equation (12) by ordinary least squares (OLS) with *Internet* as the ICT indicator. In *manufacturing* we find that the productivity effect of Internet is *negative*, especially in older plants (the second and third column). In *services*, however, the effect of Internet appears to be even larger than that of computers. The second column suggests that, after controlling for labour characteristics, Internet-equipped labour is 15% more productive. Furthermore, with Internet we *do* observe a much higher productivity effect of ICT in younger as compared to older service firms (the third column). This effect is qualitatively quite similar to that found with computers in manufacturing.

Table 10.6. **Labour productivity ($\ln(Y_{it} / L_{it})$) regressions with the share of labour using an *Internet*-connected computer at work as the ICT indicator – pooled OLS with fully robust standard errors**

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ICT: sh. of I-net equipped labour	-0.073 (0.114)	-0.201** (0.100)		0.352 (1.161)	0.294*** (0.083)	0.150** (0.070)		-0.567 (0.577)
ICT: sh. of I-net × Firm: young			0.311 (0.210)				0.402* (0.242)	
ICT: sh. of I-net × Firm: middle			-0.174 (0.125)				0.158** (0.077)	
ICT: sh. of I-net × Firm: old			-0.321** (0.136)				-0.050 (0.121)	
ICT: sh. of comp. × Labour: education				-0.484 (0.956)				0.620 (0.466)
CD: ln(physical capital stock / labour)	0.125*** (0.035)	0.103*** (0.031)	0.102*** (0.031)	0.105*** (0.036)	0.125*** (0.027)	0.111*** (0.027)	0.110*** (0.027)	0.118*** (0.026)
CD: ln(labour)	0.052*** (0.016)	0.067*** (0.016)	0.068*** (0.016)	0.049*** (0.016)	-0.021* (0.013)	-0.021* (0.012)	-0.017 (0.013)	-0.013 (0.011)
Firm: young (avg. plant age < 5)	0.047 (0.068)	0.105 (0.091)	-0.096 (0.103)	0.014 (0.079)	-0.189* (0.097)	-0.130 (0.102)	-0.286 (0.217)	-0.134 (0.104)
Firm: old (avg. plant age > 15)	0.015 (0.050)	0.055 (0.046)	0.092 (0.062)	0.038 (0.047)	0.120** (0.053)	0.126** (0.053)	0.239** (0.098)	0.138*** (0.053)
Educ.: sh. of technical, lower		-0.068 (0.316)	-0.056 (0.315)			0.137 (0.194)	0.173 (0.202)	
Educ.: sh. of technical, medium		0.867** (0.349)	0.890** (0.349)			0.614*** (0.205)	0.601*** (0.222)	
Educ.: sh. of technical, higher		0.786 (0.642)	0.736 (0.640)			1.021*** (0.262)	0.999*** (0.267)	
Educ.: sh. of non-technical, lower		0.650* (0.394)	0.640 (0.398)			0.363* (0.211)	0.381* (0.213)	
Educ.: sh. of non-technical, med.		0.300 (0.366)	0.410 (0.363)			0.621** (0.275)	0.632** (0.282)	
Educ.: sh. of non-technical, higher		-0.618 (0.805)	-0.878 (0.816)			1.199*** (0.303)	1.212*** (0.312)	
Labour: young (avg. age < 34)		-0.282 (0.255)	-0.296 (0.253)			-0.129 (0.220)	-0.138 (0.220)	
Labour: old (avg. age > 45)		-0.365 (0.232)	-0.367 (0.231)			0.173 (0.211)	0.178 (0.211)	
Labour: sh. of females		-0.831*** (0.165)	-0.836*** (0.162)			-0.114 (0.133)	-0.110 (0.132)	
Labour: education (avg. years of)				1.720*** (0.468)				0.807** (0.410)
Also incl. a constant term as well as interacted industry and time dummies					Constant, industry × time			
Observations	1,415	1,415	1,415	1,415	1,448	1,448	1,448	1,448
Adjusted R-squared	0.48	0.55	0.55	0.50	0.46	0.50	0.51	0.50

Note: ***, ***, and * respectively indicate significance at 1, 5, and 10 % level. Standard errors in parentheses.

Whereas computers are regarded a general proxy for ICT use and Internet is seen as a proxy for external electronic communication, LAN may be seen as a proxy for the role of *internal* electronic communication in the organisation considered.

Table 10.7 represents the results of estimating equation (12) by ordinary least squares (OLS) with *LAN* as the ICT indicator. Unfortunately this indicator is only available for two years, so the samples are considerably smaller. Despite this the productivity effects of ICT come through strongly and positively in both manufacturing and services. In *manufacturing*, LAN-equipped labour seems to be 15% more productive. In *services* the corresponding effect is 18%. There is also some indication of the complementary of education and ICT (see the fourth column under Services).

Table 10.7. **Labour productivity ($\ln(Y_{it}/L_{it})$) regressions with the share of labour using a *LAN* computer at work as the ICT indicator – pooled OLS with fully robust standard errors**

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ICT: sh. of comp. equipped labour	0.213***	0.149*		-1.259	0.310***	0.182**		-2.298*
	(0.082)	(0.078)		(1.080)	(0.081)	(0.076)		(1.220)
ICT: sh. of comp. × Firm: young			0.237				0.639	
			(0.200)				(0.702)	
ICT: sh. of comp. × Firm: middle			0.212**				0.171**	
			(0.103)				(0.072)	
ICT: sh. of comp. × Firm: old			0.029				0.140	
			(0.146)				(0.149)	
ICT: sh. of comp. × Labour: education				1.171				2.126**
				(0.928)				(1.044)
CD: ln(physical capital stock / labour)	0.118***	0.112***	0.111***	0.109***	0.129***	0.114***	0.115***	0.122***
	(0.034)	(0.031)	(0.031)	(0.035)	(0.027)	(0.027)	(0.027)	(0.026)
CD: ln(labour)	0.049**	0.060***	0.060***	0.047**	-0.042**	-0.049***	-0.048***	-0.034**
	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.015)	(0.015)	(0.015)
Firm: young (avg. plant age < 5)	0.076	0.137	0.127	0.030	-0.258	-0.228	-0.627	-0.224
	(0.067)	(0.093)	(0.143)	(0.078)	(0.176)	(0.179)	(0.694)	(0.181)
Firm: old (avg. plant age > 15)	0.030	0.069	0.162**	0.046	0.054	0.043	0.063	0.071
	(0.056)	(0.053)	(0.074)	(0.055)	(0.056)	(0.060)	(0.124)	(0.055)
Educ.: sh. of technical, lower		-0.016	-0.025			0.027	0.018	
		(0.374)	(0.373)			(0.260)	(0.258)	
Educ.: sh. of technical, med.		0.979***	0.970***			0.560**	0.556**	
		(0.355)	(0.353)			(0.261)	(0.264)	
Educ.: sh. of technical, higher		-0.131	-0.144			1.107***	1.109***	
		(0.555)	(0.558)			(0.384)	(0.385)	
Educ.: sh. of non-technical, lower		0.577	0.539			0.341	0.332	
		(0.440)	(0.448)			(0.229)	(0.231)	
Educ.: sh. of non-technical, medium		0.227	0.251			0.377	0.374	
		(0.404)	(0.405)			(0.394)	(0.395)	
Educ.: sh. of non-technical, higher		-0.823	-0.926			1.619***	1.634***	
		(0.821)	(0.847)			(0.347)	(0.349)	
Labour: young (avg. age < 34)		-0.233	-0.260			-0.203	-0.210	
		(0.286)	(0.289)			(0.310)	(0.313)	
Labour: old (avg. age > 45)		-0.318	-0.351			0.230	0.223	
		(0.254)	(0.249)			(0.284)	(0.285)	
Labour: sh. of females		-0.821***	-0.832***			-0.086	-0.103	
		(0.174)	(0.170)			(0.171)	(0.160)	
Labour: education (avg. years of)				0.154				-0.456
				(0.636)				(0.982)
Also incl. a constant term as well as interacted industry and time dummies					Constant, industry × time			
Observations	970	970	970	970	760	760	760	760
Adjusted R-squared	0.46	0.52	0.52	0.47	0.49	0.54	0.54	0.53

Note: ***, ***, and * respectively indicate significance at 1, 5, and 10 % level. Standard errors in parentheses.

Table 10.8 runs the three ICT indicators together. The regressions have some obvious problems not least because of collinearity between the three measures. In case of *manufacturing* the *negative* effect of Internet in older plants comes through quite clearly as does the positive effect of LAN. There is also some indication for the complementary of education and LAN. In *services* the effect of Internet is *positive* especially in younger firms (the Internet × young coefficient is significant at the 15% level). There is also some indication of complementary of education and Internet.

Based on the evidence presented in this section it seems that the excess productivity effect of ICT-equipped labour typically ranges from 8% to 18%. The effect tends to be larger in services than in manufacturing. The effect is often much higher in younger firms and can even be *negative* in older firms. Since organisational changes are arguably easier to implement in younger firms and recently established firms have by definition a new structure, we interpret this as evidence for the need for complementary organisational changes. Manufacturing firms seem to benefit from ICT-induced efficiency in *internal* communication whereas service firms benefit from efficiency in *external* communication.

Table 10.8. **Labour productivity ($\ln(Y_{it} / L_{it})$) regressions with *all* three ICT indicators – pooled OLS with fully robust standard errors**

	Manufacturing				Services			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ICT: sh. of comp. equipped labour	0.212	0.084		0.864	0.066	-0.029		1.619
ICT: sh. of I-net equipped labour	-0.341**	-0.402***		1.795	0.259**	0.168*		-1.879
ICT: sh. of LAN equipped labour	0.203	0.233**		-4.535*	0.150	0.127		-0.165
ICT: sh. of comp. × Firm: young			0.920				-1.060	
ICT: sh. of comp. × Firm: middle-aged			0.126				0.130	
ICT: sh. of comp. × Firm: old			0.032				-0.975***	
ICT: sh. of I-net × Firm: young			0.474*				1.310	
ICT: sh. of I-net × Firm: middle-aged			-0.438**				0.104	
ICT: sh. of I-net × Firm: old			-0.419**				-0.230	
ICT: sh. of LAN × Firm: young			-1.199				0.196	
ICT: sh. of LAN × Firm: middle-aged			0.284**				0.024	
ICT: sh. of LAN × Firm: old			0.158				1.238***	
ICT: sh. of comp. × Labour: education				-0.683				-1.317
ICT: sh. of I-net × Labour: education				-1.861				1.705*
ICT: sh. of LAN × Labour: education				4.051*				0.215
Non-ICT variables as above					Non-ICT variables as above			
Also incl. a constant term as well as interacted industry and time dummies					Constant, industry × time			
Observations	949	949	949	949	746	746	746	746
Adjusted R-squared	0.47	0.54	0.54	0.50	0.49	0.54	0.55	0.53

Note: ***, ***, and * respectively indicate significance at 1, 5, and 10 % level. Standard errors omitted.

10.4.3 ICT vs. non-ICT industries

Macro-level studies have shown that overall productivity trends in Finland are largely driven by rapid productivity growth in ICT-providing industries in general and in communication equipment manufacturing in particular. In the above results industry-level effects are removed with the introduction of interacted industry and time dummies. Thus, industry-level productivity levels or trends do *not* drive the findings. It is nevertheless possible that *within* ICT industries the excess productivity of ICT-equipped labour is higher than in non-ICT industries.

Table 10.9 re-estimates the Column (2) specifications of Table 10.5 for the ICT (as proxied by industries 30, 32, 64, and 72) and non-ICT industries as well as for the communications equipment industry (32), which is commonly associated with *Nokia*.[6] The sample sizes for the ICT and communications equipment industries are quite low and the results should thus be interpreted cautiously. Due to the small samples and the possible presence of one dominant company, weighted and non-weighted results are considered. Since industry dummies are not applicable for the

6. Due to data confidentiality laws the identity of firms has been hidden from us. We have not identified *Nokia* from the sample and are unaware whether it is included or not in the ICT survey(s).

estimations for a single industry (leftmost section), the ICT and non-ICT results are provided without industry dummies to facilitate comparisons.

Comparison of the coefficients in the first row reveals that the impact of ICT seems to be much higher in ICT-provision. This finding is *not* driven by the communications equipment industry, which can be inferred from the coefficient estimates of the rightmost section. Some non-ICT coefficient estimates in the middle and rightmost sections are implausible, and thus cast doubt also on the ICT-related findings. It nevertheless seems that ICT-providers are able to reap higher benefits from their own ICT use as compared to non-ICT firms and employment.

Table 10.9. **Labour productivity ($\ln(Y_{it} / L_{it})$) regressions with the share of labour using a *computer* at work as the ICT indicator for Non-ICT, ICT and communication equipment industries – pooled OLS with fully robust standard errors**

	Non-ICT				ICT (30, 32, 64, 72)				Communic. eq. (32)	
Weighted:	No	No	Yes	Yes	No	No	Yes	Yes	No	Yes
Dummies:	Time	Time*Ind	Time	Time*Ind	Time	Time*Ind	Time	Time*Ind	Time	Time
ICT: comp. eq.	0.197***	0.150***	0.122**	0.058	0.463**	0.370	0.439*	0.505**	-0.018	-0.200
	(0.038)	(0.044)	(0.053)	(0.053)	(0.201)	(0.258)	(0.252)	(0.245)	(0.432)	(0.427)
CD: ln(K/L)	0.132***	0.123***	0.169***	0.122***	0.103***	0.061**	0.107**	0.051	-0.037	0.054
	(0.018)	(0.020)	(0.026)	(0.023)	(0.034)	(0.025)	(0.042)	(0.037)	(0.080)	(0.132)
CD: ln(labour)	0.016	0.009	0.016	0.014	0.067**	0.071***	0.081***	0.077***	0.095*	0.186**
	(0.011)	(0.011)	(0.019)	(0.012)	(0.026)	(0.025)	(0.023)	(0.026)	(0.051)	(0.091)
Firm: young	-0.063	-0.077	-0.086	-0.133	0.145	0.112	0.263**	0.233*	0.624**	0.672**
	(0.059)	(0.060)	(0.079)	(0.083)	(0.100)	(0.102)	(0.108)	(0.121)	(0.280)	(0.299)
Firm: old	0.058**	0.055**	0.127***	0.057	0.095	0.046	0.056	-0.013	-0.350*	-0.342
	(0.023)	(0.024)	(0.042)	(0.039)	(0.077)	(0.081)	(0.125)	(0.127)	(0.204)	(0.272)
Ed.: tec., lo.	-0.154	-0.105	0.014	0.135	-0.204	-0.370	0.781	0.586	-1.774*	-2.487
	(0.094)	(0.103)	(0.226)	(0.207)	(0.396)	(0.410)	(0.688)	(0.658)	(0.926)	(1.984)
Ed.: tec., me.	0.146	0.203*	0.365	0.614***	-0.058	-0.051	0.600	0.685	-4.423**	-5.368**
	(0.103)	(0.118)	(0.257)	(0.202)	(0.334)	(0.341)	(0.554)	(0.553)	(1.739)	(1.983)
Ed.: tec., hi.	0.237	0.298	0.855**	0.465	0.556	0.561	1.997**	2.238***	5.734**	6.254*
	(0.256)	(0.264)	(0.337)	(0.318)	(0.356)	(0.353)	(0.852)	(0.772)	(2.659)	(3.086)
Ed.: n.-tec., lo.	-0.180	0.008	-0.089	0.343*	-0.575	-0.518	-1.332	-0.229	-1.185	-0.720
	(0.122)	(0.146)	(0.233)	(0.204)	(0.394)	(0.386)	(0.880)	(0.720)	(1.358)	(3.172)
Ed.: n.-tec., me.	0.184	0.217	0.363	0.371	-0.133	-0.174	2.763**	3.177***	2.330	2.644
	(0.127)	(0.136)	(0.322)	(0.241)	(0.637)	(0.633)	(1.184)	(1.046)	(4.671)	(7.801)
Ed.: n.-tec., hi.	0.892***	0.992***	0.483	0.996***	0.039	-0.084	0.061	-0.323	-4.363	-12.056
	(0.194)	(0.211)	(0.385)	(0.310)	(0.707)	(0.699)	(1.401)	(1.377)	(3.253)	(10.305)
Labour: young	-0.044	-0.047	-0.383	-0.392**	-0.120	-0.118	1.537**	0.650	0.186	-0.667
	(0.109)	(0.111)	(0.251)	(0.186)	(0.400)	(0.401)	(0.612)	(0.519)	(0.788)	(1.722)
Labour: old	0.035	0.052	-0.347	-0.230	0.378	0.237	1.471***	0.969*	0.639	0.218
	(0.128)	(0.130)	(0.266)	(0.173)	(0.421)	(0.415)	(0.550)	(0.510)	(0.779)	(1.118)
Labour: females	-0.393***	-0.322***	-0.459***	-0.419***	-0.006	-0.015	-0.576**	-0.876***	-1.672**	-2.087**
	(0.053)	(0.067)	(0.093)	(0.115)	(0.260)	(0.254)	(0.287)	(0.296)	(0.640)	(0.979)
Observations	2,652	2,652	2,652	2,652	264	264	264	264	47	47
Adj. R-squared	0.24	0.26	0.46	0.54	0.23	0.25	0.53	0.56	0.26	0.78

Note: ***, ***, and * respectively indicate significance at 1, 5, and 10 % level. Standard errors omitted.

10.4.4 *The presence of a firm effect*

The above results are consistent in large samples with a relatively weak set of assumptions. It is nevertheless true that pooled OLS is biased and inconsistent if the firm effect is correlated with any of the explanatory variables in (12). While we can easily do away with the firm effect by a suitable transformation, this introduces a new set of problems.

The time dimension of our data is quite short and the data is best characterised as a pooled cross-section rather than a panel, so we have a rather limited ability to deal with the possible presence of a firm effect in the usual manner. Furthermore, our firm identifiers based on legal units may be somewhat deficient in tracing the longitudinal linkages of firms.[7] As noted above, only roughly 10% of the firms in the sample are observed for the three years considered. In particular, with such short panels it is impossible to capture the effects of ICT adoption if it requires a few years to embed ICT effectively into the production system. Pakes and Griliches (1984) find that investments made three to four years earlier have a greater impact on profitability than more recent investments. Lags seem to be even longer for the formation of intangible capital *via* R&D investments. Espost and Pierani (2003), Maliranta (2002), and Rouvinen (2002) find evidence that returns to the most recent R&D investments are quite insignificant. These studies suggest that the returns are the highest after about four years. Given the time-consuming and cumulative characteristics of building the tangible capital and knowledge stocks within firms, it may well be the case that regression analysis in levels captures the productivity effects of ICT more reliably than changes. Evidence on the time lag between ICT investment and its expected effects is scarce, although the findings of Brynjolfsson and Hitt (2002) suggest that the lag might be somewhere between three to seven years.

An additional practical problem is that the "within" variation of ICT measures during the observation period is rather small.[8] Furthermore, it is very much dominated by noise resulting from a possibly serious errors-in-variable problem. Thus, estimates originated from "within" variation may be seriously biased towards zero.

We nevertheless estimated fixed effects and first differenced versions of the above model(s) as well as experimented with the Arellano-Bond type (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) panel data estimators. This gave disappointing results not only on ICT but also on other explanatory variables. Even the capital-labour ratio, the one variable having almost certainly a positive effect on labour productivity, did not come out positively and significantly in all the cases, which makes one doubt the reliability of these estimates.

This leads us to consider alternatives in studying the robustness of the results in the above section. One obvious alternative is to consider the firm effect as an omitted variable and employ instrumental variable (IV) techniques to reach a consistent estimate of the coefficients. The usual IV suspects are not available in our case, as industry and regional aggregates cannot be used (for industry data)[9] or are unavailable (for regional data) in our current data set. Indicators on the factors hampering ICT use are a potential set of instruments. Dummies indicating whether the "lack of qualified ICT

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7. Structural changes have been particularly numerous and intense among Finnish firms in the 1990s as compared to both other countries and earlier history. This is likely to weaken both the amount and the accuracy of within firm variation in our legal unit-based firm data. One option would be to make use establishment-firm links in order to produce "filtered" or "synthetic" firm units for the analysis.

8. In the case of the ICT indicators, the "between" variation (std. dev.) is from three and a half to seven and a half times larger than the "within" variation.

9. Note that the industry–time dummies already control for *all* industry-level variation.

personnel on the labour market hinders ICT use" and/or "market supply does not meet companies' ICT needs" seem to satisfy the necessary and sufficient conditions of IVs.[10] We instrumented the ICT indicator with these two IVs and estimate a weighted and non-weighted two stage least squares (2SLS) version of Column 2 in Table 10.5. With weights the ICT coefficient estimate is nearly zero with a large standard error. Without weights the ICT coefficient estimate is large and positive, but only significant at about 30% level.

10.4 Discussion

ICT and productivity studies typically estimate the elasticity of ICT capital. In order to compare our results to those obtained elsewhere, we derive a similar measure. Let us consider (3) without A, K, and $\boldsymbol{Z}$ (subscripts i and t ignored):

$$Y = L^{\beta} \Leftrightarrow Y = \left(L_0 + (1+\theta) L_{ICT}\right)^{\beta}, \tag{13}$$

where $L_0 = L - L_{ICT}$. Substituting back for L_0 and taking logs yields

$$\ln Y = \beta \ln\left(L + \theta L_{ICT}\right). \tag{14}$$

Totally differentiating gives

$$\frac{dY}{Y} = \beta \frac{\theta dL_{ICT}}{L + \theta L_{ICT}}, \tag{15}$$

which is used to derive elasticity

$$\chi = \frac{dY}{dL_{ICT}} \frac{L_{ICT}}{Y} = \beta \frac{\theta}{\left(L + \theta L_{ICT}\right)/L_{ICT}} = \beta \frac{\theta}{L/L_{ICT} + \theta}. \tag{16}$$

If we take the formula in (16), the estimates in the above section, and assume a 60% ICT-intensity, which roughly corresponds to our sample mean, we get an average elasticity of computer capital that is in the 5% to 6% range. We obtain a similar estimation result in an ICT capital elasticity specification. According to Kevin Stiroh (2003), the average elasticity of ICT capital of forty estimates in twenty international studies is about 5.4%. The elasticity of our measure of LAN capital is a little above 8%. Other results are qualitatively the same as those discussed above.

For the year 1998 we have detailed, albeit noisy, information on firms' ICT-associated expenditures. Comparing these to the estimated labour productivity gains suggest that, on average, ICT investments do not boost profitability, *i.e.* associated expenses are roughly in line with the estimated labour cost savings. Younger firms, where the effects of ICT are highest, also spend more on ICT, but proportionally less so.

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10. See, for example, Wooldridge (2002, pp. 83-4, 92, 105): (1) IVs must be partially correlated with the variable to be instrumented once the other exogenous variables are netted out. Tested by regressing the variable to be instrumented on all exogenous variables and IVs. IVs are individually and jointly significant at conventional levels. (2) IVs must be redundant in the model. Tested by estimating the model with the IVs included as regressors. IVs are individually and jointly insignificant. (3) IVs must be uncorrelated with the error term. This cannot be tested precisely, as the true coefficient estimates are unobserved. We nevertheless study the correlation with the OLS residuals and found no evidence for it.

Conclusions

As shown above, widespread use of ICT is a recent phenomenon. Thus analysing its effects on productivity is challenging, especially if there is a time lag between the introduction of a technology and the effects it might generate. There is little research and certainly no consensus on the timing of performance gains from a given ICT investment, but according to *Cisco Systems Inc.* CEO John T. Chambers "… the greatest payoff doesn't come until seven to nine years after an investment is made." (*Business Week*, 17 February 2003, p. 45). Results by Brynjolfsson and Hitt (2002) indirectly suggest that the lag might be from three to seven years. Not only are there possibly lengthy lags, it has been suggested that the immediate effect of a technology investment may even be negative (Huggett and Ospina, 2001). Thus, if anything, our study is likely to point to the lower bound of the productivity effects of ICT use.[11]

Contrary to what was believed during the new economy boom, the increase in ICT use is largely a *within* firm phenomenon; the contribution of restructuring (*between* effect) to ICT diffusion is rather marginal (see section 10.2). Even though restructuring does not seem to drive overall diffusion, this is not to say that it would not have a role to play – quite the contrary in fact. Decompositions (see section 10.3) suggest that experimentation and selection is particularly intense among young ICT-intensive plants.

Evidence from the regressions (section 10.4) seems to indicate that, after controlling for industry and time effects as well as labour and other firm-level characteristics, the "lower bound estimate" of excess productivity of ICT-equipped labour ranges from 8% to 18%. The effect is often much higher in younger firms and in ICT-providing branches and – at least the immediate effect – can even be *negative* in older firms. The interesting findings with regard to firm age are consistent with the need for ICT-complementing organisational changes. The finding on ICT-providing branches is *not* driven by the communications equipment industry but rather by ICT services.

Overall, the ICT-induced excess productivity seems to be somewhat higher in services than in manufacturing. Manufacturing firms benefit in particular from ICT-induced efficiency in *internal* communication whereas service firms benefit form efficiency in *external* communication.

Our results also suggest that it is important to carefully control for human capital related characteristics of employment when studying the effects of ICT. If this is not done, the ICT-related results can be inflated. This suggests that ICT and human capital are certainly correlated and quite likely also complementary. We only find weak evidence for this complementarity, although the issue should be studied in more detail.

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11. Also from a technical point of view we report the lower bound estimates, *i.e.* we report $\theta_{L_{ICT}}$ rather than $\beta_L \theta_{L_{ICT}}$.

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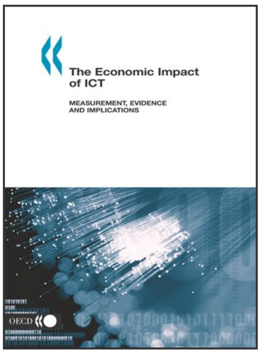

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