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Technology, human capital and labor demand

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Abstract

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This thesis consists of an introduction and four self-contained essays.

Essay 1 (with Gudmundur Gunnarsson and Erik Mellander) investigates unlike previous analyses (i) possible externalities in the use of IT and (ii) IT and human capital interactions. Examining, hypothetically, the statistical consequences of erroneously disregarding (i) and (ii) we shed light on the small or negative growth effects found in early studies of the effects of IT on productivity growth, as well as the positive impacts reported more recently. Our empirical analysis uses a 14-industry panel for Swedish manufacturing 1986-95. We find that human capital developments made the average effect of IT essentially zero in 1986 and steadily increasing thereafter, and, also, generated large differences in growth effects across industries.

Essay 2 (with Erik Mellander) investigates how changes in age structure and educational composition affect productivity growth, when educational levels are controlled for. A cost function framework is employed where workers are primarily distinguished by level of education but age and field-of-study also matter for effective labor input. The empirical analysis is based on industry data for the Swedish manufacturing sector 1985-1995. Comparisons of projections of total factor productivity growth based on alternative specifications of age structure and field-of-study composition are made for the period 1996-2005. Age structure changes matter more for growth than changes in fields-of-study composition. Substituting low- and semi-skilled workers that are at least 50 years old for workers below 30, increases growth. Increasing the share of technicians and engineers also has a positive effect. Overall, the effects are small, however: over the ten year period considered they do not increase or decrease the accumulated growth by more than one percentage point.

Essay 3 investigates whether capital-skill complementarity is the explanation for skill-biased technical change. For this to be the case, capital-skill complementarity must exist in the first place and, secondly, all technical change must be embodied, i.e. embedded in new capital equipment. To test if these conditions are satisfied, a capital-age adjusted translog production function incorporating both embodied and disembodied technical change is implemented on a 14-industry panel for Swedish manufacturing 1985-95. The findings cast doubt on the claim that capital-skill complementarity can explain sill-biased technical change. In several industries, the capital-skill complementarity hypothesis is not supported. Moreover, it is found that the demand for skilled labor is affected by both disemdodied and embodied technical change. An additional important result is that there is a negative skill-bias associated with embodied technical change.

Essay 4 uses a parametric shadow cost function approach to investigate the existence of allocative inefficiencies in the IT-sector caused by a shortage of workers within this sector, both across education levels of the workers, over time, and compared to the rest of the sectors in the economy. For this purpose a 19-industry panel for the Swedish economy for the years 1985-95 is used. The results suggest that while there are no allocative inefficiencies in the non IT-sector, this is not true in the case in of the IT-sector. The shortage of workers within this sector seems to have caused under-utilization of semi-skilled labor and over-utilization of skilled-labor. Further, allocative inefficiency in the IT-sector seem to have decreased considerably after the burst of the so-called IT-bubble in the year 2000. Another interesting result is that the additional costs caused by allocative inefficiency in the IT-sector seem to have been negligible.

Contents

Acknowledgments

This is finally the end of a long roller-coaster ride. I hope that through my work I have made a small contribution to the body of knowledge that could be a foundation for some further research in the future for me and for others. I have grown not only as a researcher but also as a person during this whole process and am now ready to proceed to a new beginning.

In this part of my dissertation I see a rare opportunity for me to officially acknowledge and thank the people who in various ways have helped me during my studies.

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Introduction

This thesis consists of four self-contained empirical studies. A common theme for the first two essays is how productivity growth has been affected by information technology on the one hand and the age structure and educational composition of labor on the other hand. The next two essays deal with how information technology has affected the demand for labor and efficiency in the IT-sector. In the following, I provide a summary and presentation of the main results of each essay.

In **Essay I**, written together with Gudmundur Gunnarsson and Erik Mellander, one of the earliest issues concerning the effects of information technology on economic activity, the so called IT-productivity paradox is examined. This paradox was formulated in response to the fact that the massive investments in information technology that started around 1980 did not seem to have any positive effects on productivity growth. One of the explanations offered for this paradox was among others that the time required before the IT investments manifest themselves in increased productivity has been underestimated [see for e.g., David (1990) and Kiley (1996)]. Another explanation put forward was that measurement errors both on the input and output side concealed the productivity effects [see for e.g., Berndt, Griliches and Rappaport (1995) and Berndt and Rappaport (2001) for the input side and Brynjolfsson (1993) for the output side]. The IT-productivity paradox was not confirmed in later studies where the data were extended to the 1990's; those studies found productivity-increasing effects of IT.

In the theoretical analysis of the paper we use a simple stylized growth model in order to investigate the consequences of disregarding possible externalities in the use of IT, and knowledge spillovers in assessments of the effects of IT on productivity growth. The model predicts that the small or negative effects found in early studies are not a consequence of measurement error but are likely to indicate a truly negative effect. The positive effects found in later studies are attributed to positive external effects in the use of IT, which are increasing in the total use of IT. Further, accounting for human capital interactions with IT (indirect effect) in the model reduces the direct effect of IT on productivity growth.

In the empirical analysis we use a 14-industry panel for Swedish manufacturing for the years 1986-95 and we first confirm the predictions generated by our theoretical model. Further we investigate how human capital interactions with IT have affected productivity growth. We find among, inter alia, that the education profile of the workers is important in determining the effects of IT on productivity growth. Another important result is that IT seems to have a positive effect on productivity growth not only in the IT-producing industries but also in the IT-using industries of the Swedish economy.

Essay II is written together with Erik Mellander and concerns the link between economic growth and demographics. We consider a number of different scenarios to investigate how the growth in total factor productivity (TFP) is affected by marginal changes in the age and fields-of study distributions of the workers at any given level of education. As a benchmark case, we assume that the 1995 TFP growth rates will repeat themselves throughout the period. The empirical analysis is carried out by using a model estimated by Mellander (1999). A panel of 24 industries in the Swedish manufacturing sector for the years 1985-95 is used.

We find that having more experienced workers is good for productivity growth primarily with respect to workers with elementary schooling. Further, the more educated the workers are, the less important experience seems to be for productivity growth. Also the scenario involving early retirement among older workers entails a decrease in overall productivity growth.

When it comes to the effects of the fields-of study we find that an increase in the share of engineers with upper secondary schooling would be particularly conducive to productivity growth. During the period of study, the observed increase in the share of those with upper secondary schooling with "other-fields-of study" as well as tertiary and postgraduate educated "business administrators" seem to have had a negative effect on productivity growth.

Essay III investigates another issue concerning the relationship between information technology and its relationship with human capital namely that of skill-biased technical change. This hypothesis was put forward by economists in order to explaining the observation that in many industrialized countries the wage premium of skilled labor has increased despite considerable increases in the supply of this kind of workers. The hypothesis of skill-biased technical change was launched by Berman, Bound and Griliches (1994) and states that technical change affects unskilled and skilled workers differently, favoring the latter, presumably because they have higher capacity for understanding and adopting new technologies. The fact that technical change affects workers with different skills unequally was explained by the fact that capital and skilled labor are complements according to Krusell et al. (2000). In order for this to be the case one has to verify the existence of capital-skill complementarity and also to distinguish between two types of technical change, namely that of disembodied and embodied technical change. Embodied technical change is the type of technical change that is embedded in (new) capital goods while disembodied technical change is not tied to capital or any other factor of production. Computers are the most obvious example of capital goods featuring embodied technical change and a new procedure for organizing the production process is an example of disembodied technical change.

In the paper we investigate the claim made by Krusell et al. (2000) that capital-skill complementarity is the explanation to skill-biased technical change. For this to be the case capital and skilled labor have to be complements and also technical change has to be embodied. Further, in the case of disembodied technical change the claim of Krusell et al. (2000) is not valid.

A translog production function is used on a 14-industry panel for Swedish manufacturing for the years 1985-95. Embodied technical change is considered for computer equipment capital only and is incorporated into the model by using Nelson's (1969) approximation formula. Disembodied technical change is captured by an index of the total use of IT in the Swedish economy.

The analysis provides evidence that not all of the technical change is of the embodied nature, which implies that capital-skill complementarity can thus not be all of the explanation for skill-biased technical change. Further, we find that capital-skill complementarity could in our case be an explanation of skill-biased technical change in the case of computer equipment capital and not in that of equipment capital. Another of the important results of the analysis is that while disembodied technical change seems to be favourable to a worker the higher hi/hers skills the opposite seem to be true for embodied technical change. The latter finding is probably due to the fact that embodied technical change seems to have been of the type favoring the production or assembly portion segment of manufacturing and during this stage of production, capital and unskilled labor are complements.

The last study of the thesis, **Essay IV** investigates the existence of inefficiencies in the Swedish IT-sector during the period of 1993-2002. The rapid growth of information technology during the past decade could have prevented the labor market in the IT-sector from clearing for a substantial period of time (Arrow and Capron, 1959). There are indications of a persistent shortage of workers in this market. The shortages created can lead to inefficiencies and in particular to allocative inefficiencies. The latter arises when the input mix is not consistent with cost minimization due to the marginal productivity values of a firm´s inputs not being equalized with the prevailing factor prices.

Allocative inefficiencies are investigated with respect to semi-skilled and skilled-labor, over time and for the IT- and non IT-sector. In order to take into account allocative inefficiecncy a shadow translog cost function is used and the data utilized within this framework is a 20-industry panel for the years 1985-95. The shadow prices are functions of a shortage indicator of workers obtained by Swedish national institute of economic research.

The results suggest that while in the non IT-sector labor was well utilized, this is not true for the case of the IT-sector. In the IT-sector the shortage of workers within this sector seem to have caused an under-utilization of semi-skilled labor and an over-utilization of skilled-labor. These results suggest that the industries in the IT-sector dealt with the shortage by increasing the working time of skilled-labor instead of trying to shift some less complicated tasks to the (formally) less skilled workers. After the year 2000, which is the year of the burst of the so-called IT-bubble, there was a considerable decrease in allocative of the IT-sector. Another important result of the paper is the finding that the additional costs incurred by the inefficiency seem to have been negligible.

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Essay I

Human Capital is the Key to the IT Productivity Paradox

1. Introduction

The IT productivity paradox was formulated in response to the fact that the massive investments in information technology (IT) that started around 1980 did not seem to have any positive effects on productivity growth. In the words of Nobel laureate Robert Solow (1987): You can see the computer age everywhere but in the productivity statistics.

In recent years, the original focus on computers has been broadened to include also communication devices: the concept of IT has been extended to ICT, information and communication technology. In this paper, we account for the development of communications equipment. We have kept the term IT, however.

In empirical studies, the IT productivity paradox has been verified in analyses based on early (pre-1990) data for the U.S. and Canada. Mostly, the results show either very small or insignificant effects of IT on productivity growth; see for instance Harris & Katz (1991) and Parsons, Gotlieb, & Denny (1993). Indeed, some studies have reported significantly negative effects; cf. Loveman (1988) and Berndt & Morrison (1995). Some of the explanations suggested for these counter-intuitive results are: the time required for IT investments to yield productivity increases has been underestimated, the magnitude of the investments have been overestimated and measurement problems on both the input side and the output side have concealed the productivity effects.

However, a couple of more recent studies, using data extending to the end of the 1990's, have found productivity-increasing effects of IT. Oliner & Sichel (2000) argue that the reason why there were no effects earlier is that, in the U.S., IT investments did not really take off until 1995. When they did, the effects were substantial, however: Oliner & Sichel claim that IT accounted for about two-thirds of the acceleration in the labor productivity between the first and second halves of the 1990's.

Bresnahan, Brynjolfsson, & Hitt (2002), while focusing primarily on skill-biased technical change rather than productivity, make an important contribution towards the resolution of the IT productivity paradox by extending the idea of capital-skill complementarity hypothesis discussed by Griliches (1969) and Lucas (1990). Bresnahan et al. (op. cit.) argue that too much attention has been paid to IT investments and too little attention has been paid to work organization and human capital structure. Accounting for both IT and human capital, they find that the balance between the two is crucial. Firms with high levels of both IT and human capital are found to be the most productive. More interesting: firms with low levels of *both* IT and human capital are shown to be more productive than firms that are high on IT and low on human capital, or vice versa.

The framework we suggest in this paper is similar to the Bresnahan et al. (op. cit.) approach in the sense that we, too, conjecture that human capital is a key element in the explanation of the IT productivity paradox. However, we extend the analysis by incorporating a phenomenon often discussed in the context of endogenous growth theory, namely knowledge spillovers. While it seems very natural to consider knowledge spillovers in an evaluation of the productivity effects of IT, these have barely been discussed in earlier studies.

The next section contains a review of some attempts to explain the IT productivity paradox. In Section 3 we develop a simple stylized growth model. By means of this model we discriminate between some of the suggested explanations for the IT productivity and, second, propose a way to account for knowledge spillovers.

Our empirical analysis is based on data for 14 industries in the Swedish manufacturing sector observed annually during the period 1986-95. It appears that in the Swedish manufacturing sector the productivity-enhancing effects of IT started to show already in the first half of the 1990s, i.e. a couple of years earlier than, e.g., in the U.S. Otherwise, the developments in Sweden seems to have been qualitatively similar to that in several other countries. Our data are described in Section 4 and the results are provided in Section 5. Section 6 contains a summary of our results and our conclusions.

2. Literature review: attempts to explain the paradox

For brevity, we here only provide a very condensed and selective list of some of the explanations suggested for the IT productivity paradox.[1]

1) *Investments in IT became massive only towards the end of the 1990s.* Thus, early analyses were unable to capture positive growth effects from IT simply because, at the time, these investments were still comparatively small. Studies using later data should be able to discern positive growth effects. This view is supported by the study by Oliner & Sichel (2000). However, this explanation says nothing about the significant negative effects of IT on productivity estimated by, e.g., Loveman (1988) and Berndt & Morrison (1995).
2) *It takes time before the productivity-enhancing effects of a new technology can be realized.* This point has perhaps been most convincingly made by David (1990). From an empirical point of view, this explanation is similar to the previous one. An important difference, however, is that this explanation can account for (initial) negative effects of IT on productivity, provided that the diffusion of IT use is associated with learning costs that decrease over time, as a function of the increasing number of users. This explanation also points to the importance of (positive) externalities. More wide-spread knowledge about (how to exploit) IT will speed up the rate of diffusion. The resulting increase in people with access to IT will raise the benefits accruing to individual users, which will further accelerate diffusion. The importance of this spiralling effect has been especially notable in the 1990's, with the rapidly expanding use of email and the Internet.
3) *No account has been taken of the complementarity between IT and skilled workers.* Although the capital-skill complementarity hypothesis was put forward already by

[1] For a more extensive discussion see, e.g., Triplett (1999). Also, for the view that there is essentially no paradox to explain, because the importance of the introduction of IT has been vastly exaggerated, compared to the significance of other technological developments like the adoption of electricity, see Gordon (2000).

Griliches (1969), the connection between IT and human capital has almost invariably been disregarded in assessments of the productivity effects of IT.[2] Presumably, this is primarily due to lack of data. However, by matching two different data sets Bresnahan, Brynjolfsson, & Hitt (2002) have overcome this problem. Splitting their data into four categories according to whether firms are high or low on IT and human capital, they find high levels of productivity in firms that are either high on both IT and human capital *or* low in both of these dimensions. Relatively lower levels of productivity are found in firms that are high in one of the two dimensions and low in the other.[3] Using a different approach, Kaiser (2003) also finds strong evidence for complementarity between expenditures on IT capital and outlays for IT personnel.

4) *IT is a general purpose technology (GPT), the efficient implementation of which requires changes in work practices and skill upgrading.* This explanation contains elements of explanations 2 and 3. The idea is that the introduction of GPTs like IT will initially lead to a slowdown in productivity, as it takes time to implement and learn to use the GPT efficiently. In particular, assuming skilled labor to have a learning advantage over unskilled labor, the theory holds that skill premia will rise, inducing an increased supply of skills. When the increased supply comes about and the work organization is properly adapted to the GPT, productivity starts increasing again. The notion of GPTs was introduced by Bresnahan & Trajtenberg (1995) and the relation between GPTs and productivity growth is discussed in, e.g., Helpman & Trajtenberg (1998), and Greenwood & Yorukoglu (1997).

5) *Mismeasurement of outputs.* According to this explanation, the use of information technology has increased the quality of existing products and services and created new goods, neither of which are (fully) captured in the official statistics. This has led to a downward bias in the estimated growth effects; see, e.g., Brynjolfsson (1993) and Dean (1999). Nevertheless, it is essential to point out, like Lee & Barua (1999) do, that

[2] However, complementarity between IT and skilled workers has been documented in several studies of labor demand and skill-biased technical change. Two seminal contributions are Berman, Bound, & Griliches (1994) and Autor, Katz, & Kreuger (1998). For a study using Swedish data, see Mellander (1999).

[3] A related approach is taken by Siegel (1997), who considers the possibility that the investments in IT may induce enhanced efficiency of labor which, in turn, positively affects productivity growth. He finds some, although not unambiguous, support for this hypothesis.

efficiency related gains in the production of the old goods should still be accounted for by conventional output measures. That is to say, while mismeasurement of output certainly is part of the puzzle it cannot resolve it entirely.

6) *Mismeasurement of inputs*. On the input side the issue of mismeasurement is less clear-cut than on the output side. On the one hand, it can be argued that early (U.S.) measures of IT were overstated because they included equipment that one would not ordinarily associate with IT like, e.g., typewriters and accounting machinery.[4] On the other hand, the often noted difficulties to adjust for quality increases in IT price indexes implies a tendency to underestimate the volumes of IT investments.[5] And the presence of positive externalities in the use of IT, cf. the second point above, points in the same direction. Failure to account for these externalities will, again, bias measures of IT inputs downwards.

7) *Overinvestments in IT, in the latter half of the 1980s.* This explanation has been suggested by Morrison (1997), based on the finding that in U.S. manufacturing industries estimated benefit-cost ratios (Tobin's q) for IT capital dropped significantly below 1 by the mid 1980's. It is natural to interpret the term overinvestment in a relative sense here, i.e. that IT investments were too large compared to outlays on other factors of production, notably human capital; cf. points 3 and 4.

There are thus rather diverse results on the connection between IT and growth, and the explanations for these findings are quite diverse, too.

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[4]These were included in Bureau of Economic Analysis category Office Computing and Accounting Machinery; c.f. Berndt & Morrison (1995). After 1982 this category was replaced by Information Processing and Related Equipment, see Lee & Barua (1999).

[5]For a hedonic approach to the estimation of price indexes for computers, see Berndt, Griliches & Rappaport (1995) and Berndt & Rappaport (2001). Observing that IT involves non-computer equipment, too, Lee & Barua (1999) have turned upside down the argument about how quality adjustment affects the measured volumes of IT. In their examination of the study by Loveman (1988), they argue that by applying a computer price index to all types of IT Loveman *overestimated* the volumes of IT investments, as computer prices have fallen faster than the prices of other IT products. While this criticism is probably foremost valid with respect to early definitions of IT that involved many items whose IT character could be questioned, the argument is supported by Jorgenson's (2001) study of relative prices for different kinds of IT equipment in the US since the late 1940s.

3. A stylized model

We here consider a stylized version of the model that we use in our empirical analysis. Our discussion serves two purposes. The first is to reconcile the different results of the earlier studies and to discriminate between some of the explanations that have been suggested for the IT productivity paradox. The second purpose is to consider how knowledge spillovers and capital-skill complementarity might affect productivity growth.

Our stylized model captures four features: i) measurement error in the IT input variable(s), ii) mismeasurement of output, iii) positive externalities in the use of IT, and iv) the connection between IT and human capital.

The analysis is consistent with both a neoclassical growth theory framework and with endogenous growth models. We can thus here disregard the fact that these two theoretical frameworks have different implications for the empirical analysis, notably with respect to how IT and human capital are operationalized.[6]

Regarding feature i., it was noted in Section 2 that the IT measurement error can be both negative and positive. A simple specification allowing for this is

$$IT_t^* = IT_t + w_t \tag{1}$$

where IT_t^* is the observed measure of IT in period t, IT_t the true measure and w_t a random error, such that

$$E\left(w_t\right) = 0,\ \ Var\left(w_t\right) = \sigma_w^2,\ \ Cov\left(IT_t, w_t\right) = 0. \tag{2}$$

With respect to feature ii., non-recorded quality improvements in output should introduce a downward bias in measures of productivity growth (cf. point 5 in Section 2). Like the mismeasurement of IT, the mismeasurement of output is likely to vary over time, cf. Basu et al. (2003). We therefore specify the difference between the firm's true rate of TFP growth, g_t, and the observed rate, g_t^*, as a random variable with positive expectation, β_0, according to

$$g_t - g_t^* = \beta_0 + u_t, \quad \beta_0 > 0, \tag{3}$$

and

$$E(u_t)=0,\ \ E(u_t^2)=\sigma_u^2,\ \ Cov(u_t,w_t)=0. \tag{4}$$

Feature iii. can be modelled by assuming that the productivity effects from *IT* at the firm and industry level are affected by the use of *IT* in the aggregate economy; see the last paragraph of point 2, Section 2. Assuming that there is an index of the Total Use of IT in the Swedish Economy, $TUITE$, we posit that $TUITE$ has the effect of scaling up the IT input. Using an increasing function, ψ, and allowing for a delayed impact on the rate of growth we arrive at the following direct effect of IT on g_t:

$$\beta_{1t}\cdot IT_{t-1};\ \ \beta_{1t}=\psi\left(TUITE_{t-1}\right) \text{ and } \psi'>0. \tag{5}$$

The scaling effect can thus be expressed in terms of a time-varying parameter, β_{1t}. Note that we do *not* assume that this parameter is positive, *a priori*.

The motivation for (5) is that, by definition, an externality is an effect, which is not accounted for by individual firms and, hence, shows up in TFP growth. In a neoclassical context, this would mean that the capital rental price of IT would overstate the real cost of IT capital.[7] In an endogenous growth context, as in, e.g., Barrro and Sala-i-Martin (1999) it is natural to relate to a learning-by-investing mechanism; as successively more firms invest in IT, the knowledge about the properties of the new technology increases and becomes more widespread.

With respect to feature iv., our analysis will be based on the maintained hypothesis that information technology and human capital are complements, in accordance with, e.g., Bresnahan et al. (2002) and Kaiser (2003). We model the complementarity by means of an interaction variable, taken to affect g_t positively. Allowing, again, for a delayed impact we get an indirect effect of IT on g_t:

$$\beta_2\cdot\left(IT\times HC\right)_{t-1};\ \ \beta_2>0 \tag{6}$$

Ordinarily, interaction effects should be captured already in the measure of productivity

[6]The empirical specification of the model will be discussed in Section 4.2.

[7]Siegel (1997) tries to capture IT externalities within a neoclassical framework. However, instead of considering the total use of IT in the economy he uses a measure of the IT investments made by the industry's suppliers.

growth.[8] In the context of externalities in the use of IT and/or measurement error in the IT input, the interaction effect may not be properly accounted for, however. There may be knowledge spillovers arising through networks: employees working with computers form networks (via the Internet) with colleagues in other firms, networks which facilitate the transfer of knowledge.[9]

Taking the total effect of IT on g_t to be the sum of the direct effect (5) and the indirect effect (6) and using (3) we obtain the following equation:

$$g_t^* = -\beta_o + \beta_{1t} IT_{t-1} + \beta_2 \left(IT \times HC \right)_{t-1} - u_t \tag{7}$$

By (7), the effect of "true" IT on the observed rate of TFP growth equals

$$\frac{\partial g_t^*}{\partial IT_{t-1}} = \beta_{1t} + \beta_2 HC_{t-1} \, . \tag{8}$$

Note that although the effect of IT on productivity growth is increasing in human capital, the total effect can be negative, provided that β_{1t} is negative and sufficiently large in magnitude.

Before proceeding to analyse the implications of our simple model, a word of caution is in order. A causal interpretation, from IT and HC to g_t^*, is justified only if the one year lag on IT and HC makes it possible to treat these variables as predetermined. This, in turn, hinges upon the absence of serial correlation in the data. This is an empirical matter that we consider in Section 5.2

Using the framework given by equations (1) - (8) we now discuss three issues that have arisen in connection with earlier studies:

I. Can the negative effects of IT on productivity growth found in studies based on pre-1990 data be explained by measurement error in the IT variable as argued by Lee & Barua (1999), or are the results indicative of a truly negative return to

[8]We are assuming here that the TFP growth measure corresponds to a flexible representation of the technology, implying that it allows for interactions between inputs; see Section 4.1

[9]One might wonder why we allow for both first- and second-order effects of IT on productivity growth but only for a second-order effect of HC. The reason is that the features i - iv above, do not involve mismeasurement in human capital and also not externalities in human capital *per se*. The externalities that we consider are associated with IT, either through IT investments or through the use of IT. However, from an *empirical* point of view there might nevertheless be a place for a first-order effect of HC in the model. This

early IT investments, as argued by Morrison (1997)?

II. Why is it that models similar to the one just outlined yield positive returns when applied to later data?

III. If complementarity between IT and skilled labor is allowed for, like in Bresnahan et al. (2002), what will happen to the estimated direct effect?

Assume, first, that g_t^* is simply regressed on IT_{t-1}^*, using data for the pre-1990 period and post-1990 period, respectively. This implies that the measurement error in IT is ignored, that the variable $\left(IT \times HC\right)_{t-1}$ is omitted, and that no account is taken of the fact that β_{1t} is a time-varying coefficient. For illustrative purposes we will here assume that the function ψ is a step function, taking on the values $\overline{\beta}_{1,\text{pre-90}}$ during the pre-1990 period $\overline{\beta}_{1,\text{post-90}}$ in the post-1990 period.

To derive the probability limit of the OLS estimate of β_{1t} under these conditions, we apply a result stated in Lam & Schoeni (1993).[10] This yields

$$\text{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right) = \overline{\beta}_{1,\mathrm{K}} - \overline{\beta}_{1,\mathrm{K}} \cdot \lambda + \beta_2 \widehat{\theta}\left(1-\lambda\right), \quad \mathrm{K} = \text{pre-90, post-90} \tag{9}$$

where the IT measurement error is accounted for by the parameter λ , defined as

$$\lambda \equiv \frac{Var\left(w\right)}{Var\left(IT^*\right)}, \tag{10}$$

and $\widehat{\theta}$ is the coefficient from a hypothetical regression of $IT \times HC$ on *IT*:

$$\widehat{\theta} = \frac{Cov\left(IT \times HC, IT\right)}{Var\left(IT\right)}, \quad \widehat{\theta} > 0. \tag{11}$$

From (9) it can be seen that the bias in the estimate of $\overline{\beta}_{1,\mathrm{K}}$ has two components. The first, $-\overline{\beta}_{1,\mathrm{K}} \cdot \lambda$, is the measurement error bias (MEB). The second component, due to omission of the variable $IT \times HC$, is the omitted variable bias (OVB). While the OVB is invariably positive, given the assumptions $\beta_2 > 0$ and $\widehat{\theta} > 0$, the sign of the MEB is determined by

point is discussed in Section 5.2.

[10]In a returns to schooling context, Lam & Schoeni (op. cit.) consider how the estimated effect on earnings from another year of schooling is affected when data on ability are lacking and there is measurement error in

the sign of the true parameter $\overline{\beta}_{1,K}$. If $\overline{\beta}_{1,K}$ is positive, the MEB will be negative, and if $\overline{\beta}_{1,K}$ is negative, the MEB will be positive.

Equation (9) can be used to derive bounds on the probability limit of the OLS estimate $\widehat{\overline{\beta}}_{1,K}$. These bounds are given in Table 1, for various assumptions about the true parameter and the magnitude of the omitted variable bias.

Table 1: Ranges for the probability limit of the OLS estimator of $\overline{\beta}_{1,K}$, for different signs of the true effect and different magnitudes of the omitted variable bias

a)	$\overline{\beta}_{1,K} > 0 \;\Rightarrow\; 0 \le \text{plim}\left(\widehat{\overline{\beta}}_{1,K}\right) \le \overline{\beta}_{1,K} + \beta_2\widehat{\theta}$
b)	$\overline{\beta}_{1,K} > 0$ *and* $\;\Rightarrow\; 0 \le \text{plim}\left(\widehat{\overline{\beta}}_{1,K}\right) \le \overline{\beta}_{1,K} + \beta_2\widehat{\theta}$ $\beta_2\widehat{\theta} > \left\lvert\overline{\beta}_{1,K}\right\rvert$
c)	$\overline{\beta}_{1,K} < 0$ *and* $\;\Rightarrow\; \overline{\beta}_{1,K} + \beta_2\widehat{\theta} \le \text{plim}\left(\widehat{\overline{\beta}}_{1,K}\right) \le 0$ $\beta_2\widehat{\theta} < \left\lvert\overline{\beta}_{1,K}\right\rvert$

Note: The index K denotes either pre-90 or post-90

We can now consider issue I. As can be seen in Table 1, the estimated effect of IT on productivity growth can be negative *only* if the corresponding true effect is negative. In this case, c), the true effect is negative *and* smaller than the lower bound of plim $\left(\widehat{\overline{\beta}}_{1,\text{pre-90}}\right)$; this is so because the omitted variable bias, $\beta_2\widehat{\theta}$, is positive. Furthermore, this conclusion is unaffected by measurement error in the IT variable. The upper bound of plim $\left(\widehat{\overline{\beta}}_{1,\text{pre-90}}\right)$ is equal to zero, irrespective of whether there is measurement error or not. Our analysis thus supports Morrison's (1997) suggestion of overinvestment in IT during the latter part of

the schooling variable.

the 1980's, as overinvestment would, eventually, result in a negative effect of IT on productivity. And, as our conclusion is invariant to measurement error in the IT variable, we reject the claim in Lee & Barua (1999) that measurement errors were behind estimated negative effects of IT on productivity growth.[11]

We next consider point II., i.e. why analyses on more recent data find positive effects of IT on productivity growth, thus reversing the results of earlier studies. The surge in IT investments, coupled with falling computer prices, meant that IT became available to a rapidly increasing number of people. That, in turn, increased the positive externalities associated with the use of IT, cf. equation (5). As mentioned above, we will for simplicity model this by specifying:

$$\beta_{1t} = \begin{cases} \overline{\beta}_{1,\text{pre-90}} & \text{for} \quad t \le 1990 \\ \overline{\beta}_{1,\text{post-90}} & \text{for} \quad t > 1990 \end{cases} \quad \overline{\beta}_{1,\text{post-90}} > \overline{\beta}_{1,\text{pre-90}} \tag{12}$$

It should be noted that (Beta1Step) is not sufficient to determine the sign of $\overline{\beta}_{1,\text{post-90}}$. If $\overline{\beta}_{1,\text{pre-90}} < 0$ then $\overline{\beta}_{1,\text{post-90}}$ may be negative, too. Unfortunately, the sign of the estimate $\widehat{\overline{\beta}}_{1,\text{post-90}}$ is no help here. In Table 1, we see that $\text{plim}\left(\widehat{\overline{\beta}}_{1,\text{post-90}}\right) > 0$ is consistent with both $\overline{\beta}_{1,\text{post-90}} > 0$ and $\overline{\beta}_{1,\text{post-90}} < 0$; cf cases a) and b), respectively. However, we can discriminate between the two cases by expanding the simple OLS regression to include a vector of proxy variables for the omitted variable, i.e. $IT \times HC$. This will affect the estimate of $\overline{\beta}_{1,\text{post-90}}$ differently depending on the sign of the true parameter $\overline{\beta}_{1,\text{post-90}}$. To show this, denote vector of proxy variables by $\mathbf{P}$, and the corresponding estimate of $\overline{\beta}_{1,\text{K}}$ by $\widehat{\overline{\beta}}_{(1,\text{K})\cdot\mathbf{P}}$. Then

[11]Actually, Lee & Barua state that the negative contribution of IT is attributable primarily to the choices of the IT deflator and modelling technique. However, they do not provide any assessment making it possible to disentangle the impacts of these two factors.

$$\operatorname{plim}\left(\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}\right) = \overline{\beta}_{1,\mathrm{K}} - \overline{\beta}_{1,\mathrm{K}} \tfrac{\lambda}{1-R^2_{IT^*\times HC,\mathbf{P}}} + \beta_2 \widehat{\theta}(1-\lambda)\cdot\phi\left(IT^*, IT^*\times HC, \mathbf{P}\right) \tag{13}$$

where $R^2_{IT^*\times HC,\mathbf{P}}$ denotes the R^2 obtained when $IT^*\times HC$ is regressed on $\mathbf{P}$, and $\phi(\cdot)$ is a function that under fairly general conditions satisfies $0<\phi(\cdot)<1$.[12]

Comparing (9) and (13) we note that

$$\overline{\beta}_{1,\mathrm{K}} > 0 \Rightarrow \operatorname{plim}\left(\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}\right) < \operatorname{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right). \tag{14}$$

The implication (14) is due to the fact that the inclusion of proxy variables affects the measurement error bias (MEB) and the omitted variable bias (OVB) in the same direction when $\overline{\beta}_{1,\mathrm{K}} > 0$. With respect to the MEB, the fact that $\left(1-R^2_{IT^*\times HC,\mathbf{P}}\right) \in]0,1[$ implies that including proxies makes the MEB larger in magnitude, i.e. smaller because of the minus sign. The OVB, while positive, becomes smaller, too, because $0<\phi(\cdot)<1$.

On the other hand, if $\overline{\beta}_{1,\mathrm{K}} < 0$ the effect of the proxy variables is ambiguous, the ambiguity being due to the fact that in this case the MEB and the OVB change in different directions.

Thus, by studying the effects of including proxy variables we should be able to infer the sign of the true parameter $\overline{\beta}_{1,\text{post-90}}$. If $\overline{\beta}_{1,\text{post-90}}$ is indeed positive, then the estimate of $\overline{\beta}_{1,\text{post-90}}$ should be positive when human capital variables are excluded from the regression and this positive estimate should decrease towards zero when proxy variables for human capital are included.

The analysis also provides the answer to issue III. It shows that the answer depends on the sign of the true direct effect. If the true direct effect is positive, allowing for indirect effects will decrease the estimated direct effect, cf. (14). If, on the other hand, the true

[12] Like (9), this equation draws on Lam & Schoeni (1993). They provide a similar expression to assess the effect on the estimated return to schooling when a proxy variable for the missing ability measure is included in the regression.

direct effect is negative, allowing for indirect effects will have an ambiguous impact on the estimated direct effect.

4. Data and empirical specification

Our empirical analysis covers 14 industries in the Swedish manufacturing sector, observed annually over the period 1986-95. The industry codes are given in Table 2. To indicate the relative size of the industries we also show their shares in manufacturing employment in the middle of the observation period. The data are from the official statistics produced by Statistics Sweden; from the National Accounts, the Employment Register, the Labor Force Surveys, various Investment Surveys and the Trade Statistics.

Table 2: The industries considered and their shares in total manufacturing employment in 1991.

Industry code	Industry	Employment share
3100	Food, Beverages and Tobacco	9.4
3200	Textile, Apparel & Leather	3.0
3300	Saw Mills and Wood Products	8.5
3400	Pulp, Paper and Printing & Publishing	14.7
3500	Chemical, Plastic Products. and Petroleum	7.9
3600	Non-Metallic Mineral Products	3.3
3700	Basic Metals	4.0
3810	Metal Products	11.5
3820	Machinery & Equipment, not elsewhere classified	13.5
3830	Electrical Machinery, not elsewhere classified	8.1
3840	Transport Equipment, except Shipyards	12.3
3850	Instruments, Photographic & Optical Devices	2.2
3860	Shipyards	0.8
3900	Other Manufacturing	0.8
3000	Total Manufacturing	100.0

Note: The classification system used here is very close to the ISIC codes.

The cross-sectional dimension of the data set has been determined by the most detailed break-down of IT investments provided in the Investment Surveys. In the time series dimension, the starting point is given by the first year of the Employment Register. The end point is the result of a change in the industrial classification system, making it impossible to extend the time series beyond 1995.

4.1 The growth rate in total factor productivity

The yearly TFP growth rates have been computed by means of a Törnqvist index. This index corresponds to the translog production function and allows for interactions among inputs like, e.g., complementarity between IT and human capital.[13]

Suppressing industry indexes and denoting the volume of gross output by Y and the volume of input i by X_i, the TFP growth rate g, is defined as

$$g_t \equiv \Delta \ln TFP_t = \Delta \ln Y_t - \Delta \ln X_t \quad t = 1986,....,1995 \tag{15}$$

where Δ is the difference operator, defined such that $\Delta \ln Z_t \equiv \ln Z_t - \ln Z_{t-1}$. The growth in aggregate input, X_t is given by:

$$\Delta \ln X_t = \sum_{i=1}^{8} \overline{w}_{i,t} \Delta \ln X_{i,t},. \tag{16}$$

where the weights $\overline{w}_{it}$ are defined in terms of average cost shares according to

$$\overline{w}_{i,t} = \frac{1}{2}\left(\frac{P_{i,t-1}X_{i,t-1}}{\sum_{k=1}^{n} P_{k,t-1}X_{k,t-1}} + \frac{P_{i,t}X_{i,t}}{\sum_{k=1}^{n} P_{k,t}X_{k,t}} \right), \tag{17}$$

and P_i is price of input i.

We consider the following eight inputs, which will be discussed below:

K_C = Stock of computer equipment capital,

K_M = Stock of non-computer equipment capital,

K_S = Stock of structure capital,

L_1 = # of full-time employees with elementary school (less than 9 years),

L_2 = # of full-time employees with 9 year compulsory school,

L_3 = # of full-time employees with upper secondary school,

L_4 = # of full-time employees with tertiary and postgraduate education,

IG = Intermediate goods.

Figure 1 shows how the industry-weighted average of TFP growth has evolved over time.

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[13]Cf. Jorgenson et al. (1973) and Caves et al (1982).

While the period 1986-90 showed low but stable growth, the growth rates during 1991-95 were much higher and also more volatile. Also, Figure 2 shows that the variation around the average is smaller in 1991-95 than in 1986-90. Thus, the higher average growth in the first half of the 1990s is not merely the result of high growth rates in some large industries.As noted in the introduction, the turning point apparently occurred quite early in Sweden. Stiroh, (2002) for instance, estimates that the breakpoint in U.S. manufacturing was passed in 1993.

Figure 1: Weighted averages of TFP growth rates in Swedish manufacturing 1986-1995. Industry weights equal to employment shares

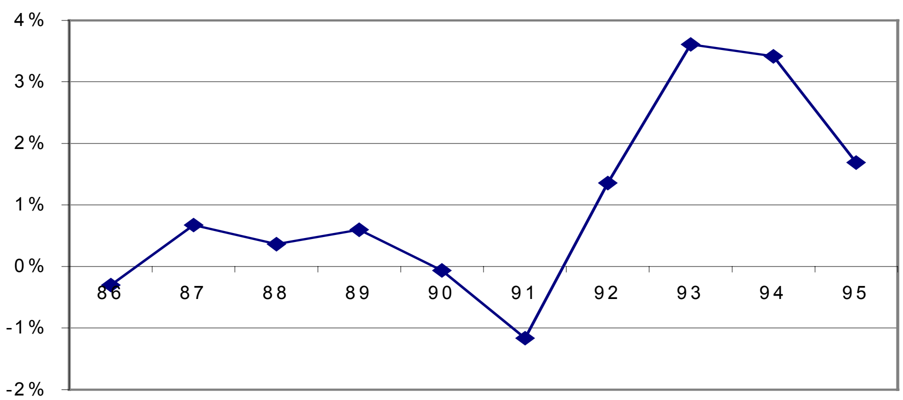
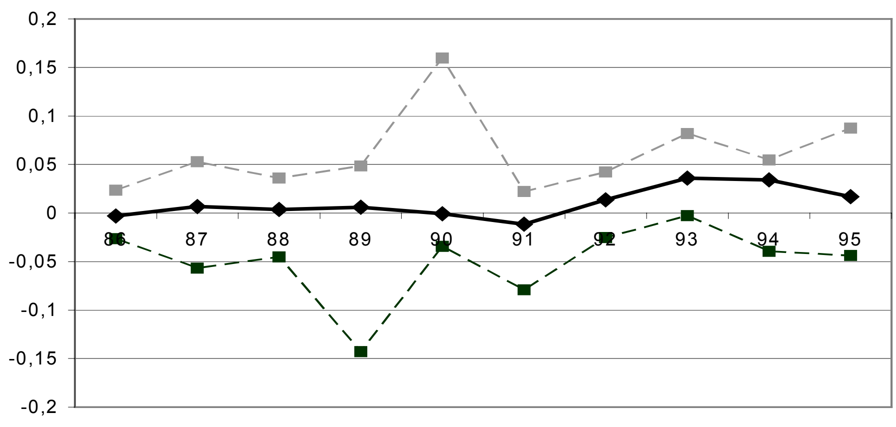


Figure 2: The industry variation around the weighted average. All observations lie within the bounds given by the dashed lines.



It can be argued, of course, that the increase in TFP growth in the latter half of the period is not only due to IT developments, but also to business cycle changes. We thus control for the business cycle in the empirical analysis, cf. Section 4.5.

4.2 Specification of the explanatory variables

We consider three alternative specifications of the explanatory variables.

The first, due to neoclassical growth theory as originally formulated by Solow (1956), implies that the explanatory variables should be specified in terms of *growth rates*. In a neoclassical context, the primary reason for explaining variations in TFP growth by means input growth rates is presence of input measurement error. While less natural, externalities can also be used as a motivation.[14]

The second framework is endogenous growth theory, which predicts that the *levels* of (some) inputs determine the rate of productivity growth. Endogenous growth theory explicitly deals with the rôle of externalities in explaining growth; see, e.g., Barro & Sala-i-Martin (1999). There are also endogenous growth models where growth is increased by devoting resources to R&D [Romer (1990) and Aghion & Howitt (1992)].Since resources devoted to R&D are essentially resources devoted to sophisticated capital equipment (IT) and highly educated workers, these models provide a motivation for the current study. Another argument can be derived from the literature on GPTs: successful implementation of a new GPT and the generation of skills needed to operate it efficiently is a cumulative process. As such, it should be better captured by the developments of stocks (of IT and human capital) than by yearly flows, i.e. growth rates.

The third framework is due to Jones' (1995, 1999) critique of endogenous growth models. Jones (1995) argues that the claim that the level of R&D should determine the rate of growth is inconsistent with empirical data. He notes, however, that a simple way to avoid that increases in the levels of inputs can increase growth without limit is to substitute input *proportions* for input levels. For instance, if resources devoted to R&D can be approximated by "research labor" then, instead of having the number of research workers determining the rate of growth, one could have the share of research workers in total employment.

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[14]A study framed in the neoclassical tradition, which considers both measurement errors and externalities is Siegel (1997).

As there are no clear theoretical arguments for preferring one of these specifications in favor of the others, we have estimated models according to each one of them. Our general conclusions can be formulated as follows. Similar to the experience of Benhabib & Spiegel (1994), the neoclassical specification with explanatory variables in growth rates yielded largely insignificant results. The level specification of the original endogenous growth models to a larger extent resulted in significant estimates but these were often implausible with respect to sign. The input proportions specification yielded the best results in terms of significance, signs and goodness-of-fit. We thus focus on this alternative.[15]

4.3 Measures of IT equipment and IT use

As our measure of IT, we use the share of computers in the total capital stock, K_C/K. The computer capital stock has been constructed by means of data on computer investments collected through investment surveys conducted by Statistics Sweden. The computer investments cover investments made both for office use and for use in the production process, e.g., CNC (computer numerically controlled) equipment and CAD / CAM - systems.[16] For the manufacturing sector as a whole, computer investments for use in the production process were 3-4 times as large as those for office use, during the period that we study.

By means of the computer investments data we have broken down the industry-specific stocks of equipment capital provided in the National Accounts into computer capital stocks, K_C, and stocks of non-computer equipment, K_M. Details on the computation are provided in the Appendix.

Table 3 shows the shares of computers, non-computer equipment and structures in the capital stock, for the beginning, middle and end of the period.[17] In Table 3, we see that, for the manufacturing sector as a whole, the computer share in the capital stock more than doubled over the period 1985-94, from 7.9 percent to 17.3 percent. This is especially

[15]However, results corresponding to the rates and levels specifications are available on request.
[16]The definition of IT investments employed here differs from definitions used in some recent U.S. studies. For example, Gordon (2000), Jorgenson & Stiroh (2000), and Oliner & Sichel (2000) define IT investments as investments in hardware, software, and telecommunications.
[17]The capital stocks for year *t* are defined as January 1.

remarkable in view of the fact that computer capital depreciates much faster than other types of capital; we have assumed the rate of depreciation for computer capital to be 1/3.

Table 3: Capital stock shares in Swedish manufacturing

Industry	Computers			Equipment			Structures		
	1985	1990	1995	1985	1990	1995	1985	1990	1995
3100	2.8	5.5	7.8	48.6	48.8	48.7	48.6	45.7	43.5
3200	3.5	6.6	6.9	60.7	56.4	49.0	35.9	37.0	44.1
3300	3.0	17.2	12.6	47.1	33.2	39.1	49.9	49.6	48.3
3400	9.2	13.8	14.1	56.0	54.2	53.4	34.8	32.0	32.5
3500	4.0	7.0	12.1	61.4	60.4	55.5	34.6	32.6	32.4
3600	2.0	6.1	6.7	50.8	50.5	49.9	47.2	43.4	43.4
3700	2.2	9.9	10.8	56.6	50.6	51.8	41.2	39.4	37.3
3810	8.8	18.0	15.6	44.8	41.0	44.1	46.5	41.0	40.3
3820	13.4	17.8	21.0	33.5	42.0	40.5	53.1	40.1	38.5
3830	16.1	16.2	32.7	41.7	48.5	32.2	42.2	35.3	35.1
3840	19.7	21.0	36.2	30.0	36.0	25.2	50.4	43.0	38.6
3850	23.6	15.7	21.0	39.7	56.4	49.5	36.7	27.9	29.5
3860	1.9	3.1	7.2	42.3	34.9	30.2	55.8	62.0	62.5
3900	2.1	5.0	6.5	37.6	38.9	35.2	60.4	56.2	58.3
3000	7.9	13.4	17.3	49.2	47.8	44.9	42.9	38.9	37.8

Figure 3: Index of total use of IT in Sweden, 1984=100

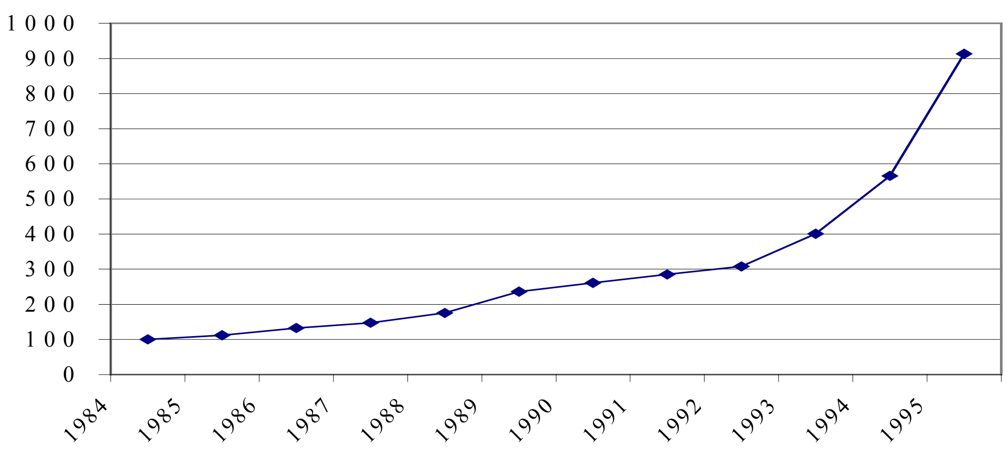


Table 3 also shows that in relative terms the largest increases in the computer shares took place between 1985 and 1990, rather than between 1990 and 1994. It can also be seen that there is a lot of variation across industries. This is important because the relatively short period covered by our data makes cross-sectional variation crucial in our empirical analysis.

To model the externalities associated with IT, we use an index of the Total Use of IT in the Swedish Economy, *TUITE*, cf. (5). This index includes both computers & peripherals, and communication equipment. It is defined as

$$TUITE_t = PROD^N_{IT,t} + IMP^N_{IT,t} - EXP^N_{IT,t} \tag{18}$$

$PROD^N_{IT,t}$, $IMP^N_{IT,t}$, and $EXP^N_{IT,t}$ denoting volumes of production, imports and exports of IT at the national level. Figure 3 shows the evolution of *TUITE*.

It can be seen that the use of IT has increased extremely rapidly, especially from 1992 and onwards; between 1992 and 1995 the increase was threefold.

Both K_C / K and *TUITE* are included in the regressions we with a one year lag, again to avoid endogeneity problems.

4.4 The human capital data

The human capital variables have been constructed by means of the Swedish Employment Register and the Labor Force Surveys. The Employment Register contains employee information on industry, level of education and fields-of-study, age, sex, and immigrant status, and yearly earnings. The Labor Force Surveys provide data on work hours per week, by industry and sex, enabling an approximate conversion of number of employees into full-time equivalents.[18].

Just like the use of capital, employment of labor is endogenously determined. In the empirical analysis, the human capital variables are thus also lagged one year, relative to productivity growth. Accordingly, the cross-classifications of labor for 1985, 1990 and 1994 in Table 4 are to be related to productivity growth rates in 1986, 1991 and 1995, respectively.

The four cells in the upper left corner of the three sub-tables in Table 4 are identically zero, because the cross-classification by fields-of-study is possible only for

[18]The approximate nature of the conversion is due to the fact that the Labor Force Survey does not contain work hours by level of education.

labor with at least upper secondary school. For the latter, quite detailed field-of-study information is available, however. The labels engineering and business administration are used for brevity only; both encompass several subfields.

The table shows that the human capital in the Swedish manufacturing sector changed dramatically during the period that we are studying. For instance, in 1985 almost half of the workers (49 percent) had no more than 9 years of schooling. In 1994, the share was 1/3. And, at the other end of the distribution, the share of workers with tertiary education almost doubled, from 9 to 16 percent. There is also considerable cross-section variation; in the empirical analysis we employ cross-classifications like Table 4 that differ both by to industry and year.

Table 4: Employment shares in Swedish manufacturing, by level of education and fields-of -study, 1985, 1990 and 1994.

1985:				
	Field-of-study			
Level of education	Engineering	Business administration	"other"	Σ
< 9 years	0	0	0.30	0.30
9 years	0	0	0.19	0.19
Upper secondary	0.25	0.08	0.09	0.42
Tertiary	0.06	0.02	0.01	0.09
Σ	0.31	0.10	0.59	1.00
1990:				
	Field-of-study			
Level of education	Engineering	Business administration	"other"	Σ
< 9 years	0	0	0.22	0.22
9 years	0	0	0.17	0.17
Upper secondary	0.29	0.09	0.10	0.48
Tertiary	0.08	0.03	0.02	0.13
Σ	0.37	0.12	0.51	1.00
1994:				
	Field-of-study			
Level of education	Engineering	Business administration	"other"	Σ
< 9 years	0	0	0.18	0.18
9 years	0	0	0.16	0.16
Upper secondary	0.31	0.09	0.11	0.51
Tertiary	0.10	0.04	0.02	0.16
Σ	0.41	0.13	0.47	1.00

In addition to levels of education and fields-of-study we also account for the workers' age. The age structure can matter in two different ways. On the hand, an education's IT content is higher the more recently the education was obtained, i.e. the younger the worker. This would point to a negative relation between age and productivity growth. On the other hand, older workers have accumulated more work experience than younger workers. If skills acquired in the workplace are more important for productivity than computer skills acquired in school, then the relation between age and productivity growth should be positive instead. To empirically assess which of these two opposing forces that dominate the other we use the following variable

$$\frac{\text{\# 16-29 year olds}}{\text{\# [(16-29) + (50-74)]year olds}}. \qquad (19)$$

The idea underlying this variable is to capture effects of relative changes in tails of the age distribution; all employees in our data belong to the age interval 16-74 years.[19] It should be noted that the ratio (19) can change even if the total number of 16-29 year olds plus the number of 50-74 year olds doesn't change. Thus, e.g., substituting a given number of older workers with an equal number of younger worker will increase the ratio.[20]

4.5 Control variables

To account for cyclical variations in TFP growth, we have used a business cycle indicator, BCI, for the Swedish manufacturing sector, cf Figure 4. The indicator contains information about orders, stocks of finished goods, and expected production.[21]

Comparing Figure 4 and Figure 1, we see that the BCI captures the turning points in

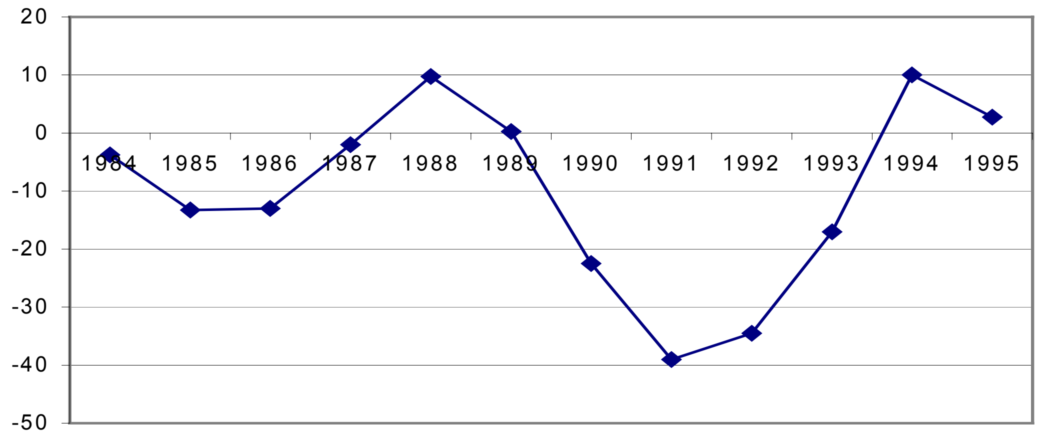
[19]In terms of years, the right tail is longer than the left tail. However, the number of people working beyond the retirement age of 65 is very small. Hence, for practical purposes the tails can be considered to be equally long.

[20]The fact that we model age structure effects by means of (19) should not be taken to mean that we deny the importance of changes in the share of 30-49 year olds for productivity growth; as shown by Malmberg (1994) workers aged 40-49 have made substantial positive contributions to growth in Sweden (along with 50-64 year olds) and Feyrer (2002) obtains similar results for a data set covering 108 different countries. However, unlike these authors we are not primarily interested in the direct link between age demographics and productivity, but on effects working via interactions between workers of different ages and IT. It is then natural to focus on the age categories that differ the most in this respect, i.e. the youngest and the oldest workers.

[21]The indicator has been constructed by the Swedish Institute for Economic Analysis (Konjunkturinstitutet).

TFP growth quite well. However, the *BCI* cannot explain the relative magnitudes of growth at different points in time. In particular, it does not capture that TFP growth was much higher during 1991-95 than during 1986-90.[22]

Figure 4: The business cycle indicator (*BCI*) for the Swedish manufacturing sector 1986-1995.



To take into account that computer investments partly depend on other capital investments, we include the share of non-computer equipment in total capital, K_M / K.[23] As $K_C / K + K_M / K + K_S / K = 1$ by definition, including K_M / K together with K_C / K, means that we fully control for the industries' capital structures.

Finally, we include the shares of females and immigrants among the employees. Gender might be important for two reasons. Weinberg (2000) argues that computers create job openings for women by replacing physically demanding blue-collar jobs by jobs that require computer knowledge. Second, Lindbeck & Snower (2000) point out that modern work organizations are increasingly characterized by multi-tasking. If women are better suited to multi-tasking than men, as is often claimed, this should favor firms with a large female labor share.

Regarding immigrants the direction of causality is more ambiguous. On the one

[22]We do not want to use time dummies to control for the time variation that is common to all industries. Using time dummies amounts to eliminating the general time profile of the endogenous variable, i.e. the profile given in Figure 1. But that time profile is part of what we want to explain; one thing we want to test is whether our simple model can capture the change in the TFP growth pattern that occurred between the end of the 1980s and the beginning of the 1990s.

[23]In this respect we follow earlier studies; see, e.g., Berndt and Morrison (1995).

hand, it can be conjectured that the increased international communication brought about by IT could be facilitated by a work-force comprising employees with different cultural backgrounds. On the other hand, imperfect knowledge of the host country language might have an adverse effect on productivity.

5. Results

In the first part of this section we test the empirical implications of the stylized model in Section 3, on our Swedish data. In the next subsection we consider various econometric issues. To focus on methodological aspects, the analysis is conducted within a modelling framework entailing a univariate representation of human capital. Based on our results in this section we decide upon a basic formulation of the model and an appropriate estimation method. In the last subsection we extend the basic model through multivariate specifications of human capital.[24]

Before discussing the results we will briefly comment upon three features that are common to all the regressions.

First, the estimations are based on weighted least squares (WLS), where the different industries are weighted by their shares in manufacturing employment. Methodologically we thus follow, e.g., Berman, Bound, & Griliches (1994) and Kahn & Lim (1998). The motivation for the WLS procedure can be found in the latter paper: it is reasonable to assume the data for small industries to be noisier than the data for large industries. This assumption can be modelled by assuming that the standard errors of the (unweighted) residuals are inversely proportional to the square of employment. Weighting industries by employment shares will then make the residuals homoscedastic.

Second, the following control variables are always included in the regressions: the (contemporaneous) business cycle indicator, BCI, the (lagged) share of non-computer equipment capital in the total capital stock, K_M / K, and the shares of females and

[24]While not ideal, this sequential approach is necessary due to the fact that our data set is rather small. Considering the issues of model formulation, estimation methods, and multivariate specifications of human capital simultaneously, we would simply run out of degrees of freedom.

immigrants among the employees.

Third, we do not explicitly account for possible measurement error in the IT variable, because we lack information on this issue.

5.1 Testing the implications of the stylized model

The first point made in Section 3 was that the negative effects of IT on productivity growth reported in studies using early (pre-1990) data are not mere statistical artefacts. To see what can be said of the Swedish manufacturing sector in this respect, we estimate the following equation for the first half of our study period:

$$\text{1986-90:} \qquad g_{ht}^{*} = -\underset{(1.56)}{0.039} + \text{ controls} - \underset{(0.11)}{0.006} \cdot \frac{K_C}{K}_{h,t-1}, \quad R^2 = 0.19 \qquad (20)$$

where absolute values of t-statistics are in parentheses.[25] The effect of IT, i.e. the coefficient of $\left(K_C / K\right)_{h,t-1}$ is negative. The theoretical analysis tells us that, although the estimate is insignificant, this indicates that IT had a negative impact on growth in Sweden, too, during the latter part of the 1980s.

The intercept is negative as expected (although insignificant). According to the theoretical analysis, this means that the observed rate of productivity growth, g_{ht}^{*}, underestimates the true rate, g_{ht}, by, on average, 3.6 percent; cf. (3).

The second point made in Section 3 was that if the effect of IT on productivity growth turned positive in the 1990's then we would expect, first, a positive estimate of the impact of IT when ignoring human capital variables and, second, that this positive estimate should decrease after inclusion of human capital variables. The following regression shows that the first condition is satisfied:

$$\text{1991-95:} \qquad g_{ht} = -\underset{(1.83)}{0.072} + \text{ controls} + \underset{(2.80)}{0.204} \cdot \frac{K_C}{K}_{h,t-1}, \quad R^2 = 0.51 \qquad (21)$$

The coefficient for $\left(K_C / K\right)_{h,t-1}$ is now positive, and strongly significant. It can also be noted that the intercept is still negative, as expected, and that it has increased in magnitude.

[25]To save space, we do not report the coefficients for the control variables here, as they are of no interest with respect to theoretical implications that we consider.

This, too, is in line with expectations: one effect of the positive impact of IT will be quality improvements in output; to the extent that these are not captured in the data output growth and, hence, productivity growth will be (further) underestimated.

To check the second condition we include the share of workers with tertiary education as a crude proxy for skilled labor. Interacting it with K_C/K we obtain:

$$\text{1991-95:} \qquad g_{ht} = -\underset{(1.18)}{0.067} + \text{ controls } + \underset{(1.02)}{0.184} \cdot \frac{K_C}{K}_{h,t-1}$$
$$+ \underset{(0.12)}{0.066} \cdot \left(\frac{\#Tertiary}{\#Employees} \times \frac{K_C}{K} \right)_{h,t-1}, \quad R^2 = 0.52 \qquad (22)$$

The inclusion of the interaction variable decreases the estimated direct effect of IT from 0.204 to 0.184, i.e. the second condition is satisfied, too.

To summarize: these very simplistic regressions based on our stylized model point to a (small) negative effect on TFP in Swedish manufacturing during the second half of the 1980s and a positive effect after 1990. That is to say, they indicate a development qualitatively similar to the one experienced in the US, but with the turning point occurring somewhat earlier.

5.2 Econometric issues

In this section we will consider the following four issues: (1) the modelling of the time-varying effects of IT; c f (5), (2) the potential presence of first-order effects of human capital on TFP growth, in addition to the second-order interaction effect given by (6), (3) industry fixed effects, and (4) serial correlation.

Our starting point is the last specification of the previous subsection, i.e. (22). We here estimate that model for the entire period of study, 1986-95, cf column I of Table 5.[26] It can be seen that in contrast to the results obtained for the 1991-95 period the point estimate of the direct effect of IT on TFP growth is negative. Thus, when the impact is not allowed to vary over time, the positive effect during 1991-95 reported in (22) is dominated by a negative impact during 1986-90.[27]

[26]In this section we also report the estimates obtained for the control variables.
[27]This is verified when we apply the specification used in (22) to data for 1986-90. This yields an estimate of

Having thus established the need for a time-varying effect, we turn to the first issue, the specification of an explicit form for the function $\psi\left(TUITE\right)_{t-1}$. We have chosen to approximate ψ by a linear function since our data only cover ten years, making it difficult to precise estimate higher order approximations:

$$\psi\left(TUITE\right)_{t-1} = \gamma \cdot TUITE_{t-1}; \quad \gamma > 0,$$

where γ is a parameter and $TUITE$ the index described in Section 4.3.[28]

The effect of incorporating (23) can be assessed by comparing columns I and II in Table 5. It is clear that all the parameter estimates are affected. In particular, the point estimate of the direct effect of IT changes from -0.0875 to 0.0002. And while the indirect effect decreases, the two changes do not cancel each other out; the partial derivative of $g_{h,t}$ with respect to $\left(K_C / K\right)_{h,t-1}$ [cf. (8)] increases in magnitude. As the time-varying specification is in line with our theoretical model and does have an impact, we will stick to it in the following.

The next issue concerns the possibility of direct, first-order, effects of human capital on $g_{h,t}$. While our theoretical analysis does not imply that human capital should have a direct effect on growth - cf. footnote 10 - there might still be empirical grounds for such a direct effect. To assess this possibility we compare columns II and III in Table 5, which differ only by the inclusion of the human capital variable in column III. It can be seen that the direct effect of human capital is small and very imprecisely estimated. With respect to the other estimates, the only one affected is the coefficient measuring the indirect, interaction, effect. That coefficient becomes smaller and insignificant. Taken together, it appears that the inclusion of a direct human capital effect has the clear disadvantage of creating multicollinearity problems but no discernible empirical advantage. Henceforth, we

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the direct effect of IT that is equal to -0.314 and significant at the 1 % level.

[28]A disadvantage with the linear form is that it cannot allow the effect of IT on TFP growth to change sign over time. As a result, the partial derivative (8) cannot be negative, under the assumptions made in Section 3. However, when we turn to a multivariate specification of human capital, in Section 5.3, there is no reason to restrict all the IT and human capital interaction effects to be positive. The partial derivative of TFP growth with respect to IT might then change sign over time. It will be seen that this does indeed happen in our estimations.

will therefore not consider direct effects of human capital.

Table 5: Alternative model specifications, given univariate measure of human capital

Dependent variable: g_{ht}	I	II	III	IV	V
Intercept	-0.0239 (0.976)	-0.0515 (2.720)	-0.0471 (2.313)	0.0974 (0.894)	-0.0545 (3.207)
Control variables:					
BCI_t	0.0002 (2.046)	0.0003 (2.569)	0.0003 (2.526)	0.0002 (1.094)	0.0003 (2.697)
$\left(\frac{K_M}{K}\right)_{h,t-1}$	0.0880 (2.133)	0.1179 (3.181)	0.1072 (2.259)	0.1478 (1.998)	0.1245 (3.644)
$\left(\frac{\#Females}{\#Employees}\right)_{h,t-1}$	0.0104 (0.325)	0.0010 (0.313)	0.0121 (0.371)	-0.3340 (1.394)	0.0078 (0.267)
$\left(\frac{\#\text{Im}migrants}{\#Employees}\right)_{h,t-1}$	-0.3010 (2.334)	-0.1868 (1.327)	-0.1972 (1.369)	-0.5453 (1.581)	-0.1586 (1.225)
Direct effect of IT:					
$\left(\frac{K_C}{K}\right)_{h,t-1}$	-0.0875 (1.009)				
$\left[TUITE \times \frac{K_C}{K}\right]_{h,t-1}$		0.0002 (1.430)	0.0002 (1.441)	-0.0001 (0.483)	0.0002 (1.948)
Direct effect of human capital:					
$\left(\frac{\#Tertiary}{\#Employees}\right)_{h,t-1}$			0.0349 (0.363)		
IT and human capital interaction:					
$\left(\frac{\#Tertiary}{\#Employees} \times \frac{K_C}{K}\right)_{h,t-1}$	1.0826 (3.276)	0.4961 (1.957)	0.3248 (0.606)	1.3426 (1.973)	0.4225 (1.798)
Industry dummies	No	No	No	Yes [a]	No
Correction for AR(1) residuals	No	No	No	No	Yes [b]
R^2	0.34	0.34	0.34	0.44	0.39

a The reference industry is 3100 = Food, Beverages and Tobacco
b Iterative Parks (1967) procedure, second-round estimates.

The third issue, allowing for industry fixed effects amounts in this context, to allow for cross-industry differences in the expected mismeasurement in output, cf. (3). While desirable, this generalization is quite costly in terms of degrees of freedom. Comparing columns II and IV in Table 5, we see that allowing for industry fixed effects results in the estimate of the direct effect of IT becoming less significant, both economically and statistically, while the economic significance of the indirect effect is substantially increased. The fixed effects themselves take on implausible values, however. For industry 3100 = Food, Beverages and Tobacco, which is the reference industry, the fixed effect is given by the intercept. While insignificant, the estimate of the intercept says that the mismeasurement in output in industry 3100 is such that, on average, the (true) rate of productivity growth is *overestimated* by 9.7 percent. For the other industries, the fixed effects are given by deviations from the reference level of 9.7 percent, determined by means of estimated coefficients on industry dummies. These coefficients imply that the estimated fixed effects are positive for all the other industries as well.[29] As we find it really hard to believe that IT has resulted in TFP growth being overestimated in every industry we will disregard industry-specific fixed effects from now on.

The issue of serial correlation, finally, is important because the interpretation of the lagged explanatory variables as predetermined is valid only if the regression residuals fulfil the assumption of being random disturbances and, hence, not correlated over time. As our panel only covers a ten-year period, formal tests for autocorrelation will, unfortunately, have very low power. Nevertheless, it is possible to estimate the parameters of a simple autoregressive structure. To this end we apply an iterated version of the procedure suggested by Parks (1967) to correct for first-order autocorrelation in a multiple-equation context. The assumed autocorrelation structure is given by:

$$u_{h,t} = \rho_h u_{h,t-1} + e_{h,t}\,, \quad |\rho| < 1 \tag{24}$$

where the $e_{h,t}$ are white noise disturbances. Note that the autocorrelation parameter, ρ, is allowed to vary across industries. We apply this structure to the model given by column II in Table 5. The first-round estimates of the ρ_h are obtained by application of (24) to the estimated residuals of the column II specification. All 14 estimates fulfil the requirement that $|\rho| < 1$. As judged from the t-statistics, only one estimate is significantly different from zero, at the 10 % level. Still, the first-round estimates, denoted by $\widehat{\rho}_{1h}$, are used to

[29]The coefficients, which should be added to the intercept, are, by industry, 3200: 0.0693, 3300: -0.0684, 3400: -0.0526**, 3500: -0.0262, 3600: -0.090*, 3700: -0.0766, 3810: -0.0600, 3820: -0.0879, 3830: -0.0211, 3840: -0.0838, 3850: -0.084*, 3860: -0.0934, 3900: 0.0193, where * and ** denote significantly different

estimate the model:

$$y_{h,t}^{*}\left(\widehat{\rho}_{1h}\right)=\mathbf{x}_{h,t}^{*}\left(\beta,\widehat{\rho}_{1h}\right)+u_{h,t}^{*}\widehat{\rho}_{1h} \tag{25}$$

where

$$\begin{aligned}
y_{h,t}^{*}\left(\widehat{\rho}_{1h}\right) &= \left(1-\widehat{\rho}_{1h}\right)^{\frac{1}{2}} y_{h,t}, \quad \text{for } t=1986 \\
y_{h,t}^{*}\left(\widehat{\rho}_{1h}\right) &= y_{h,t}-\widehat{\rho}_{1h}\cdot y_{h,t-1}, \quad \text{for } t=1987,...,1995 \\
\mathbf{x}_{h,t}^{*}\left(\beta,\widehat{\rho}_{1h}\right) &= \left(1-\widehat{\rho}_{1h}\right)^{\frac{1}{2}} \mathbf{x}_{h,t}^{*}\left(\beta\right), \quad \text{for } t=1986 \\
\mathbf{x}_{h,t}^{*}\left(\beta,\widehat{\rho}_{1h}\right) &= \mathbf{x}_{h,t}-\widehat{\rho}_{1h}\cdot \mathbf{x}_{h,t-1}, \quad \text{for } t=1987,...,1995
\end{aligned} \tag{26}$$

the 1986 variables being constructed according to the Prais-Winsten transformation. The resulting β-estimates, were qualitatively similar to the ones in column II of Table 5 with small differences in magnitude and significance.

By means of the $u_{h,t}^{*}\left(\widehat{\rho}_{1h}\right)$, second-round estimates $\widehat{\rho}_{2h}$ were obtained. Two of these estimates were significantly different from zero at the 10 % level, thus indicating no improvement with respect to autocorrelation, as compared to the original specification (where only one of the estimated autocorrelation parameters was significantly different from zero at the 10 % level). The estimate of the vector β obtained from the regression model transformed by means of the $\widehat{\rho}_{2h}$ was extremely close to the original β estimate; compare columns V and II in Table 5. From the table it can be seen that the t-statistics are very close, too. But again, there was no discernable improvement with respect to the residuals; of the $\widehat{\rho}_{3h}$ estimates one was significant, at the 5 % level. Upon further iterations, the initial pattern was repeated: the estimates of the structural parameters shifted back and forth between one alternative similar to the original column II specification and one alternative extremely close to this specification. In no case was there any improvement with respect to the serial correlation of the residuals, as compared to the column II specification. Thus, there is no strong indication that the residuals of the model in column II of Table 5 are autocorrelated and application of a standard procedure to correct for

from zero at the 10 and 5 % level, respectively.

possible autocorrelation has no effect on the parameter estimates and seems to make the residuals less well-behaved.

Based on the results of this section we conclude that, in line with the theoretical arguments in Section 3, it seems important to allow the effects of IT to vary over time. We do not find that our modelling framework needs to be extended to account for the other three issues that we have considered - potential first-order effects of human capital on TFP growth, industry fixed effects, and serial correlation. Using specification II in Table 5 as our starting point we now proceed to consider more detailed, multivariate specifications of human capital.

5.3 Multivariate specifications of human capital

Apart from indicating the need for relative measures (cf. Section 4.2) theory does not provide any guidance regarding the implementation of a more detailed specification of human capital. We have constructed variables such that the model can tell the effects of marginal changes in the educational structure.

The effect that we are interested in is given by the partial derivative of total factor productivity growth with respect to this measure:

$$\frac{\partial g_{ht}}{\partial \left(K_C / K\right)_{h,t-1}} = \sum_{i=1}^{m} \widehat{\theta}_i \cdot X_i \tag{27}$$

where $\widehat{\theta}_j$ denotes an estimated coefficient and X_j represents an associated human capital variable. The variance of this partial derivative is equal to

$$Var\left[\frac{\partial g_{ht}}{\partial \left(K_C / K\right)_{h,t-1}}\right] = \sum_{i=1}^{m} X_i^2 \cdot Var\left(\widehat{\theta}_i\right) + 2\sum_{i=1}^{m}\sum_{j>i}^{m} X_i X_j Cov\left(\widehat{\theta}_i \widehat{\theta}_j\right) \tag{28}$$

As the variance computation is a bit complicated we will, to begin with, merely consider the individual terms in (27), implying that we only have to consider the corresponding t-ratios.

Table 6 reports the results of three different specifications. In column I we have allowed for the possibility that, in addition to tertiary educated workers, employees with upper secondary education also belong to the firm's skilled workers.

Table 6: Growth regressions allowing for externalities in the use of IT.

Dependent variable: g_{ht}	I	II	III
Intercept	-0.0273 (1.132)	-0.0244 (0.952)	-0.0225 (1.226)
Control variables:			
BCI_t	0.0002 (2.082)	0.0002 (1.902)	0.0002 (2.000)
$\left(\frac{K_M}{K}\right)_{h,t-1}$	0.0586 (1.426)	0.0545 (1.168)	0.0547 (1.753)
$\left(\frac{\#Females}{\#Employees}\right)_{h,t-1}$	0.0201 (0.592)	-0.0021 (0.051)	
$\left(\frac{\#\mathrm{Im}migrants}{\#Employees}\right)_{h,t-1}$	0.0159 (0.110)	0.0440 (0.205)	
Direct effect of IT:			
$\left[TUITE \times \frac{K_C}{K}\right]_{h,t-1}$	0.00006 (0.505)	0.00001 (0.096)	
Direct effect of human capital:			
$\left[\frac{\#Tertiary}{\#(Upper\ \mathrm{sec.} + Tertiary)} \times \frac{K_C}{K}\right]_{h,t-1}$	0.6460 (2.061)		
$\left[\frac{\#Tertiary\ Engineers}{\#(Upper\ \mathrm{sec.} + Tertiary\ Engineers)} \times \frac{K_C}{K}\right]_{h,t-1}$		0.8497 (3.413)	0.8779 (5.289)
$\left[\frac{\#Tertiary\ Bu\sin ess\ adm}{\#(Upper\ \mathrm{sec.} + Tertiary\ Bus.\ adm.)} \times \frac{K_C}{K}\right]_{h,t-1}$		-0.8646 (2.039)	-0.8324 (2.383)
$\left[\frac{\#Tertiary\ "Other"}{\#(Upper\ \mathrm{sec.} + Tertiary\ "Other")} \times \frac{K_C}{K}\right]_{h,t-1}$		0.9498 (1.198)	0.8779 (5.289)
$\left[\frac{\#Upper\ \mathrm{sec.}}{\#(9\ years + Upper\ \mathrm{sec.})} \times \frac{K_C}{K}\right]_{h,t-1}$	0.4240 (1.812)	0.9104 (2.996)	0.8779 (5.289)
$\left[\frac{\#16-29\ year\ olds}{\#(16-29+50-74\ year\ olds)} \times \frac{K_C}{K}\right]_{h,t-1}$	-0.8122 (3.464)	-1.2996 (3.393)	-1.2593 (5.877)
R^2	0.403	0.437	0.437

The number of employees with tertiary education has been related to the number of employees with upper secondary or tertiary education. Similarly, the number of upper secondary educated workers has been normalized by the number of workers with 9 years of education or upper secondary education. We also use the variable (19) to account for the age structure aspect of human capital.

Clearly, accounting for upper secondary education and the age structure are important extensions. The corresponding parameter estimates are strongly significant. Interestingly, the indirect effect of IT associated with the age structure is negative. This implies that the negative effect of lost work experience caused by old workers retiring outweighs the positive effect of the entry of young workers with high IT content in their basic education. Comparing column I of Table 6 with column II of Table 5 we see that the more detailed modelling of human capital renders the estimated direct effect of IT smaller and that among the control variables only the business cycle indicator stays significant.

The next step is to disaggregate the measures of human capital even further, by fields of study; cf. column II of Table 6. We find considerable differences across fields. In particular, while there is a positive indirect effect of IT associated with the relation between engineers with university education and engineers with upper secondary education there is a negative indirect effect connected with the corresponding categories in business administration. While these differences are somewhat counter-intuitive, there are results in the literature that point in this direction. For example, Murphy et al. (1991) claim that while "entrepreneurs" affect growth positively "rent-seekers" are harmful to growth. Proxying entrepreneurs and rent-seekers with engineers and lawyers, respectively, they find empirical support for their claim. As our category Business administrators include lawyers, this finding is relevant for our results. Further, Mellander and Skedinger (1999) show that in the mid 1990s wage premia for university education were much higher among business administrators than engineers in seven European countries, including Sweden, in spite of an engineering degree requiring more years of study. A possible interpretation is that the university wage premium for business administrators is too high, relative to their contribution to productivity.

The see if the regression model in column II can be expressed in a more parsimonious way, we test the following composite hypothesis:

i. The coefficients of $\left[TUITE \times \left(\frac{K_C}{K}\right)_h\right]_{t-1}$, $\left[\frac{\text{\# Females}}{\text{\# Employees}}\right]_{h,t-1}$ and $\left[\frac{\text{\# Immigrants}}{\text{\# Employees}}\right]_{h,t-1}$ are zero.

ii. The coefficients of $\left[\frac{\text{\# Tertiary Engineers}}{\text{\# (Upper sec. + Tertiary Engineers)}} \times \frac{K_C}{K}\right]_{h,t-1}$,

$\left[\frac{\text{\# Tertiary ?Other?}}{\text{\# (Upper sec. + Tertiary ?Other?)}} \times \frac{K_C}{K}\right]_{h,t-1}$ and $\left[\frac{\text{\# Upper sec.}}{\text{\# (9 years + Upper sec.)}} \times \frac{K_C}{K}\right]_{h,t-1}$ are equal .

With respect to hypothesis ii) it should be emphasized that equality among the coefficients does *not* imply that the associated indirect effects of IT on productivity growth are equal. If the coefficients are equal, the corresponding indirect effects will be determined by the relative magnitudes of the human capital variables. Among these, the ratio $\frac{\text{\# Upper sec.}}{\text{\# (9 years + Upper sec.)}}$ is invariably the largest.

As indicated by the fact that there is no difference between the R^2 s in columns II and III, the composite hypothesis cannot be rejected at any standard level of significance. We thus end up with a model containing only six parameters, which explains 44 percent of the variation in total factor productivity growth across industries and over time!

What, then, are the relative magnitudes of the indirect effects in our preferred specification, i.e. column III in Table 6. For the manufacturing sector as a whole this question can be answered by means (27) and Table 4. The largest positive indirect effect is the one associated with the ratio $\frac{\text{\# Upper sec.}}{\text{\# (9 years + Upper sec.)}}$; for a marginal increase in the share of computers in total capital the effect varies between 0.60 percentage points in 1986 and 0.67 percentage points in 1995. The largest negative indirect effect, which is the one channelled through the age structure, i.e. the ratio $\frac{\text{\# 16 -- 29 year olds}}{\text{\# (16 - 29 + 50 - 74 year olds)}}$, decreases in magnitude over time, from -0.68 percentage points in 1986 to 0.60 percentage points in 1995.[30]

The next to largest positive indirect effect is associated with the relation between university educated engineers and engineers with upper secondary education, the ratio $\frac{\text{\# Tertiary Engineers}}{\text{\# (Upper sec. + Tertiary Engineers)}}$; the indirect effect increases from 0.17 percentage points in 1986 to

[30]To save space, the age structure data have not been provided in Section 4.4. However, for the years 1985 and 1994 the age structure ratio is equal to 0.536 and 0.479, respectively, reflecting a declining inflow of young people and ageing of the incumbents.

0.21 percentage points in 1995. This effect is however offset by the negative indirect effect connected to business administrators, which decreases from -0.17 percentage points in 1986 to -0.26 percentage points in 1995. Finally, a positive indirect effect stemming from the relation between employees with "other" university and upper secondary education, respectively, makes up the balance: this positive effect increases from 0.09 percentage points in 1986 to 0.14 percentage points in 1995.

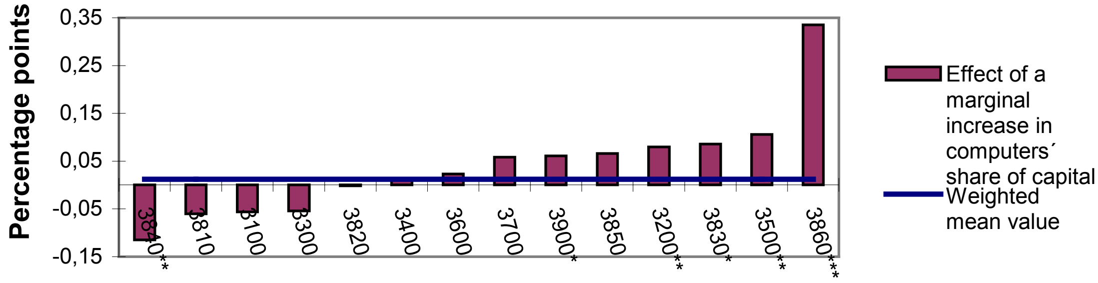
While these results for the entire manufacturing sector provide a general feeling for the time profile of the effect of IT on total factor productivity growth, an important feature of the model is that it allows the effect of marginal increases in computers' share to vary over time and by industries. This is illustrated in Figures 5a-c, which are based on computations using specification III in Table 6. The diagrams show the distributions of the partial derivatives (27) across industries at three points in time, 1986, 1991 and 1995. The estimates' precisions have been computed according to (28). The estimates can be interpreted as answering the following question: If the share of computers in total capital increases by 1 percent, what is the resulting change in the rate of growth in total factor productivity, in percentage points. The bars indicate the effects for individual industries. The solid line is a weighted average effect, where the industries are weighted by their employment shares.

Looking at the development over time, we see that the marginal effects of computer investments have increased steadily over time. The weighted average effect rises from about 0.01 percentage point in 1986 to 0.05 in 1991, ending up at 0.17 percentage points in 1995. These average changes have been caused by upward shifts in the entire distributions of effects across industries. For instance, while only two industries record effects above $\frac{1}{10}$ of a percentage point in 1986, effects of this magnitude are found in six industries in 1991 and in 11 in 1995. In the latter year, the point estimates are 0.25 or higher in five industries, indicating that a 1 percent increase in computers' share in total capital increases the rate of TFP growth by $\frac{1}{4}$ of a percentage point or more.

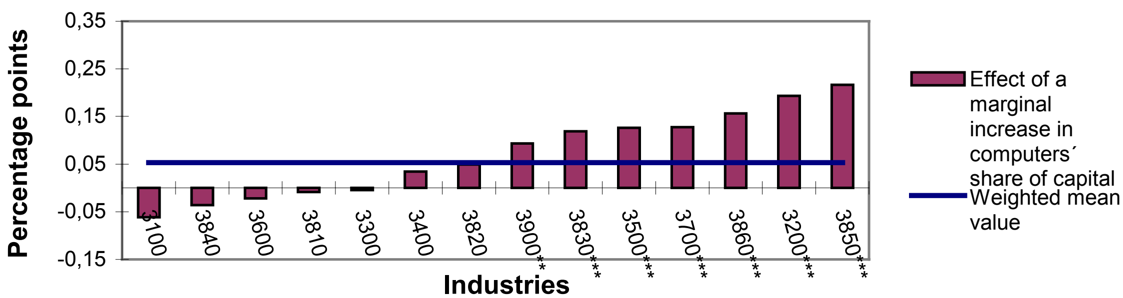
Among the three years covered by Figure 5a-c, the largest variation across industries is found in 1986. In that year the spread is 0.46 percentage points, the range being given by

Figure 5: Distributions over industries of the effects of a marginal increase in computers´ share of capital on TFP growth; regression III in Table 6, evaluated in 1986, 1991 and 1995.

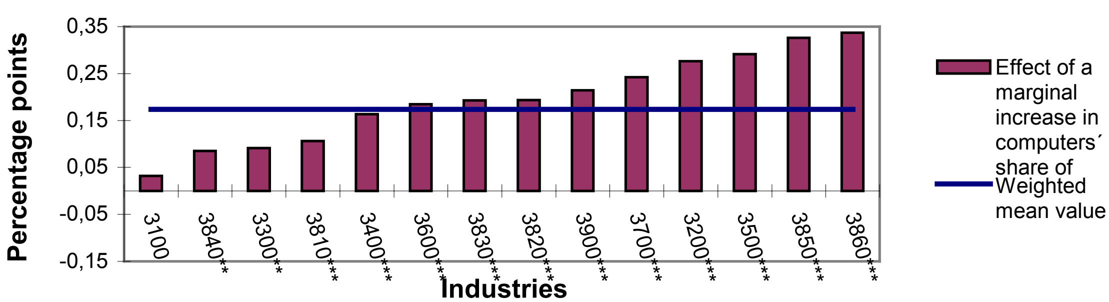
a:1986



b:1991



c:1995



Note: Stars indicate significance level: “*” denoting 10 percent, “**” 5 percent and “***” 1 percent.

a negative effect of -0.12 percentage points in 3840 = Transportation and a positive effect of 0.34 percentage points in 3860 = Shipyards.[31] In 1991 and 1995 the spread is considerably smaller - about 0.30 percentage points in both years. Moreover, in 1995 the effects are positive in *all* industries. There are thus two findings pointing to a fundamental difference between the beginning and the end of the period that we study: compared to 1986 the variation across industries is smaller in 1995 *and* the estimated effects are confined entirely to the positive domain, unlike 1986 when about a third were negative.

In line with our basic hypothesis of the importance of human capital, a comparison of Figure 5 and Table 3 shows that the industries that had the largest increases in the shares of computers in total capital were not in general the industries that had the largest growth-enhancing effects of IT. For instance, the industries 3300 = Saw Mills and Wood Products and 3700 = Basic Metals increased the relative size of their computer capital stock dramatically between 1985 and 1990; cf. Table 3. These investments did not result in top-ranking marginal effects of IT in either 1991 or 1995, however; see Figure 5. Conversely, industry 3850 = Instruments, Photographic & Optical Devices experienced very large IT-induced growth effects in 1991 and 1995. In this industry the share of computers *decreased* between 1985 and 1990 –cf. Table 3. Instead, the share of skilled workers increased strongly in this industry.[32]

Finally, a notable result is that, compared to the U.S., we find positive impacts of IT on growth in a broader spectrum of industries. According to Gordon (2000), in the U.S. the effects of computer investments were essentially zero outside the IT-producing industries and the industries producing durable manufacturing goods. In the Swedish manufacturing sector, these industries roughly correspond to: 3810, 3820, 3830, 3840, 3850, and 3860; see Table 2. From Figure 5 it can be seen that while we find large marginal effects in some of these industries, notably in 3850 = Instruments and 3860 = Shipyards, we also see examples of negative or very small effects as in, e.g., in 3810 = Metals and 3840 =

[31]The shipyards rank very high in 1991 and 1995, too. Since the Swedish shipyards have undergone major structural changes since the mid 70's and have been facing severe problems with low and, sometimes, negative profits this industry could be seen as a potential outlier. To check this, we reestimated the model given by column III in Table 6, leaving out the shipyards. The parameters changes were entirely negligible, however. The reason is the WLS estimation procedure where the industries are weighted by employment; the shipyards account for less than 1 percent of manufacturing employment, during the period studied.

[32]The latter fact cannot be inferred from the paper but can be seen when the Table 4 is broken down by

Transportation. On the other hand, there are several industries outside this group recording large positive effects like 3200 = Textiles and 3500 = Chemicals.[33]

However, while our results certainly seem to indicate that the human capital variables are essential, one might wonder about the importance of the computer capital share, K_c / K. Is this variable really essential, too, or can the human capital variables do the job by themselves? This is an important question because our interpretation of human capital being the key to the IT productivity paradox relies on the assumption that it is the *interaction* between K_c / K and human capital that matters. To check if this is the case it is necessary to conduct a non-nested test of whether K_c / K should be included in the growth equations or not. To this end we use the J test proposed by Davidson and MacKinnon (1981). The results of applying this test to the specifications I and II in Table 6 are given in Table 7. Note that the results concern the testing of *two* hypotheses. An intrinsic feature of a non-nested test is that there is no natural null hypothesis. Being a specification test, the non-nested test merely investigates how two alternative models fit the data.

Table 7: Test statistics for non-nested tests of the presence of in the growth equation; critical value at 1% significance level ±2.57

	Model	
	I	II
H_o : include K_c/K H_a : exclude K_c/K	-0.389	-0.686
H_o : exclude K_c/K H_a : include K_c/K	3.193	4.112

Note: i) the model specifications refer to the columns in Table 6

ii) "include K_c/K" refers to the regressions in Table 6 while "exclude K_c/K" means setting $K_c/K = 1$ in those regressions

iii) the test statistic is asymptotically normally distributed.

industry.

[33]Using more recent U.S. data than Gordon (op. cit) and dummy variable techniques, Stiroh (2002) finds indications of substantial effects of IT after 1995 not only in industries producing IT and durable goods, but also in IT-intensive industries, defined as industries having above median shares of computers in total capital. He does not link these findings to human capital structures, however.

In the first row of Table 7 we provide the test statistics for the case when the specifications in Table 6 constitute the null hypotheses. The alternative, H_a, corresponds to when K_c / K = 1 in the regressions. In none of the tests can the null be rejected at any standard level of significance.

In the second row, the roles of the null hypothesis and the alternative hypothesis have been reversed. The null is very clearly rejected in favor of the alternative.

These results provide strong evidence for the model specifications in Table 6 and reject the alternative specifications where $K_C / K = 1$. Put differently, the outcomes give convincing support for the notion that it is the interaction between IT capital and human capital that drives our results. This conclusion is further strengthened by the fact that it is quite unusual that non-nested tests yield results as clear as in this case; often the tests produce inconsistent results (reject both of the null hypotheses) or inconclusive results (reject neither).[34]

6. Summary and conclusions

Our principal conclusion from this study is that human capital is the key to the IT productivity paradox. We substantiate this general conclusion with both theoretical and empirical results.

Our theoretical analysis investigates the consequences of erroneously disregarding human capital aspects in assessments of the effects of IT on productivity growth. Specifically, we consider a model where IT affects growth both directly and indirectly, through complementarity with human capital, and analyze what happens to the estimate of the direct effect when the indirect effect is omitted.

Regarding the negative effects of IT on growth reported in several studies using early (pre-1990) U.S. data, our conclusion is that these results are likely to indicate a truly negative effect, as suggested by Morrison (1997), rather than be a consequence of

[34]The reason why we have not performed the test on specification III in Table 6 is that the Davidson-MacKinnon test cannot be applied to models incorporating linear constraints. Pesaran and Hall (1998) discuss non-nested tests allowing for general linear restrictions. However, given the very clear outcomes of the tests reported in Table 7 and the fact that, statistically, the specifications II and III in Table 6 are very close we

measurement error, as argued by, e.g., Lee and Barua (1999).

The positive relation between IT and productivity growth found in studies based on more recent data is in our theoretical analysis attributed to positive external effects in the use of IT. These external effects are assumed to be increasing in the total use of IT, implying that as more and more IT capital is accumulated, the growth effects change from negative to positive.

In the empirical analysis, we first confirm that the predictions generated in the theoretical analysis are valid for our data on the Swedish manufacturing sector. We then proceed to include successively more information about interactions between IT and human capital. As shown by the theoretical analysis, accounting for indirect effects of IT in this way reduces the estimated direct effect. Eventually, the direct effect finally vanishes altogether.

We end up with a model that is very parsimonious in terms of parameters but, nevertheless, explains well over 40 percent of the variation in total factor productivity growth across industries and over time. In this model, all the interaction variables between IT and human capital are highly significant.

In general, the maintained hypothesis of complementarity between IT and skilled workers is confirmed. The largest indirect effects of IT on growth are associated with workers having upper secondary education, relative to workers with only 9 years of education. Disaggregating by fields of study, we find the next to largest effect to be associated with the relation between university educated engineers compared to engineers with upper secondary education.

An exception to the complementarity relation between IT and skilled labor concerns workers within the field of business administration and law. For these, the relation between university educated and workers with upper secondary education gives rise to a negative indirect impact on productivity growth. In the spirit of Murphy et al. (1991), we interpret the negative estimate as indicating rent-seeking behavior among business administrators and lawyers.

Regarding the connection between human capital and the age structure we find that replacing workers aged 50 or older by workers below 30 has a negative impact on

have not taken the trouble to formulate such a general test.

productivity growth rates. This indicates that, during the period studied, the advantage of many of the younger workers of having become acquainted with IT during their school years did not outweigh the work experience acquired by the older workers. This negative indirect effect is quite large but decreasing, due to a declining inflow of young people to the manufacturing sector.

For the manufacturing sector as a whole, the model predicts that in the beginning of the period, in 1986, a 1 percent increase in the share of computers in total capital increased productivity growth by 0.01 percentage points only, i.e. an entirely negligible effect. In the middle of the period, in 1991, this average effect had grown to 0.05 percentage points, while at the end of the period, in 1995, it was up to 0.17 percentage points.

The variation in effects across industries decreases over time. Moreover, while the effects of IT on growth are negative in several industries in 1986, the effects are positive in all industries in 1995. In five of them the estimated effect was 0.25 or higher, saying that a 1 percent increase in computers' capital share increased productivity growth by at least $\frac{1}{4}$ of a percentage point.

To check that our results are not driven solely by human capital developments but by complementarity between IT and human capital, we perform non-tested tests for the presence of the IT variable in the growth equations. These tests provide very strong support for the complementarity hypothesis.

In line with our basic hypothesis, we find that the industries were the (relative) increases in computer capital have been particularly large are not necessarily the industries that show the largest marginal effects of IT on productivity growth.

With respect to differences in effects across industries, we also relate our findings to the claim in Gordon (2000) that IT has increased productivity growth only in a small number of U.S. industries. We show that, unlike in the U.S., the Swedish IT development has had positive effects outside the sectors producing IT and durable manufacturing goods. We find strongly positive effects also in, e.g., the chemical industry and, even more interesting, in the textile industry.

Regarding policy considerations, one conclusion is immediate: measures to promote increased use of IT should be followed up by measures promoting skill upgrading, especially from elementary to upper secondary education. Another implication is that measures aimed at facilitating early retirement among older workers, in order to make more room for young labor market entrants, can be (strongly) harmful for growth.

It should be remembered, however, that our study is based on data ending quite a few years back. Our results on the age structure might have changed during recent years. Investigating whether this is the case is an important task for future research. Also, it should be noted that our findings concern only the manufacturing sector and cannot be extended to the service sector or the economy as a whole. While analyses of the service and the entire economy lie beyond the scope of the present paper because of data limitations, we believe that such analyses are important tasks for future research.

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APPENDIX: Computation of capital rental prices and the splitting of equipment capital into computer capital and machinery

The Swedish National Accounts (SNA) provides data on capital stocks of equipment and structures (buildings) by 2- or 3-digit industries. To simplify the notation, we here suppress industry indices and denote the equipment stocks by $K_{E,t}$ and the stocks of structures by $K_{B,t}$. The stocks are defined such that the period t stock denotes the stock as of January 1, year t .

The perpetual inventory method used in the SNA to compute the stocks implies that they can be closely approximated by the following accumulation formula

$$K_{i,t} = \left(1-\overline{\delta}_i\right) K_{i,t-1} + I_{i,t-1}, \quad i = E, B. \tag{A.1}$$

The capital rental prices for equipment and structure capital are constructed according to

$$P_{K_i,t} = P_{I_i,t-1}\left[r_{t-1} + \overline{\delta}_i \frac{\left(P_{I_i,t|t-1}\right)^e}{P_{I_i,t-1}} - \left(\frac{\left(P_{I_i,t|t-1}\right)^e - P_{I_i,t-1}}{P_{I_i,t-1}} \right) \right] \tag{A.2}$$

where $P_{K_i,t}$ denotes the rental price for type i capital at the beginning of period t, $P_{I_i,t-1}$ is the gross investment price index for type i capital and period $t-1$, r_{t-1} is a long-term interest rate measured at the very end of period $t-1$, and $\left(P_{I_i,t|t-1}\right)^e$ is the expected value of the investment price index for type i capital in period t, given information about this index up to (and including) period $t-1$. The difference $\left(P_{I_i,t|t-1}\right)^e - P_{I_i,t-1}$ measures the expected windfall profit (loss) that accrues to the owner of the capital asset through an increase (decrease) in the renewal cost.[35]

Like the $\overline{\delta}_i$, the P_{I_i} are obtained from the SNA. The interest rate r is measured by means of the nominal rate on Swedish long-term industrial bonds. The expectional variable $\left(P_{I_i,t|t-1}\right)^e$ is implemented by means of a univariate Kalman filter.[36]

The rental prices are normalized to unity in a base-year t_o - here set to 1991 - yielding:

$$\widehat{P}_{K_i,t} = \frac{P_{K_i,t}}{P_{K_i,t_o}}. \tag{A.3}$$

To preserve the property that price × quantity = cost, the quantity of capital is normalized

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[35]The rental price formula (A.2) corresponds to the one given by equation (B4) in Jorgenson & Stiroh (2000). The only difference being that Jorgenson and Stiroh (op. cit.) assume perfect foresight with respect to the investment price index, thus substituting $P_{I_i,t}$ for $\left(P_{I_i,t|t-1}\right)^e$.

[36]This filter amounts to modelling the price index by means of a transition equation and a measurement equation. The former models the "true" investment price index as a random walk, incorporating a drift in the form of a deterministic quadratic time trend. The measurement equation models the observed price index as the sum of the "true" index and a random error.

accordingly, i.e.

$$\widehat{K}_{i,t} = P_{K_i,t_o} K_{i,t} \tag{A.4}$$

such that $\widehat{P}_{K_i,t} \widehat{K}_{i,t} = P_{K_i,t} K_{i,t}$.

To obtain the computer capital stock, we split the equipment stock K_E into K_{E_C} and K_{E_M} where subindex C denotes Computers and subindex M stands for machines (that are not computers). In analogy with (PIM):

$$K_{E_C,t} = \left(1 - \delta_{E_C}\right) K_{E_C,t-1} + I_{E_C,t-1} \tag{A.5}$$

To make (A.5) operational, we have to decide on a value for δ_{E_C} and on an initial value for K_{E_C}.

We have set $\delta_{E_C} = 1/3$. One motivation is that in the SNA depreciation rates for equipment (including computers) varies between 0.16 and 0.21. As computer capital depreciates much faster than other types of equipment δ_{E_C} should considerably larger than 0.21, making $\frac{1}{3}$ a rather reasonable number. It is also close to the depreciation rate of 0.315 (from the Bureau of Economic Analysis) employed by Jorgenson & Stiroh (op. cit.).

The initial value for K_{E_C} is obtained by extrapolating gross investments, I_{E_C}, backwards. To this end, we have assumed that investments during the period 1980-1994 can be approximated by the arithmetic average of the 1985 and 1986 gross investments.

For the computation of the TFP growth rate according to Section 5.1, we also need a capital rental price for computer capital. The computation of this rental price is very similar to (A.2). For the gross investment price index $P_{I_{E_C},t}$ we use an import price for computers and peripherals, normalized to unity in 1991. Unfortunately, this index can only be computed for 1984-1995. During this period the index shows a continuous decrease in the price of computers and peripherals, at an increasing rate. Between 1984 and 1985 the rate of decrease was very small, only 0.1 %, while between 1994 and 1995 the index fell by 14.3 %. The arithmetic mean of the rates of price decreases over the period was around 6.5 %.[37]

As our time series on $P_{I_{E_C},t}$ is so short we cannot model the expected investment price index by means of a Kalman filter. Instead we have simply fitted a linear trend to the log-differences of the index, to estimate the average rate of decrease in the yearly price reductions, i.e. the discrete analogue of the second order derivative. We obtain an estimate of -1.24 percent annually, implying that for computer capital the last term within brackets in (A.2) is equal to zero in 1985 and the falls cumulatively by -1.24 each year, to reach -

[37]This may seem like a rather small rate of price decrease. It is smaller than similar estimates for the US but the difference is not as large as one might think. For comparison, Jorgenson and Stiroh (2000) report an average rate of decrease in the price of computer investments equal to 12.8 percent over the period 1985-1995. For communications investment they find a much smaller rate of decrease, namely 0.6 percent over the same period. Thus, the decline in prices differs substantially between different types of computer-related equipment. In our case, it might be that the prices of peripherals have not fallen as fast as the prices of computers. Unfortunately, we cannot check this conjecture, as there is no separate price index for computers.

12.4 percent in 1995.

Given the stock of computer capital and the computer capital rental price we can consistently solve for the expenditures on (non-computer) machinery equipment. Denoting these expenditures by $V_{K_{E_M},t}$ we get

$$V_{K_{E_M},t}\left(\equiv \widehat{P}_{K_{E_M},t}\widehat{K}_{K_{E_M},t}\right)=\widehat{P}_{K_E,t}\widehat{K}_{E,t}-\widehat{P}_{K_{E_C},t}\widehat{K}_{E_C,t} \tag{A.6}$$

because rental expenditures on computers and non-computer machinery have to add up to total rental expenditures on equipment capital.

The final step is determine $\widehat{P}_{K_{E_M},t}$ and $\widehat{K}_{K_{E_M},t}$. To solve for $\widehat{P}_{K_{E_M},t}$, we first assume that the rental price of equipment capital can be approximated by a translog aggregate of $\widehat{P}_{K_E,t}$ and $\widehat{P}_{K_E,t}$:

$$\begin{aligned}\Delta\ln\widehat{P}_{K_E,t} \quad &= \quad \tfrac{1}{2}\left(S_{t-1}+S_t\right)\cdot\Delta\ln\widehat{P}_{K_{E_C},t} \\ &\quad + \tfrac{1}{2}\left[\left(1-S_{t-1}\right)+\left(1-S_t\right)\right]\cdot\Delta\ln\widehat{P}_{K_{E_M},t}\end{aligned} \tag{A.7}$$

Where

$$S_t=\frac{\widehat{P}_{K_{E_C},t}\widehat{K}_{E_C,t}}{\widehat{P}_{K_{E_C},t}\widehat{K}_{E_C,t}+V_{K_{E_M},t}}. \tag{A.8}$$

Solving for $\Delta\ln\widehat{P}_{K_{E_M},t}$, we obtain

$$\begin{aligned}\Delta\ln\widehat{P}_{K_{E_M},t} \quad &= \quad \frac{1}{\frac{1}{2}\left[\left(1-S_{t-1}\right)+\left(1-S_t\right)\right]}\cdot\Delta\ln\widehat{P}_{K_E,t} \\ &\quad - \frac{\frac{1}{2}\left(S_{t-1}+S_t\right)}{\frac{1}{2}\left[\left(1-S_{t-1}\right)+\left(1-S_t\right)\right]}\cdot\Delta\ln\widehat{P}_{K_{E_C},t}\,.\end{aligned} \tag{A.9}$$

The equation (A.9) determines the rate of change in $\widehat{P}_{K_{E_M},t}$ but not its level. However, the level is determined by the normalization that $\widehat{P}_{K_{E_M},t}$, just like $\widehat{P}_{K_E,t}$ and $\widehat{P}_{K_{E_C},t}$, should be equal to unity in the base-year. Thus,

$$\widehat{P}_{K_{E_M},t_o}\equiv 1.0. \tag{A.10}$$

Given $\widehat{P}_{K_{E_M},t}$ we can finally solve for $\widehat{K}_{K_{E_M},t}$ according to

$$\widehat{K}_{K_{E_M},t}=\frac{V_{K_{E_M},t}}{\widehat{P}_{K_{E_M},t}}, \tag{A.11}$$

which constitutes the final step in the break-down of the equipment capital stock into computer capital and (non-computer) machinery capital.

Essay II

Age, Type of Education and Productivity Growth

1. Introduction

In the 1990's, much research effort was devoted to explaining the shift in labor demand from low-skilled to high skilled workers. In the process, it became very clear that earlier productivity analyses, treating labor as homogenous, had failed to account for the fact that labor with different skills play very different roles in production and with respect to their contribution to productivity growth. Empirical studies in which workers were distinguished by level of education strongly indicated that, since the 1980s, in the industrialized countries technical change had a negative impact on the productivity growth contribution from low-skilled labor, while the reverse was true for high-skilled labor. There was a skill-bias to technical change, in the jargon of this literature. A seminal paper in this field is Berman, Bound and Griliches (1994). It was soon followed by a large number of studies, for instance, Machin (1996), Machin and Van Reenan (1998), and Morrison Paul and Siegel (2001). For studies using Swedish data, see Mellander (1999) and Hansson (2000).

Meanwhile, a different strand of literature has investigated the link between economic growth and demographics. The underlying idea is that workers of different ages, and thereby different working experiences, could well have differential impacts on production and productivity growth, cf Card and Lemieux (2001). Empirical analyses have supported this conjecture. Moreover, the results imply that the growth contribution from older workers exceeded that of younger workers, a finding consistent with the interpretation that a worker's experience is an important determinant of his/her productivity; see, eg., Malmberg (1994) and Lindh and Malmberg (1999). However, as these studies did not control for the workers' education they did not allow a clear distinction between the roles of experience, on the one hand, and skills, on the other hand.

Furthermore, it is conceivable that there is a qualitative dimension to experience as well, in addition to the purely quantitative aspect measured by the number of years of experience. Experience from some fields may simply be more beneficial to growth than experience from other fields. For instance, experience from computer-related work may be more productivity enhancing than experience from administrative tasks; cf. Card and DiNardo (2002).

Against the background of the skill-biased technical change literature, this discussion about experience raises the following question: how much do length and type of experience contribute to growth when one controls for the level of education? Answering this question requires data that are very rich with respect to skills: both levels of education and fields-of-study are needed. In addition information about years of work experience or, at least worker age, is needed.

In this paper, we address the question just raised. To this end, we use a cost function estimated by Mellander (1999) on data for 24 industries in the Swedish manufacturing sector 1985-1995.[1] In that model, labor is divided into four main categories corresponding to different levels of education. The labor input corresponding to each of these categories ("effective labor") is modeled as a function of the number of workers with a given level of education *and* (i.a.) their fields-of-study composition and age structure. Accordingly, we will use the age as a proxy for years of experience.

In the model, productivity growth is determined by exogenously given time trends. In accordance with the notion of skill-biased technical change the impacts of these trends are allowed to vary across effective labor inputs associated with different levels of education. Among workers with a given level of education, the age structure and the field-of-study composition will affect the impact of technical change through the link between worker characteristics and effective labor input.

In a number of different scenarios we consider how the growth in total factor productivity *(TFP)* is affected by various changes in the age structure and the fields-of-

[1] More updated estimates would be preferable. However, due to changes in the definitions in the underlying data, estimations using more recent information can only use data from 1993 and onwards. At the time of writing those time series were not long enough to enable estimation. However, as the purpose of this paper is to investigate how different characteristics of labor affect productivity growth, rather than make productivity forecasts, the fact that our information is a bit dated should be of minor importance.

study composition of the work force, over the 10 years period 1995-2005. Projections based on changes in the age structure and fields-of-study compositions that are in accordance with the developments during the 1985-1995 with are compared to projections based on age and fields-of-study distribution that differ from the historically observed patterns.

We make separate projections with respect age structure and fields-of-study compositions, to be able to separate the effects of changes in these two dimensions. With respect to the age structure our alternative projections are based on two "experiments". The first of these implies that the share of younger workers is increased at the expense of older ones, while the second type of scenarios implies just the opposite, i.e. a rise in the share of older workers and a smaller share of younger workers. These experiments will allow us to check whether our data confirm or refute the results in Malmberg (op cit) and Lindh and Malmberg (op cit). Regarding the fields-of-study compositions our alternative projections are based on experiments that all have the common feature that they imply a larger share of workers with engineering and technical knowledge. This allows us to test whether compliance with the often voiced need for an increased share of technical personnel in manufacturing would indeed increase productivity.[2]

In the next section, we provide an overview of the data. Section 3 contains a brief description of the underlying model and computations. The computational experiments that we have carried out are outlined and motivated in Section 4. The results are discussed in Section 5, and we conclude in Section 6.

2. The data

We make use of the data set employed by Mellander (1999). It covers 24 industries in the Swedish Manufacturing sector over the years 1985-1995 and consists of industry data from the Swedish National Accounts (SNA) merged with information from the Swedish Register of Employment.

[2] According to Brown and Campbell (2001), implementation of skill-biased technical change, through automation of information handling, often goes in parallel with an increased share of technicians and engineers. By taking the skill-biased technical change as given and increasing the share of technical personnel, we should be able to shed some light on the cause-and effect issues underlying the simultaneous occurrence of the two phenomena.

For the computations that we carry out in this paper we use the year 1995 as our starting point. How employment was distributed across the industries considered during that year is shown in Table 1.

Table 1: The industries considered and their shares in total manufacturing employment 1995.

Industry Code	Industry	Employment share 1995, %
3110	Food	8.6
3130	Tobacco & Beverages	0.8
3200	Textile, Apparel & Leather	2.3
3310	Saw Mills & Planing Mills	2.4
3320	Other Wood Products	6.0
3410	Pulp	0.9
3420	Paper & Paperboard	3.7
3430	Products made of Pulp, Paper & Paperboard	1.8
3440	Printing & Publishing	7.7
3510	Industrial Chemicals incl. Plastic Materials	2.3
3520	Other Chemical Products	3.1
3530	Petroleum Refineries, Petroleum & Coal Products	0.3
3550	Rubber Products	0.9
3560	Plastic Products	2.1
3600	Non-Metallic Mineral Products	2.5
3710	Iron & Steel	3.5
3720	Non-Ferrous Metals	1.0
3810	Metal Products	11.7
3820	Machinery & Equipment, not elsewhere classified	12.9
3830	Electrical machinery, not elsewhere classified	8.8
3840	Transport Equipment, except Shipyards	12.3
3850	Instruments, Photographic & Optical Devices	2.9
3860	Shipyards	0.7
3900	Other Manufacturing	0.7
3000	Total Manufacturing	100.0

Note: The classification system used here is very close to the ISIC codes

As can be seen from the table, a wide spectrum of industries is represented. To economize on space we will not report results for each and every industry in this paper. Instead, we will explicitly consider only the manufacturing sector as a whole, and two distinct types of industries, within this aggregate. One of these is a high technology industry, namely industry 3440 = Printing & Publishing, while the other is rather low-tech industry, industry 3810 = Metal Products.

The human capital data utilized contains information about the number of employees by industry, their level of education and fields-of-study, age, gender and their immigrant status.

The classification of workers according to educational level is by industry and encompasses the following levels:

Level 1 = Elementary school (compulsory shorter than 9 years),

Level 2 = 9 years compulsory school,

Level 3 = Upper secondary school,

Level 4 = Tertiary and postgraduate education.[3]

Level 1 consists mainly of workers older than 40 years, since from 1968 the 9 year compulsory school constitutes the minimum schooling requirement in Sweden.

One classification of the workers that is of primary interest to our analysis is the one that separates them according to age groups for any given level of education. We here consider four different age intervals: 16-29, 30-39, 40-49 or 50-74 years old.

Further, we classify workers according to four different fields-of-study (FoSs) at a given education level. We label these fields as follows:

FoS1= General education

FoS2= Administration, economics, social science and law

FoS3 = Industry, crafts, natural sciences and technology

FoS4= Other fields-of-study

It should be noted that partition by fields-of-study is possible only for workers with at least upper secondary school, i.e. workers with educational Levels 3 and 4.

In the following, we will often identify technicians and engineers with the fields-of-study category FoS3.

The hares of the different age groups and fields-of study categories at different educational levels are shown in Table 2.

According to the rightmost column of the table, the four age categories (summed over levels of education) make up almost equally large portions of the age distribution. This is not the case with respect to fields-of-study; here technicians and engineers and individuals with "general education" dominate strongly, accounting for 41 percent and

[3] A more disaggregated classification at the upper end of the educational spectrum is not very meaningful since the separation of, e.g., individuals with a Bachelor's degree from the other workers in category 4 would result in numbers too small to permit statistical analyses.

37 percent, respectively, of the employed workers. It should also be noted that in terms of the different levels of educational levels, Level 3, upper secondary schooling, accounts for by far the largest share, 52 percent. Accordingly, changes in the age structure or the fields-of-study composition affecting workers within this category should have a strong impact on productivity growth.

Table 2:Employment shares in Swedish manufacturing by age groups and fields-of-study categories, at the four levels of education in 1995.

Industry 3000		**Level of education**				
		1	2	3	4	Sum
Age	16-29	0,001	0.037	0.167	0.040	0.245
	30-39	0.004	0.055	0.134	0.055	0.247
	40-49	0.042	0.047	0.112	0.042	0.244
	50-74	0.114	0.019	0.104	0.027	0.264
	Sum	0.161	0.158	0.516	0.164	1
Fields of study	FoS1	0.161	0.158	0.046	0	0.365
	FoS2	0	0	0.091	0.040	0.131
	FoS3	0	0	0.311	0.101	0.412
	FoS4	0	0	0.069	0.023	0.092
	Sum	0.161	0.158	0.516	0.164	1

FoS1 = General education, FoS2 = Administration, economics, social science and law,
FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

3. Computational procedure

We begin by giving a brief overview of the properties of the cost function that we use in our computations, focusing on the relationship between the rate of growth in total factor productivity *(TFP)* and the characteristics of the employed personnel. We then turn to our application of this model, i.e. to the post-sample projections of TFP growth under various assumptions about the age structure and the fields-of-study composition of the workers.

3.1. The model

The cost function, estimated by Mellander (1999), is a generalized Leontief variable cost *(VC)* function of the following form:

$$VC = Y\left[\sum_i \sum_j \alpha_{ij} P_i^{1/2} P_j^{1/2} + \gamma_{SS} \sum_i P_i \left(S/Y\right) + \sum_i \delta_{iS} P_i \left(S/Y\right)^{1/2}\right] \tag{1}$$

$$i, j = L_1, L_2, L_3, L_4, E, M$$

where

$$\alpha_{ii} = \lambda_{i0} + \lambda_{it} t$$

In this model there are six variable inputs: the four categories of labor, L_1, L_2, L_3, and L_4, equipment capital, E, and intermediate goods, M. One input, structure capital, S, is considered to be quasi-fixed, i.e. fixed in the short run. The level of output is denoted by Y, the prices of the variable inputs by P_i where $i = L_1, L_2, L_3, L_4, E, M$. The price of structure capital is denoted P_S. The state of the technology is represented by a time index, t. Skill-biased technical change is accounted for by allowing the parameters α_{ii} to be linear functions of time, where the λ_{i0} and λ_{it} are estimated parameters.

To evaluate the effects of changes in the workers´ age structure and fields-of-study composition, we make use of the following multiplicative decomposition of the prices of labor, suggested by Mellander (op cit):

$$P_{L_i} = P_{N_i} B_i^{-1} \tag{2}$$

According to this decomposition, the price of effective labor, P_{L_i}, is the product of average labor costs for category i workers, P_{N_i}, and the inverse of an index, B_i, that controls for five kinds of labor characteristics: age, sex, immigrant status, field-of-study, and weekly work hours. We will return to these characteristics and the definition the B_i index below.

These characteristics are denoted by H_{ijk} where $i = L_1, L_2, L_3, L_4$, index j denotes a given characteristic like, e.g., age, and k denotes a specific category associated with this characteristic like 30 – 39 year olds. The various characteristics, i.e. age, sex, immigrant status, field-of-study, and weekly work hours are aggregated into the B_i index by means of CES aggregator function, cf. the Appendix.

For simplicity, we focus on equilibrium effects. In equilibrium, variable costs are given by:

$$VC^* = Y\left[\sum_i \sum_j \alpha_{ij} P_i^{1/2} P_j^{1/2} + \gamma_{SS} \sum_i P_i \left(S^*/Y\right) + \sum_i \delta_{iS} P_i \left(S^*/Y\right)^{1/2}\right] \tag{3}$$

where S^* denotes the optimally adjusted stock of structure capital. At this point, total costs are given by:

$$TC^* = VC^* + P_S S^* \tag{4}$$

As the technology is characterized by constant returns to scale in equilibrium, the equilibrium rate of change in total factor productivity *(TFP)* is equal to the dual rate of technical change. And the dual rate of technical change is given by the negative of the relative time derivative of total costs. Hence:

$$\frac{dTFP}{TFP} = -\frac{\partial TC^*}{\partial t}\frac{1}{TC^*} \equiv -\varepsilon^*_{Ct} \qquad (5)$$

How, then, can changes in the age structure and fields-of-study composition affect the rate of *TFP* growth? According to (1), technology changes will affect total (variable) costs through interaction with the prices of the variable inputs. Thus, the derivative $\partial TC^*/\partial t$ in (5) involves the prices of labor, P_{Li} which, in turn, involves age and field-of-study, through the B_i index in (2).

Notice that the specification of the α_{ii} allows the effects of technical change to vary across inputs. In particular, the effects are allowed to vary across labor with different levels of education, i.e. L_1, L_2, L_3, L_4., which in the cost function are represented by the prices P_{Li} where i = 1,2,3,4. By the specification of the α_{ii} and the P_{Li}, technical change is assumed to act effective labor input, rather than separately on workers with a given level of education, a given age and a given field-of-study. This means that when we compare the effects on *TFP* growth from, e.g., two alternative age structures the difference will be solely determined by just the difference in age structure.[4]

The starting point of the computations are the following elasticities:

$$\frac{\partial}{\partial H_{ijk}}\left(\frac{dTFP}{TFP}\right)\frac{H_{ijk}}{dTFP\big/_{TFP}} \qquad (6)$$

where H_{ijk} is an argument in the B_i index in (2). The index i represents the educational levels*,* i = 1,2,3,4. The index j refers to five worker characteristics included in the B_i index – age, sex, immigrant status, field-of-study and weekly work hours. The index *k,* finally, represents a given category with respect to one of the *j* characteristics. As can be seen in Table 2 the characteristics age and field-of-study are each represented by five

[4] This could alternatively be achieved by a more flexible specification of the cost function where technical change is allowed to by educational level, age group and field-of-study category. The effect of the age structure could then be inferred by comparing the estimated effects of technical change for two groups of workers with the same level and type of education but belonging to different age groups. The estimation of such a model would be extremely demanding in terms of degrees of freedom, however.

categories.[5] To take a specific example, H_{113} denotes the share of workers with the lowest level of education (i =1), whose ages (j = 1) are 40-49 years (k = 3).

The partial derivative in (6) yields the equlibrium effect of a change in the characteristic H_{ijk} on TFP growth. Using (5), equation (6) can be expressed as follows::

$$\frac{\partial}{\partial H_{ijk}}\left(\frac{dTFP}{TFP}\right) = -\frac{\partial \varepsilon_{Ct}^{*}}{\partial H_{ijk}} = -\left(\frac{\partial^2 TC^*}{\partial H_{ijk}\partial t} - \varepsilon_{Ct}^{*}\frac{\partial TC^*}{\partial H_{ijk}}\right)\frac{1}{TC^*} \quad (7)$$

The terms on the right hand side of (7) can be further expanded according to:

$$\frac{\partial TC^*}{\partial H_{ijk}} = \frac{\partial TC^*}{\partial P_{L_I}}\frac{\partial P_{L_i}}{\partial B_i}\frac{\partial B_i}{\partial H_{ijk}} \quad (8)$$

and

$$\frac{\partial^2 TC^*}{\partial H_{ijk}\partial t} = Y \times \lambda_{it} \times \frac{\partial P_{L_i}}{\partial B_i}\frac{\partial B_i}{\partial H_{ijk}}\,. \quad (9)$$

Equations (8) and (9) make it clear the only way in which age structure and the fields-of-study composition can have different impacts on productivity growth is via their different roles in the index B_i. This index is specified to be of the CES (Constant Elasticity of Substitution) form and is given by:

$$B_i = \left[\sum_{j=1}^{J_i} \nu_{ij}\left(\sum_{k=1}^{Kji}\left(1+\theta_{ijk}\right)H_{ijk}\right)^{-\rho_i}\right]^{-\frac{1}{\rho_i}} \quad (10)$$

where θ_{ijk}, ν_{ij} and ρ_i are parameters that have been estimated alongside the other parameters of the cost function, cf Mellandet (op cit). For a given characteristic, the θ_{ijk} are the weights attached to different categories. For instance for the characteristic age the weights are attached to the different age groups. The ν_{ij} are the weights at the next level of aggregation – they weigh together different characteristics.; $\sum_{j=1}^{Ji} \nu_{ij} = 1$. Finally, ρ_i is the substitution parameter that determines the degree to which different characteristics can be substitute for one another.[6]

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[5] Each of the age and fields-of-study distributions have four different categories, as can be seen from *Table 2*.

[6] The parameter ρ was estimated to be 0.45 implying an elasticity of substation equal to 0.69, i.e. smaller than it would be if the aggregator function had been of the Cobb-Douglas form (in which case the elasticity of substitution would have been unity).

Having computed the elasticities (6) in accordance with (7) – (10) we use them as weights on the rates of changes in the age structure and the fields-of-study compositions according to:

$$\frac{\partial}{\partial H_{ijk}}\left(\frac{dTFP}{TFP}\right)\frac{H_{ijk}}{dTFP/TFP}\frac{dH_{ijk}}{H_{ijk}} \tag{11}$$

A convenient property of (11) is that to aggregate effects over categories, we can simply sum the relevant outcomes. For instance, to obtain the effect on productivity growth resulting from all changes in the age distribution for workers with level 1 education in a given industry we sum according to:

$$\sum_{k=1}^{4}\frac{\partial\left(dTFP/TFP\right)}{\partial H_{11k}}\frac{H_{11k}}{dTFP/TFP}\frac{dH_{11k}}{H_{11k}} \tag{12}$$

To obtain the corresponding effect for the entire manufacturing sector we sum the industry effects, and so on.

3.2. Description of alternative projections

We consider two basic types of projections. The first amounts to assuming that history repeats itself. The second type consists of specifications based on stylized assumptions relating to earlier findings in the literature and to the public debate about the age structure and fields-of-study composition in the manufacturing industry.[7] Specifically, with respect to workers' age structure we consider the discussions about using early retirement of older workers as a device to facilitate entry to the labor market for younger workers and contrast these discussions to research findings about larger productivity contributions from older workers than from their younger colleagues [see, e.g. Malmberg (1994), Lindh and Malmberg (1999)]. And with respect to the fields-of-study composition we consider the effects of increasing the share of technicians and engineers among the employees, a change often discussed both in the scientific literature [Brown and Campbell (2001), Card and DiNardo (2002)] and in the popular debate.

In the experiment where we assume that history repeats itself we extrapolate the (average) historical changes of the sample shares corresponding to the different age and

[7] Below, we will refer to these projections as "stylized projections", for short.

fields-of-study distributions respectively, over period 1985 – 1995. These changes can be seen in Table 3.

Table 3: Changes in the sample shares corresponding to age groups and fields-of-study between 1985 and 1995, by level of education, in % per annum, used for the "History.repeats itself" – projections A1 and F1, respectively.

Total manufacturing		Level of education			
		1	2	3	4
Age	16-29	-0.02	-2.80	-0.53	-0.51
	30-39	-1.35	+0.28	+0.17	-0.21
	40-49	-0.73	+1.99	+0.06	+0.34
	50-74	+2.10	+0.53	+0.30	+0.38
Fields of study	FoS1	0.0	0.0	-0.12	--
	FoS2	--	--	-0.09	+0.09
	FoS3	--	--	-0.03	+0.02
	FoS4	--	--	+0.24	-0.11

FoS1 = General education, FoS2 = Administration, economics, social science and law,
FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

With respect to the age distribution, Table *3* shows a tendency towards a decrease in the shares of 16-29 year category, at each educational level for manufacturing as whole. This implies, of course, that the overall share of this age group in manufacturing employment must have decreased, too. The opposite development can be seen for those aged 50-74.

When it comes to fields-of-study we see a marked increase in the "Other fields-of-study" – category for those with upper secondary school (Level 3). This increase is partly balanced by a decrease in the share of the same category among the employees with university education (Level 4). With respect to the field-of-study FoS2 = Administration, economics, social science, and law, a rather modest decrease at educational Level 3 is entirely offset by an equally large increase at Level 4. It is worth noting that the changes in the shares of technicians and engineers (FoS3) are almost negligible. It thus appears that the discussions about the needs to recruit more engineers have not left much of an imprint in actual practice.

The general tendencies noted with respect to Table *3* can be seen also in the corresponding tables for the two industries 3440 and 3810. To save on space, we do not reproduce those tables here.

Next, we turn to the stylized projections concerning changes in the age structure. The basic question posed here is whether we will gain the most in terms of productivity growth by increasing the share of younger workers at the expense of the older ones, or vice versa.

The corresponding assumptions are outlined in Table *4*. The magnitudes of the changes in the sample shares have been chosen so as to not deviate much from the actual changes between 1985 and 1995 (cf. Table 3).

Table 4: Changes in the sample shares corresponding to age groups by level of education, in %. Projections A2 – A4. (For Projection A1, cf Table 3).

		Proj. A2: "Youngsters in, oldies out"	**Proj.. A3** Smooth version of Proj. A2	**Proj. A4** Reverse of Proj. A2
		Level of education		
		1,2,3,4	1,2,3,4	1,2,3,4
Age	16-29	+1.5	+1.0	-1.5
	30-39	0.0	+0.5	0.0
	40-49	0.0	-0.5	0.0
	50-74	-1.5	-1.0	+1.5

In projection A2 we consider what would happen if we increase the inflow of young workers, those between 16 and 29, and balance this increase by an equally large decrease in the share of workers between 50 and 74. This set-up is applied to all levels of education. This is a scenario consistent with letting older workers retire early. The compensating inflow of young workers could be achieved by providing them with incentives to enter the job market early.

Projection A3 is in the same spirit as A2, but in A3 the changes are less dramatic and affect workers in all age categories.

In projection A4 we do the opposite to projection A2. That is, we let young people enter the labor market later while at the same time we decrease the outflow of older workers. This could be obtained, e.g., by extending compulsory education and giving older people economic incentives to retire later. As this is just the reverse of projection A2 there is actually no need to include it explicitly, because, by symmetry, the results can be obtained just by multiplying the results of A2 by -1. However, for easy reference we provide the results for A4 explicitly, too.

As can be seen from Table 4 all the set-ups such that the changes “cancel out”. Accordingly the number of employees is not affected, only the age structure.

It is hard to formulate *a priori* expectations about the outcomes of these projections. For both the younger and the older workers there are mechanisms working in opposite directions.

For the younger workers, a positive contribution to growth probably comes from the fact that they have the most recent, updated, educations. This positive effect could of course be outweighed by lack of working experience. The size of such a negative effect will depend on the degree to which the education is adapted to fit real life work. It could be the case that the education provides the tools in terms of knowledge, but gives insufficient guidance on how to use these tools in specific job situations.

For the older workers the direction of the effects on productivity growth is also ambiguous. Is the contribution to productivity growth decreasing in age, due, e.g., to older worker having obsolete educations, or could it be the case that older workers affect productivity growth positively through their extended working experience?

Next, we consider the stylized fields-of-study projections. The experiments in Table 5 all have the property that the share of this group is increased.

Table 5: Changes in the sample shares corresponding to fields-of-study by level of education, in %, Projections F2 – F5. (For projection F1, cf Table 3).

Fields-of-study	**Proj. F2:** “Marketing out, technicians in”		**Proj. F3:** “Generalists out technicians in”		**Proj. F4** Strong version of Proj. F2		**Proj. F5** Strong version of Proj. F3	
	Level of education							
	3	4	3	4	3	4	3	4
Field-of-study1 (FoS1)	0.00	--	-0.05	--	0.00	--	-0.25	--
Field-of-study2 (FoS2)	-0.10	-0.10	0.00	0.00	-0.50	-0.50	0.00	0.00
Field-of-study3 (FoS3)	+0.10	+0.10	+0.10	+0.15	+0.50	+0.50	+0.50	+0.50
Field-of-study4 (FoS4)	0.00	0.00	-0.05	-0.15	0.00	0.00	-0.25	-0.50

FoS1 = General education, FoS2 = Administration, economics, social science and law,
FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

In projection F2 we increase the share of technicians and engineers at the expense of business administrators, sales staff, etc. In F3, we balance the increased share of technicians and engineers by decreases in the shares of workers in the categories

"General education" and "Other fields-of-study". Projections F4 and F5 are similar to projections F2 and F3, respectively, but the changes are much larger. In fact, the changes are very large, in a historical perspective, cf. Table 3.

4. Results

We present the results according to a three-step procedure. In the first step we report the elasticities (6) of TFP growth with respect to changes in individual age and fields-of-study categories. In the second step we apply these elasticities to the rates of changes in Tables 3 – 5, to obtain the growth effects of alternative developments of the age structures and fields-of-study compositions, according to (11) and (12). Finally, we estimate the corresponding effects over a ten year period.

4.1 Growth elasticities

The elasticities in equation (6) are evaluated for 1995, i.e. the last year of the period used to estimate the underlying cost function. The elasticities with respect to marginal changes in the shares of the different age categories, by level of education, are provided in Table *6,* for the high technology industry, 3440, the low-technology industry, 3810 and for the total manufacturing sector.

A general observation is that the elasticities are very small. For instance, according to the second row in the next to last column in Table *6*, a 1 percent increase in the share of level 3 workers aged 30-39 will increase TFP growth by 0.018 percent. However, a 1 percent increase in the share is a very little change indeed; according to Table 2 it amounts to a change of .0013 percentage points. A change in the share of 1 *percentage point*, on the other hand, would correspond to change of 7.5 percent.

We see that the contributions to productivity growth from marginal increases in the age of those with the highest level of education are smaller than for those with the lowest level of education. Actually, we see that the effects on productivity growth from marginal changes in the age distribution of workers with tertiary and post-graduate education (Level 4) are virtually zero, both in the high-tech and low-tech industries and in total. We take this to imply that with respect to those with the highest level of education the age distribution is "right" in the sense that altering the shares of different age categories will not have any impact on productivity growth.

On the other hand, when it comes to those with the lowest level of education (level 1), things seem to be different. Here, we would gain (in terms of increasing productivity growth) by increasing the share of the more experienced workers, i.e. those that are 40 years old or older.

Table 6: Elasticities of TFP growth with respect to changes in the age distributions, 1995.

		Age			
		16-29	30-39	40-49	50-74
3440 = Printing & Publishing (hi-tech)					
Level of education	1	0.002	0.005	0.036	0.043
	2	-0.001	0.017	0.003	0.018
	3	-0.006	0.020	0.035	0.018
	4	-0.001	3E-04	0.002	0.001
3810 = Metal Products (low-tech)					
Level of education	1	0.003	0.009	0.052	0.036
	2	4E-04	0.024	0.003	0.012
	3	-0.007	0.023	0.040	0.015
	4	0.002	-0.001	-0.004	-0.002
Total manufacturing					
Level of education	1	0.002	0.007	0.047	0.036
	2	3E-05	0.020	0.003	0.011
	3	-0.004	0.018	0.030	0.012
	4	0.001	-4E-04	-0.002	-0.001

In general we see that increasing the share of older workers contributes most to productivity growth when it comes to educational level 1. This result may be specific to the estimation period for the underlying model, i.e. 1985-1995. During this period many industries in the Swedish manufacturing sector underwent considerable restructuring. In that process there was a need for workers with experience of the obsolete systems to be replaced. Much of that experience was embodied in workers with (very) low levels of education. However, that being a transitional effect, it is unlikely to be repeated.

Somewhat surprisingly, the elasticities for the high-tech industry 3440 and the low-tech industry 3810 are quite similar. The only noticeable difference is that elasticities for the oldest workers are higher for 3440, at all levels of education. This finding which may well be attributable to the reason put forward in the preceding paragraph.

The effects of marginal changes in the field-of study distributions on productivity growth can be seen in Table 7. We notice that we have most to gain by increasing the share of technicians and engineers with upper secondary education (level 3). This holds regardless if we are considering industry 3440, or 3810 or the total manufacturing sector. Also, balancing such increases by reductions in the shares of administrators, sales personnel etc (FoS2) or those with "Other fields-of-study" (FoS4) seems to be a good idea as the elasticities for these latter categories are quite small.

Table 7: Elasticities of TFP growth with respect to changes in fields-of-study, 1995

		FoS			
		1	2	3	4
3440 = Printing & Publishing (hi-tech)					
Level of education	1	-	-	-	-
	2	-	-	-	-
	3	0.036	0.006	0.024	0.002
	4	-	0.002	0.001	-0.001
3810 = Metal Products (low-tech)					
Level of education	1	-	-	-	-
	2	-	-	-	-
	3	0.011	0.003	0.056	0.002
	4	-	-0.003	-0.004	0.001
Total manufacturing					
Level of education	1	-	-	-	-
	2	-	-	-	-
	3	0.014	0.003	0.039	0.002
	4	-	-0.002	-0.002	0.001

FoS1 = General education, FoS2 = Administration, economics, social science and law,
FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

Another general finding is that, just like with respect to the structure, the distribution of the most well-educated employees over fields-of-study appears to be close to optimal; all of the elasticities are very close to zero.

In contrast to Table 6, differences between the high-tech and the low-tech industries can be seen in Table 7. These differences pertain to employees with upper secondary education (level 3) and all fields-of-study, except "Other fields-of-study" (FoS4).

4.2 Short-run effects

Turning to the short-run projections, we notice that while the elasticities in Tables *6* and *7* are of similar magnitude, the changes in the age structure shares in Tables *3* and *4* are generally considerably larger, in absolute terms, than the corresponding changes in the fields-of-study compositions, given in Tables *3* and *5*. Accordingly, since the growth effects are obtained by multiplying the elasticities in Tables *6* and Table *7*, respectively, with the rates in Tables *3 – 4* and Tables *3* and *5*, respectively, we should expect the age structure projections to yield larger effects than the fields-of-study projections.

We begin with the projections relating to the age structure. The first projection is the one drawing on the historical developments, i.e. the "History repeats itself-projection, A1. In this projection, we compute the partial one-year productivity growth effect that would have resulted had the age distribution continued to change in the same way as it did on average over the 1985-1995 period. The overall effect is an increase in the TFP growth rate by 0.06 percentage points, as can be seen in Table *8*; the total effect is obtained by adding the entries in the row denoted "Sum", for Total manufacturing. This is a small effect: in 1995 the rate of growth in TFP estimated by Mellander (op cit) was 1.8 percent, implying that the effect computed here amounts to increasing the growth rate to 1.86 percent.

With respect to the different levels of education we see a clear pattern: the lower the level of education of the workers the higher is the contribution to productivity growth when age structure keeps on changing as it has been changing in the past.

Turning to Experiment A2, i.e. replacing 50-74 year olds by workers aged 16-29. Here, we see that the total effect becomes negative. Thus, providing access to the labor market for young individuals by making older worker retire early is not good for productivity growth. The same conclusion holds for Experiment A3, the "smooth" version of Experiment A2.[8]

The third experiment reported in Table 8, Experiment A4 is the opposite case of Experiment A2. By definition, the results for A4 are equal to the negative of the results for A2, implying that the total effect equals an increase in TFP growth of 0.087 percentage points.

[8] This result is not provided in *Table 8,* but can be found in the Appendix.

Table 8: One year incremental effects on TFP growth resulting from prjections A1, A2, and A4. Effects in percentage points

Projection A1: "History repeats itself" (cf Table 3)

		Age				
		16-29	30-39	40-49	50-74	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-3E-05	-0.007	-0.026	0.091	0.058
	2	0.003	0.005	0.006	0.010	0.024
	3	0.003	0.003	0.002	0.005	0.013
	4	0.001	-7E-05	0.001	4E-04	0.002
3810 = Metal Products (low-tech)						
Level of education	1	-7E-05	-0.012	-0.038	0.076	0.026
	2	-0.001	0.007	0.007	0.006	0.019
	3	0.004	0.004	0.002	0.005	0.015
	4	-0.001	2E-04	-0.001	-0.001	-0.003
Total manufacturing						
Level of education	1	-4E-05	-0.009	-0.034	0.076	0.033
	2	-1E-04	0.006	0.006	0.006	0.018
	3	0.002	0.003	0.002	0.004	0.011
	4	-0.001	9E-05	-0.001	-5E-04	-0.002
Total change in productivity growth: 0.06						

Projection A2: "Youngsters in, oldies out" (cf Table 4)

		Age				
		16-29	30-39	40-49	50-74	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	0.002	0	0	-0.065	-0.063
	2	-0.002	0	0	-0.027	-0.025
	3	-0.008	0	0	-0.025	-0.033
	4	-0.002	0	0	-0.002	-0.004
3810 = Metal Products (low-tech)						
Level of education	1	0.005	0	0	-0.054	-0.049
	2	0.001	0	0	-0.018	-0.017
	3	-0.010	0	0	-0.023	-0.033
	4	0.002	0	0	0.003	0.005
Total manufacturing						
Level of education	1	0.003	0	0	-0.054	-0.051
	2	5E-05	0	0	-0.017	-0.017
	3	-0.005	0	0	-0.018	-0.023
	4	0.002	0	0	0.002	0.004
Total change in productivity growth: -0.087						

Projection A4: Reverse of Experiment A2 (cf Table 4)

		Age				
		16-29	30-39	40-49	50-74	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-0.002	0	0	0.065	0.063
	2	0.002	0	0	0.027	0.025
	3	0.008	0	0	0.025	0.033
	4	-0.002	0	0	-0.002	-0.004
3810 = Metal Products (low-tech)						
Level of education	1	-0.005	0	0	0.054	0.049
	2	-0.001	0	0	0.018	0.017
	3	0.010	0	0	0.023	0.033
	4	0.002	0	0	0.003	0.005
Total manufacturing						
Level of education	1	-0.003	0	0	0.054	0.051
	2	-5E-05	0	0	0.017	0.017
	3	0.005	0	0	0.018	0.023
	4	-0.002	0	0	-0.002	-0.004
Total change in productivity growth: 0.087						

Note: The results of projection A3 are reported in the Appendix.

We now proceed to consider the projections relating to the fields-of study. As we can see in Table 9 the growth effect corresponding to the "History repeats itself"-projection F1 is negative but, more important, entirely negligible. Although projection F2: "Marketing out, technicians in" results in a positive outcome, this effect is negligible, too. The effect of substituting technicians for generalists, projection F3, is even closer to zero than the results of projections F1 and F2.

Indeed, even if the changes in the fields-of-study composition are very large, by historical standards, as in projections F4 and F5 the resulting effects are only about 1/5 of the effects obtained in the age structure projections.[9] These results agree with the fact that "reasonable" changes in the fields-of-study composition are much smaller than likely changes in the age structure; cf Tables *3 – 5*.

The small numbers aside, an interesting result is that in contrast to the effects of changes in the age structure we here find differences between industries. The low-tech industry 3810 = Metal Products benefits much more from a larger share of technicians and engineers than does the high-tech industry 3440 = Printing and Publishing. One

[9] The results of experiments F4 and F5 are provided in the Appendix.

Table 9: One year incremental effects on TFP growth resulting from projections F1, F2 and F3. Effects in percentage points

Projection F1: "History repeats itself" (cf Table 3)

		FoS				
		1	2	3	4	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0044	-0.0005	-0.0007	0.0005	-0.0051
	4	-	0.0002	2 E-05	-0.0001	0.0001
3810 = Metal Products (low-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0013	-0.0002	-0.0017	0.0004	-0.0028
	4	-	-0.0003	-0.0001	0.0002	-0.0002
Total manufacturing						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0017	-0.0003	-0.0012	0.0004	-0.0028
	4	-	-0.0002	-4E-05	0.0001	-0.0001
Total change in productivity growth: : -0.0029						

Projection F2: "Marketing out, technicians in" (cf Table 5)

		FoS				
		1	2	3	4	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0006	0.0024	0	0.0018
	4	-	-0.0002	0.0001	0	-0.0001
3810 = Metal Products (low-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0003	0.0056	0	0.0054
	4	-	0.0003	-0.0004	0	-0.0001
Total manufacturing						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0003	0.0039	0	0.0036
	4	-	-0.0003	-0.0002	0	0
Total change in productivity growth: 0.0036						

Projection F3: "Generalists out, technicians in (cf Table 5)

		FoS				
		1	2	3	4	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0018	0	0.0024	-0.0001	0.0004
	4	-	0	0.0001	0.0002	0.0003
3810 = Metal Products (low-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0005	0	0.0056	-0.0001	0.0050
	4	-	0	-0.0006	-0.0002	-0.0008
Total manufacturing						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0007	0	0.0039	-0.0001	0.0031
	4	-	0	-0.0003	-0.0001	-0.0004
Total change in productivity growth: 0.0027						

Note: The results of projections F4 and F5 are reported in the appendix.

explanation to this result might be that the high-tech industry has already exploited the productivity potential associated with hiring more technical personnel while the corresponding potential remains in the low-tech industry.

4.3 Long-run effects

Up to now we have considered how the presumed changes in the age structure and the fields-of-study composition affect productivity growth over one year only. To get a (very) rough idea of the effects in a more long run perspective we have simply used the effects that we have reported in the previous section and repeated them over a 10 years period, cf. Table 10.

As a benchmark we use the rate of TFP growth in the manufacturing sector 1995, estimated by Mellander (op cit) to be 1.8 percent per annum. This rate is assumed to prevail for ten years. Thus, in 2005 manufacturing output is predicted to be $(1.018)^{10}$ = 1.195 times the output in 1995, or 19.5 percent higher.

Table 10: Accumulated growth, in percent, in manufacturing output over the period 1995 –2005, in a benchmark case and according to the various projections. Yearly growth rates in parenthesis, in percent.

	Age structure projections			**Fields-of-study composition projections**			
Benchmark (1.8)	**A1:** (1.86)	**A2:** (1.713)	**A4:** (1.887)	**F1:** (1.7971)	**F2:** (1.8036)	**F3:** (1.8027)	**F4:** (1.818)
19.5	20.2	18.5	20.5	19.4	19.6	19.6	19.7

Notes:
1.The accumulated growth in the benchmark case is computed according to $[(1.018)^{10} - 1]\times 100$ and similarly for the different experiments.
2. To save space the results for projections A3 and F5 have not been reported in the table.

As can be seen from the above table, the long run effects are small. The largest positive effect – + 1 percent – is obtained in projection A4 where the share of workers aged 50-74 is increased at the expense of workers aged 16-29. The largest negative effect is obtained in projection A2, which is just the reverse of projection A4.

The effects on accumulated growth from changes in the fields-of-study composition are very small indeed. This is true also for projection F4 which involves changes in the share of technicians and engineers that are at least 15 times larger than those occurring during the period 1985-1995.

5. Conclusions

Starting out from the presumption that labor heterogeneity matters for productivity growth, we have in this paper considered how changes in the age structure and the fields-of-study composition of the employees in the Swedish manufacturing sector affect total factor productivity growth, given that we account for educational levels. The analyses have been carried out by means of a cost function, estimated on data for the period 1985-1995. Using this cost function we have computed the effects on total factor productivity growth from alternative age and fields-of-study distributions, over a ten year horizon. Projections where the patterns of changes in these distributions observed during the 1985-1995 period are extrapolated over the following decade have been compared to projections based on stylized assumptions of alternative patterns of changes.

The effects we find are small. Even under assumptions of changes that exceed by far historical developments the effects at most increase or decrease the accumulated growth over a ten year period by 1 percentage point. Relative to the benchmark accumulated growth of 20 percent this merely corresponds to a 5 percent increase.

The quantitatively modest effects notwithstanding, several qualitatively interesting results emerge from the analysis. First of all, changes in the age structure matter more than changes in the fields-of-study composition. Indeed, with respect to the latter one has to resort to historically unprecedented changes to produce discernible effects on productivity growth.

Regarding changes in the age structure, we find that increasing the share of workers that are at least 50 years old, at the expense of workers below 30, has a positive effect on growth. This results support earlier findings by Malmberg (1994) and Lindh and Malmberg (1999) according to workers aged 50-64 contribute more to growth than workers in other age categories. We also find that the positive influence from the older worker comes from those with low levels of education. Our age structure results do not vary by type of industry – the patterns are essentially the same for high-tech and low-tech industries.

With respect to changes in the fields-of-study compositions we find that increasing the share of technicians and engineers has a positive effect on growth. This finding confirms conjectures in the scientific literature [see, e.g., Card and DiNardo (2002)] and is also in line with common beliefs within the manufacturing sector itself. In contrast to our findings about age structure changes, changes in the fields-of-study compositions differ across industries. Our example of a high-tech industry, Printing and Publishing, benefits much less of an increased share of technicians and engineers than does our example of a low-tech industry, Metal Products. Again, it should be emphasized, however, that the impact estimated is very small in magnitude.

On a general level, the finding that our estimated effects are small can be attributed to the fact that, essentially, we treat changes in the age structure and fields-of-study composition as second order effects with respect productivity growth. The main, first order, impact of technical change (which drives productivity growth) comes on effective labor. For a given level of education effective labor is the product of the number of workers and an index of worker characteristics. Changes in the age or fields-of-study distributions only affect the index of worker characteristics. Given this property small estimates is what we should expect.

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APPENDIX: Results of projections not reported in the main text

Addendum to Table 8:

Projection A3: Smooth version of Projection A2.

		Age				
		16-29	30-39	40-49	50-74	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	0.002	0.003	-0.018	-0.043	-0.056
	2	-0.001	0.009	-0.002	-0.018	-0.012
	3	-0.006	0.010	-0.017	-0.017	-0.030
	4	-0.001	2E-04	-0.001	-0.001	-0.003
3810 = Metal Products (low-tech)						
Level of education	1	0.003	0.004	-0.026	-0.036	-0.055
	2	4E-04	0.012	-0.002	-0.012	-0.002
	3	-0.007	0.011	-0.020	-0.015	-0.031
	4	0.002	-4E-04	0.002	0.002	0.006
Total manufacturing						
Level of education	1	0.002	0.003	-0.023	-0.036	-0.054
	2	3E-05	0.010	-0.002	-0.011	-0.003
	3	-0.004	0.009	-0.015	-0.012	-0.022
	4	0.001	-2E-04	0.001	0.001	0.003
Total change in productivity growth: -0.076						

Addendum to Table 9:

Projection F4: Strong version of Projection F2

		FoS				
		1	2	3	4	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0030	0.0118	0	0.0088
	4	-	-0.0010	0.0005	0	-0.0005
3810 = Metal Products (low-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0013	0.0281	0	0.0268
	4	-	0.0014	-0.0018	0	-0.0004
Total manufacturing						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	0	-0.0015	0.0197	0	0.0182
	4	-	0.0010	-0.0009	0	0.0001
Total change in productivity growth: 0.018						

Projection F5: Strong version of Projection F3

		FoS				
		1	2	3	4	Sum
3440 = Printing & Publishing (hi-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0091	0	0.0118	-0.0005	0.0022
	4	-	0	0.0005	0.0006	0.0011
3810 = Metal Products (low-tech)						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0027	0	0.0281	-0.0005	0.0249
	4	-	0	-0.0018	-0.0007	-0.0025
Total manufacturing						
Level of education	1	-	-	-	-	-
	2	-	-	-	-	-
	3	-0.0035	0	0.0197	-0.0004	0.0158
	4	-	0	-0.0009	-0.0005	-0.0014
Total change in productivity growth: 0.014						

Essay III

The Relationship Between Skilled Labor and Technical Change

1. Introduction

During the last two decades, economists in many industrialized countries have faced the challenge of explaining the observation that the wage premium of skilled labor has increased despite considerable increases in the supply of this kind of workers. These changes provide evidence of considerable shifts in the relative demand for skilled workers. A number of explanations have been suggested in order to explain the latter.

Increased competition from low-wage countries in the Third World might have forced industrialized countries to concentrate on skill-intensive products and services, thus raising the demand for skilled workers; see, e.g., Wood (1994) and Feenstra and Hanson (1996). Or it may be that changes in firms' work organization have lead to increased skill requirements, cf. Caroli and van Reenen (2001), and Bresnahan, Brynjolfsson and Hitt (2002). However, the by far most popular explanation is the hypothesis of skill-biased technical change. This hypothesis says that technical change affects unskilled and skilled workers differently, favoring the latter, presumably because they have higher capacity for understanding and adopting new technologies. The idea was launched by Berman, Bound and Griliches (1994), and their analysis was followed up by a large number of studies [Machin and van Reenen (1998) provide an extensive survey on this issue]. The skill-biased technical change hypothesis has also been examined on Swedish data; see Hansson (1996) and Mellander (1999).

There are two problems with the skill-biased technical change hypothesis, however. The first relates to measurement: since there is no obvious way to measure technical change it is unclear how its presence should be tested. The second problem is that the skill-biased technical change hypothesis is not really an explanation – it merely raises another question, namely why technical change should affect workers with different skills unequally.

The measurement issue has spurred a lot of experimentation with different indicators of technical change in labor demand equations. A common procedure is to assume that technical change is exogenous to the firm and can be modeled by either the proportion of the workforce using computers [Autor, Katz and Kreuger (1998), Haskel and Heden (1999)] or expenditures on R & D [Berman, Bound and Griliches (1994)]. This approach is not very satisfactory, however. It is very hard to justify the exogeneity assumption: both computer capital and R&D expenditures are endogenous to the firm, just like the outlays on other factors of production.[1, 2]

The second problem with the skill-biased technical change hypothesis, i.e. that it lacks an explanation of why technical change affects skilled and unskilled workers differently, has been addressed by Krusell et al. (2000). They claim that, essentially, skill-biased technical change is just a reflection of capital-skill complementarity. The notion of capital-skill complementarity, due to Griliches (1969), predicts different relationships between capital and skilled labor on the one hand and capital and unskilled labor, on the other hand. While capital tends to replace unskilled labor, implying that the two are substitutes, the demand for skilled tends to be positively affected by increases in capital, meaning that capital and skilled labor are complements. Krusell et al. (op. cit.) argue that the increased investments in high-tech capital equipment during the last decades, caused by falling relative prices of computers, have raised the ratio of effective capital inputs per worker and, thus, in particular per skilled worker. Skilled labor and capital being complements, this has lead to an increased demand for skilled workers.[3] However, to judge the validity of this explanation it is necessary to consider the mechanisms governing the diffusion of technical change.

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[1] While this is obvious with respect to computers it is somewhat less transparent regarding R&D expenditures. The latter, however, are just outlays for specific types of equipment and specific labors, which together produce an intermediate output – reflected in, e.g., patents – that is used in a later stage of the production process.

[2] As argued by Mellander (1999), a simple, albeit very crude, indicator of technical change that escapes this objection is a simple time trend.

[3] At the same time, the demand for unskilled labor decreases, due to unskilled labor and capital being substitutes. This reinforces the effect on the skill premium.

Two forms of technical change are discussed in the literature: *embodied* and *disembodied* technical change. Embodied technical change is embedded in (new) capital goods. Computers are the most obvious example of capital goods featuring embodied technical change. Two PCs bought in different years will exhibit substantial differences in computing capacity, speed and storing capability because of the technological progress that has occurred between the two years and which is built into the computers. As this example shows, to benefit from embodied technical change one has to invest in new capital goods. This is not the case with disembodied technical change.

Disembodied technical change is not tied to capital or any other factor of production. From the perspective of an individual producer it can be viewed as an exogenous change, which at (virtually) no cost provides access to a superior production technology. An example of disembodied technical change is a new procedure for organizing the production process, like the introduction of the assembly line in the beginning of the 20th century, or the more recent just-in-time work organization schemes. As these changes amount to more efficient use of the prevailing factors of production, one can benefit from them without having to make any investments; one just has to get to know about the new procedures, which soon enough become common knowledge. It is important to note that the fact that disembodied technical is not channeled through a specific factor of production does not preclude that it might affect factors of production differently. If that is the case, the disembodied technical change is said to be non-neutral, cf. Binswanger (1974). In the context of disembodied technical change, skill-biased technical change can be defined as non-neutral technical change inducing a relative increase in the demand for skilled labor, *ceteris paribus.*

Implicitly, the explanation put forward by Krusell et al. (2000) presumes that technical change is embodied. In this case, investments in new capital, like computers, will imply increases in the capital-skilled labor ratios for two reasons: first, there are more units of capital per worker and, second, the most recent capital units are more effective than the older units. These two changes will reinforce one another in increasing the demand for skilled workers. Empirically, it will not be meaningful to try to distinguish between capital-skill complementarity and skill-biased technical change; the two will be observationally equivalent.

If, however, technical change is disembodied in nature then capital-skill complementarity and skill-biased technical change will be two completely separate phenomena. In this context, technical change can increase the demand for skilled labor even without capital investments and even if capital and skilled labor are substitutes. Conversely, if skilled labor and capital are complements then capital investments will increase the demand for labor but that will have nothing to do with technical change.

Thus, to be able to judge the importance of capital-skill complementarity for explaining the increase in the wage premium of skilled labor it is necessary to try to assess the relative importance of embodied and disembodied technical change. If all technical change is embodied, then capital-skill complementarity is *the* explanation. If, on the other hand, a large part of technical change is disembodied then capital-skill complementarity is only part of the explanation.

Interestingly, there is no discussion about the distinction between embodied and disembodied technical change in the study by Krusell et al. (2000).[4] Moreover, the production technology assumed in the empirical analysis – a CES technology – does not allow capital and skilled labor to be complements. It only allows for capital-skill complementarity in a weak sense, namely by allowing the elasticity of substitution between capital and skilled labor to be smaller than the elasticity of substitution between capital and unskilled labor.

This study is an attempt to explicitly consider the two features of the Krusell et al. (2000) study just discussed, i.e. whether technical change is embodied and/or disembodied and whether capital and skilled labor are indeed complements. In order for capital-skill complementarity to be a good proxy to skill-biased technical change two facts have to be investigated: (i) that there is no disembodied technical change and (ii) that capital-skill complementarity exists.

To be able to explicitly allow for embodied technical change, it is necessary to implement a so-called vintage model of capital; cf. Solow (1959). The distinguishing features of a vintage model is that investments are not only defined by capital expenditures; as the additions to the firm's capital are assumed to be more productive the more recently they have been made, the capital expenditures have to be *dated*. In a strict sense, this means that every investment corresponds to a unique capital object, a

[4] The same is true for the analysis by Lindquist (2001) where the model by Krusell et al. (2000) is applied to Swedish data.

property that makes empirical modeling very complicated. However, Nelson (1964) has formulated an elegant approximation to the vintage model that is much easier to implement and which will be used in this study.[5] The focus of my analysis of embodied technical change will be on computer-equipment capital. This is because computers are good reflectors of technical change. Other kinds of capital – non-computer equipment and buildings – will be modeled by means of (perpetual inventory type) capital stock measures which do not distinguish between investments made at different points in time.

To allow different categories of labor to be either substitutes or complements, the production technology will be modeled by means of flexible functional form, the translog production function [Christensen et al. (1973)]. This function also makes it possible to model non-neutral disembodied, and embodied technical change.

As far as I know, this is the first study integrating embodied and disembodied technical change into one and the same model within the context of investigating their effects on the demand for labor, thus making it possible to assess the relative importance of these two forms of technical change. Another contribution is that the integration of embodied and disembodied technical change is conducted within the framework of flexible functional form imposing few a priori constraints on the production technology.

The empirical analysis relies on data for 14 industries in the Swedish manufacturing sector 1985-1995. Three different cases are examined. In one all technical change is assumed to be disembodied while in another only embodied technical change is considered. The third case simultaneously allows for embodied and disembodied technical change. This set-up makes it possible to establish if the omission of either one of the two types of technical change, or the inclusion of both, affect the results. As an indicator of disembodied technical change, a measure of the total use of information and communication technology in the Swedish economy will be used. As this measure is defined for the entire economy it should be possible to treat it as an exogenous variable at the industry level where the empirical analysis is conducted. Another advantage is that this specification makes the comparison between disembodied and embodied technical change "fair" in the sense that both types of technical change

[5] Nelson's formulation has been used in several papers aimed at estimating the effects of embodied technical change. See, e.g., You (1976) and McHugh and Lane (1983, 1987a,b).

relate to the same phenomenon, namely the introduction of information and communication technology.

This paper is organized as follows: Next chapter provides a literature review. A brief description of the data is offered in Section 3 and in Section 4 the set-up of the model is described. Section 5 contains the results and Section 6 provides the conclusions.

2. Literature review

2.1. Skill-biased technical change literature

There is an extensive literature about the changes in the skill structure of labor demand and the impact of technical change on the demand for skilled workers. A comprehensive survey of these studies can be found in Chennels and Van Reenen (1999). I will in this section mention a few of these studies.

A strand of this literature, uses the method of first decomposing the aggregate change of the share of skilled labor into within- and between-units changes and then examine the impact of observable proxies for technical change on the within units skill changes. Berman, Bound, and Griliches (1994) introduced this method and applied it on the industry level. They found that the shift in demand for more-skilled workers since the beginning of the 1980s is mostly driven by within-industry rather than between-industry changes. They argue that the evidence found in their paper seems consistent with the view that biased technological change played a dominant role in skill upgrading. Autor, Katz, and Krueger (1998) strengthen this result by concluding that the vast majority of the secular growth in the share of college graduates in U.S. manufacturing can be attributed to within-industry changes. They show that more computer intensive industries have had a greater rate of skill upgrading. They concluded that whatever is driving the rapid rate of within-industry skill upgrading over the past few decades is concentrated in the most computer-intensive sectors of the economy.

Except for the U.S. there are evidence from other countries as well. Machin and Van Reenen (1998) conclude that the increase in the wage bill share of non-production workers in the manufacturing sectors of seven OECD countries (United States, Denmark, France, Germany, Japan, Sweden and the United Kingdom) has occurred mainly within industries.

Studies in which the authors have applied the decomposition analysis into establishment level represent a further extension of this strand of literature. Dunne, Haltiwanger and Troske (1996) is one such study in which it is found that the aggregate change in the non-production labor share in the US manufacturing sector during 1972-1987 is dominated by within plant changes in the non-production labor share. Other studies yield similar results for other countries; cf. Haskel and Heden (1999) for the case of U.K and Aguirregabiria and Alonso-Borrego (2001) for the case of Spain.

In the literature about how industry and plant-level skill upgrading is affected by technical change there has been a variety of proxies used for technical change. Bartel and Lichtenberg (1987) estimate a restricted variable cost function for U.S. manufacturing industries for 1960, 1970, and 1980 and examine the impact of the age of capital on the share of highly educated workers. They find a positive association between younger capital and the share of highly educated workers and conclude that this provides strong support for the hypothesis that highly educated workers have a superior ability to adopt the new technology. Furthermore, they find that the impact of the age of capital on the share of educated workers is more pronounced in R&D intensive industries. In a similar spirit, Chun (2003) uses the age of IT capital as a proxy for the adoption of IT, but he also uses the IT capital stock as a proxy for the use of IT. A notable feature of his analysis is that he assumes all kinds of capital including that of computers to be quasi-fixed, i.e. fixed in the short run (one year). He divides workers into educated (college equivalents) and less educated (high school equivalents), and concludes that the use of IT is complementary with educated workers and that educated workers have a comparative advantage in the adoption of IT. In some of his model specifications he includes a measure of R&D expenditure to output, and finds a positive relationship of this measure and the relative demand for educated workers.

Berndt, Morrison and Rosenblum (1992) examined the impact of investments in high-tech capital on the demand for skilled labor. In their paper they examine how the share of non-production workers in total employment is affected by a capital-intensity measure and a measure of the share of high-tech capital in total capital. They found that skill upgrading towards more educated workers occurs along with increases in the ratio of high-tech capital in total capital. Berman, Bound, and Griliches (1994) examined the within industry skill upgrading in the U.S. manufacturing sector during the 1980´s. As their proxy for (exogenous) technical change they used the share of computer investments and the share of R&D expenditures. They found that the increase in non-production labor input is positively correlated with these measures. Autor Katz, and Krueger (1998) examine the impact of technical change on the within industry shifts toward more educated workers. They use indicators such as employee computer usage, computer capital per worker, and the rate of computer investment and show that approximately one-third of the increase in within-industry skill upgrading in US manufacturing from the 1980´s and 1970´s can be attributed to these measures. Further they show that the R&D over sales ratio has had a substantial positive impact on skill upgrading.

Proxies for skill-biased technical change are also investigated at the plant level. Dunne, Haltiwanger and Troske (1996) use data on U.S. manufacturing plants for the years 1972-1998. As technology indicators they use a firm level measure of the R&D stock and changes in ownership structure. They find significant R&D skill complementarity and a positive correlation of changes in the ownership structure with the increase in the non-production labor share. Another paper using plant level data is that of Doms, Dunne and Troske (1997). In this paper the authors use information on adoption and use of new automation technologies. When using cross section estimation for the year 1988 they find evidence that plants that use a large number of new technologies employ relatively more educated workers. On the other hand, when controlling for the plant specific fixed effect using data for the period 1977-1992 they do not find evidence that adoption of technology has any impact on the increase in the non-production worker share within plants.

There are several studies from other countries than the U.S., explaining the impact of various technology variables on changes in the share of skilled labor. Hansson (1996) examines and finds evidence of skill-biased technical change for the case of Sweden. He finds that R&D intensive industries and industries with high shares of technicians have been more likely to increase their share of skilled labor. Mellander (1999) controlling for a number of educational and demographic characteristics, also finds evidence of skill biased technical change for the case of Sweden. In his paper he uses a time trend as an indicator of technical change. This proxy for technical change is also used in Lindquist, and Skjerpen (2000) for the case of Norway.[6] Both of these studies find evidence of skill-biased technical change. In their study of the U.K., Haskel and Heden (1999) disaggregate labor into manual (more educated) and non-manual (less educated) and find that computers seem to be altering the production process away from manual labor rather than away from less educated labor. By using an estimated level of computer investments in the U.S. industry as an instrument in order to control for the endogeneity of computerization they confirm the robustness of these results. Aguirregabiria, and Alonso-Borrego (2001) examine Spanish firms for the manufacturing sector for the years 1986-1991. They estimate labor demand functions for white- and blue-collar workers. They break down white-collar workers into four occupations namely managers, professionals, commercials, and clerical workers. The stock of R&D capital and the stock of technological capital (based on successful innovations externally generated and purchased by the firm) as well as a measure of adoption of R&D and technological capital are used as indicators of the technology. They find small and imprecise elasticities with respect to R&D capital, adoption of R&D and technological capital. As for the adoption of technical capital it seems to increase the demand for commercial workers and lower that of blue-collar workers.

In recent years there has been an interest of studying how technical change is related to organizational changes in firms´ production process. Bresnahan, Brynjolfsson and Hitt (2002) examine data for 300 large U.S. firms. They find that increased demand for skilled labor is complementary with information technology, organizational change, and new products and services. Caroli and Van Reenen (2001) use a panel of British and French establishments to investigate the effects of organizational changes on skill upgrading. They offer support for the hypothesis of skill-biased organizational change by finding first of all that organizational changes reduce the demand for unskilled workers in both countries. Secondly, they find that organizational changes are negatively associated with increases in regional skill price differentials (a measure of the relative supply of skill). The third of their findings is that organizational changes lead to greater productivity increases in establishments with larger initial skill endowments.

[6] In Mellander (1999) the time trend is labor-type specific, while in the case of Lindquist, and Skjerpen (2000), the time trend is industry specific.

In total one can say that there is evidence that the observed increase in the share of skilled workers has mainly occurred within sectors and plants. This lends support to the hypothesis that technical change could explain the increase in the demand for skilled workers in total employment. Several studies try to corroborate the effect of technical change on the demand for skilled labor by including measures of R&D intensity and computerization in labor demand equations. While positive relations are often found, the use of these variables runs the risk of introducing endogeneity problems, which makes it hard to judge the results. In this strand of literature there is no discussion about the distinction between embodied and disembodied technical change.

2.2. Embodied technical change literature

As mentioned earlier there is no paper as far as I know that tries to explicitly investigate the relation between embodied technical change and skill-biased technical change. Solow (1959) was the first one to introduce the concept of embodied technical change. The embodied nature of a substantial fraction of technical progress was considered unimportant by Denison (1964) and irrelevant in the long run by Phelps (1962). However, in recent years theoretical and empirical contributions to growth and business cycle theory have shown the importance of embodied technical change for explaining several stylized facts of the U.S. economy, such as the productivity slowdown, the decline in the relative price of investment goods and the persistent rise in the equipment to output ratio.[7] It is also shown that the nature of technical progress is relevant to understanding the labor market, in particular its implications on unemployment, and job creation and destruction.[8]

A shortcoming in the discussion about embodied technical change has been the lack of reliable estimates of the rate of technical change that is embodied in equipment capital. One could divide this strand of literature into two camps, that of the price-based, and that of the production-based estimates of embodied technical change. The first camp uses Gordon´s (1990) quality-adjusted price indices for producers´ durable equipment (PDE) in order to identify embodied technical change. The relative rate of decline of Gordon´s (1990) equipment price deflators puts the annual rate of embodied

[7] See Boucekkine, del Rio and Licandro (1999), Greenwood and Yorukoglu (1997), Hornstein and Krusell (1996), among others.
[8] See for e.g. del Rio (2001).

technical change no higher than 4%. Hornstein and Krusell (1996), Gort and Wall (1998) and others argue that these price-based estimates are likely to understate the true rate of embodied technical change. Further, some economists have argued that the advent of information technology and its incorporation has slowly pushed the average rate of embodied technical change higher (see Greenwood and Yorukoglu (1997), among others).

The second camp uses data on production and capital stock age using an approach due to Nelson (1964). The estimates found within this camp are five to seven times higher than the price-based estimates. For instance, the results of Bahk and Gort (1993) correspond to a 15-21 percent annual rate of growth of embodied technical change. A recent paper by Hobijn (2001) is an interesting addition in this strand of literature. Using data from 4-digit U.S. manufacturing industries he estimates the rate of embodied technical change to be around 12 percent, by means of an Euler investment equation. This figure is very close to that of Sakellaris and Wilson (2001), who develop a production-side approach that provides alternative estimates of embodied technical change without relying on accurate measurement of price indices for producer durable equipment. They find that the annual rate of embodied technical change is between 8 and 17 percent with their preferred estimate being 12 percent.

3. Data

The data used covers 14 industries in the Swedish manufacturing sector for the period 1985-1995. The codes and names of the industries considered are given in detail in Table 1 below. As an indicator of the relative size of the industries, Table 1 provides us with the employment share of each industry for the midpoint of the observation period, year 1990.

The data used are produced by Statistics Sweden and include the Swedish National Accounts (NA), the Employment Register (ER), the Labor Force Surveys (LFS), various Investment Surveys (IS) and the Trade Statistics (TS). The breakdown of the IT investments provided in the IS determines the cross-sectional dimension of theThe starting point for the data is given by the first year of the ER, and a change in the industrial classification system has made it impossible to extend the time series beyond 1995.[9]

Table 1: The industries considered and their shares in total manufacturing employment in 1990.

Industry code	Industry	Employment share 1990, %
3100	Food, Beverages and Tobacco	9.0
3200	Textile, Apparel & Leather	3.1
3300	Saw, Mills and Wood Products	8.4
3400	Pulp, Paper and Printing & Publishing	14.2
3500	Chemical, Plastic Products and Petroleum	7.8
3600	Non-Metallic Mineral Products	5.1
3700	Basic Metals	3.9
3810	Metal Products	12.3
3820	Machinery & Equipment, not elsewhere classified	13.0
3830	Electrical Machinery, not elsewhere classified	7.9
3840	Transport Equipment, except Shipyards	11.7
3850	Instruments, Photographic & Optical Devices	2.1
3860	Shipyards	0.8
3900	Other Manufacturing	0.7
3000	Total Manufacturing	100.0

Note: The classification system used here SNI69, is very close to the ISIC codes.

3.1. Capital stocks

When it comes to data on capital, we will have three different categories: computer equipment capital, non-computer equipment capital, and structure capital (buildings). The net capital stocks on equipment and structures are from the national accounts (NA) from Statistics Sweden[10] and are computed according to the Perpetual Inventory method. The variation across industries in the depreciation rates is considerably higher than the variation over time. Thus, the capital stock can be very close approximated by:

$$K_{ij,t} = (1 - \overline{\delta}_{ij})K_{ij,t-1} + I_{ij,t-1}$$

Where $K_{ij,t}$ is the capital stock of type *i*, in industry *j*, at the beginning of period *t*. The time-average SNA depreciation rate for capital of type *i* in industry *j*, is represented by

[9] More details about the data can be found in Appendix A.

[10] Two types of stocks are published by the SNA, namely "gross stocks" and "net stocks". For our purposes, the latter differ from the former in that the assumed rates of depreciation are consistently higher for the net stocks than for the corresponding gross stocks.

the $\overline{\delta}_{ij}$, and $I_{ij,t-1}$ denotes gross investments in capital of type *i* in industry *j* during period *t*-1.

Table 2 provides us with the development of the gross investment shares for the different types of capital over time. As can be seen from the table above the share of computer investments in total investments has in many industries more than doubled from 1985 to 1990. The increase was largest for industries 3700= Basic Metals, and 3860= Shipyards. Further, we see that all industries have doubled their share in 1994 compared to 1985. The largest increase occurred in 3840= Transport Equipment, except Shipyards, 3500= Chemical, Plastic Products and Petroleum, 3600= Non-Metallic Mineral Products, and in 3860= Shipyards.

As mentioned earlier the computer has been widely used as an "indicator" of technical progress and thus distinguishing it from the other types of capital is crucial for our analysis. The investment surveys (IS) provided by Statistics Sweden provide information on computer investments making it possible to brake down the equipment

Table 2: Gross investment shares in Swedish manufacturing, 1985, 1990, and 1995 (% of total investments).

Industry	Computers			Equipment			Structures		
	1985	1990	1994	1985	1990	1994	1985	1990	1994
3100	3.4	4.8	17.0	68.8	73.2	67.1	27.8	22.0	15.9
3200	4.7	7.8	27.1	76.0	44.5	61.4	19.3	47.8	11.5
3300	4.4	8.1	25.0	70.2	69.5	54.7	25.4	22.5	20.2
3400	4.5	17.6	28.0	79.6	64.0	57.4	15.9	18.4	14.6
3500	2.7	9.3	23.5	77.6	69.9	54.0	19.8	20.7	22.5
3600	1.8	6.1	14.7	86.0	67.2	71.6	12.2	26.7	13.7
3700	3.6	29.4	24.1	85.7	61.6	66.1	10.7	8.9	9.7
3810	8.4	12.3	34.7	68.0	65.4	51.4	23.6	22.2	13.8
3820	13.4	27.3	38.4	60.8	63.1	52.5	25.8	9.6	9.1
3830	12.3	19.6	70.3	69.9	62.4	19.8	17.8	17.9	9.9
3840	9.2	26.6	81.1	63.2	50.6	13.0	27.6	22.8	5.9
3850	11.7	10.0	37.8	70.3	69.6	53.4	18.0	20.4	8.8
3860	3.3	15.7	26.3	65.6	39.1	38.2	31.1	45.2	35.5
3900	1.5	5.7	6.2	58.7	65.8	81.6	39.8	28.5	12.2
3000	6.4	16.8	37.6	72.3	63.3	48.1	21.3	19.9	14.3

capital stock into computer capital stock and the stock of non-computer equipment.[11] The computer investment data include investments made for office use as well for use in

[11] A detailed description of the computation of the computer capital stock and the corresponding rental prices can be found in the Appendix A.

the production process, e.g., CNC (computer numerically controlled) equipment and CAD/CAM – systems.[12]

The average rates of depreciation for equipment capital in the NA are between 16 and 21 percent. Unfortunately there are no depreciation rates given for computer capital in the Swedish national accounts. Therefore I chose a depreciation rate very close to that used by the U.S. Bureau of Economic Analysis (1997) for office, computing and accounting equipment.[13] This rate equals 0.31 from 1978 forward and therefore a constant rate of depreciation of 1/3 for the estimation of computer equipment capital does not seem unreasonable in my case.

Due to the high depreciation rate for computers, the development of the computer capital stock shares is less dramatic than those of the investment shares as can be seen by comparing Table 2 and Table 3. This is especially true for the period of the early 1990`s. For the entire period though, the increase of the stock shares of computers are still quite remarkable. Except for three industries all industries have doubled, or more than doubled, their share in 1995 compared to 1985.

Table 3: Capital stock shares in Swedish manufacturing, 1985, 1990, and 1995 (% of total capital).

Industry	Computers			Equipment			Structures		
	1985	1990	1995	1985	1990	1995	1985	1990	1995
3100	2.8	5.5	9.5	48.6	48.8	48.3	48.6	45.7	42.2
3200	3.5	6.6	9.2	60.7	56.4	46.4	35.9	37.0	44.4
3300	3.0	17.2	14.7	47.1	33.2	37.7	49.9	49.6	47.6
3400	9.2	13.8	16.8	56.0	54.2	51.4	34.8	32.0	31.7
3500	4.0	7.0	15.6	61.4	60.4	52.4	34.6	32.6	32.0
3600	2.0	6.1	6.9	50.8	50.5	49.3	47.2	43.4	43.8
3700	2.2	9.9	11.2	56.6	50.6	52.0	41.2	39.4	36.8
3810	8.8	18.0	19.5	44.8	41.0	41.4	46.5	41.0	39.2
3820	13.4	17.8	24.5	33.5	42.0	38.2	53.1	40.1	37.2
3830	16.1	16.2	44.5	41.7	48.5	24.2	42.2	35.3	31.2
3840	19.7	21.0	44.2	30.0	36.0	20.4	50.4	43.0	35.4
3850	23.6	15.7	29.8	39.7	56.4	43.5	36.7	27.9	26.8
3860	1.9	3.1	12.2	42.3	34.9	27.5	55.8	62.0	60.4
3900	2.1	5.0	5.7	37.6	38.9	36.3	60.4	56.2	58.0
3000	7.9	13.4	21.4	49.2	47.8	42.1	42.9	38.9	36.4

[12] More details can be found in Gunnarson et al. (2001).

[13] For details on computer depreciation patterns, see Oliner (1994), Oliner and Sichel (1994), and Fraumeni (1997).

3.2. Human capital data

The human capital data will provide information about workers and their level of education. I will distinguish among four types of labor with the following education levels: (1) Elementary school (compulsory shorter than 9 years), (2) 9 years compulsory school, (4) Upper secondary school, and (4) Tertiary and postgraduate education. Skilled labor category is defined by education level 3 and 4.

Table 4: Employment shares in Swedish manufacturing, 1985, 1990, and 1994 (% out of total employment).

Level of education	Year		
	1985	1990	1994
Less than 9 years	30	22	18
9 years	19	17	16
Upper secondary	42	48	51
Tertiary	9	13	16
Sum	100	100	100

From Table 4 we see that the shares of those with upper secondary and tertiary schooling has increased over the years, while that of those with less than 9 years and 9 years of schooling has decreased over time.

3.3. Measures of the age of computer equipment capital and IT use

When incorporating embodied technical change in the model we will have to make use of the age of computer equipment capital. This is going to be measured in the following way:

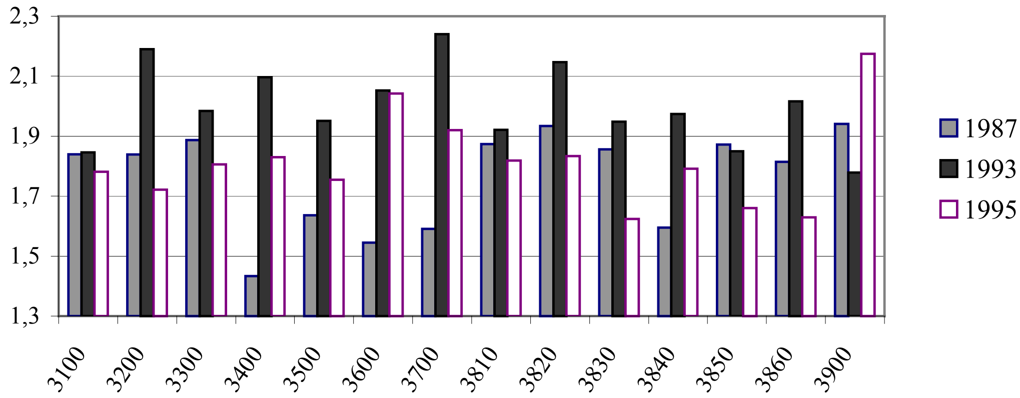
$$G_t = \frac{\sum_{v=0}^{t}(t-v)I_v}{K_t}$$

and

$$\sum_{v=0}^{t} I_v = K_t$$

where I_v is the net investment of computer equipment capital of vintage v. In the estimation of the age of computer equipment variable we have again assumed a depreciation rate of 1/3.

Figure 1: Average age of computer equipment capital, 1987, 1993, and 1995



As can be seen from Figure 1, there is both time series and cross-sectional variation in the average age of the computer equipment capital. Further, the average age of capital is lower in year 1987 compared to year 1993 in 11 out of 14 industries.

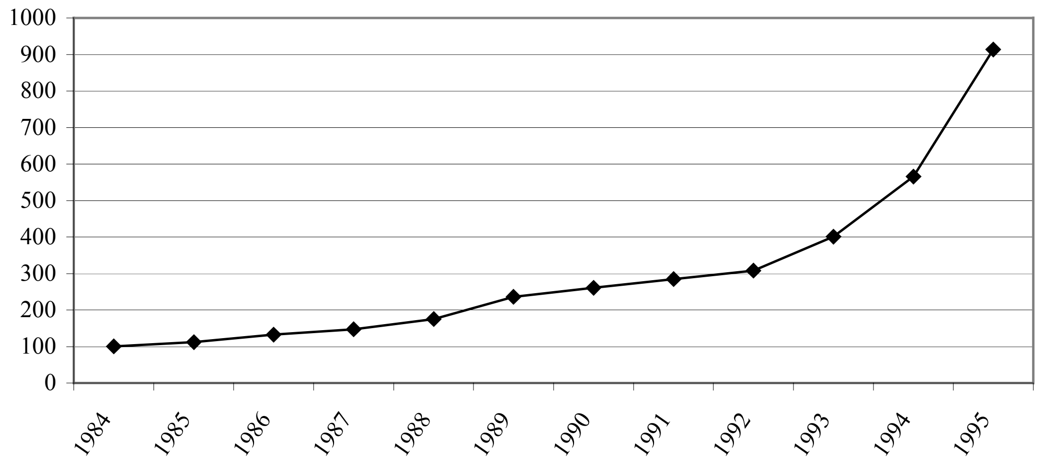
An explanation of this fact could be that there was "overinvestment " in computer capital in 1987 leading to the computer capital stock being too large. This fact might have lead firms to invest less in computers the following years, leading to a higher average age of computers (this is the case for year 1993). Eventually though, firms would have to increase their investments in computers which would cause a fall in the average age in computer capital. The latter is reflected in Figure 1 by the fact that in 1995 the average age of computers in almost all of the industries seems to be lower compared to that of 1993.

Our measure of disembodied technical change will be the total use of IT, TUIT, depicted in Figure 2. This measure includes computers & peripherals, and communication equipment. It is defined in the following way:

$$TUIT_t = PROD_{IT,t}^{N} + IMP_{IT,t}^{N} - EXP_{IT,t}^{N}$$

$PROD_{IT,t}^{N}$, $IMP_{IT,t}^{N}$, $EXP_{IT,t}^{N}$ denote the volumes of production, imports and exports of IT at the national level respectively. These are all in fixed (1991) prices and thus measure the volume development of IT. As can be seen from Figure 2 this measure has had a remarkable development over time. This is especially true after 1992. Between 1992 and 1995 the increase of TUIT was threefold.

Figure 2: Index of total use of IT in Sweden, 1984=100.



4. Set-up of the model

4.1. Technical change

The two views of technical change, namely that of embodied and disembodied, differ distinctively in their treatment of capital. In models of disembodied technical change the concept of capital is one in which investment goods of different generations (or "vintages") differ only by some fixed factor associated with wear, tear, and retirement. If we assume for simplicity that the loss of productive efficiency due to such wear and tear proceeds at a constant rate δ, then the amount of capital available at any point in time will be the weighted sum of the surviving vintages:

$$K_t = I_t + (1-\delta)I_{t-1} + ... + (1-\delta)^t I_0 \tag{1}$$

The δ weights convert each vintage of investment into new-machine equivalents, so that one unit five-year-old capital is equivalent in production to $(1-\delta)^5$ units of new capital. Thus the stock K_t can be interpreted as the number of new machine equivalents implied by the stream of past investment.

The treatment of capital is different when considering the embodied view of technical change. According to that view successive vintages of investment also embody differences in technical design. The technology is not the same across vintages, but is improving over vintages. This assumption captures the intuitive notion that technical progress in, say, computers is linked to improvements in the design of new machines and that a computer of vintage 1990 will tend to be more efficient at producing output, ceteris paribus, than a machine of vintage 1980, even if there is no physical loss of capacity. In this view, capital stock computed as per equation (1), that is under the assumption that design improvements can be ignored, will tend to understate the true productivity of the capital stock.

In order to incorporate improvements in the quality of capital in my model, I will make use of a so-called vintage model introduced by Solow (1959). According to this model effective capital, X_{Jt}, can be written in the following way when one assumes that advancing technology permits the quality of new machines to improve at the annual rate λ:[14]

$$X_{Jt} = \sum_{0}^{t} X_{K_{vt}} (1+\lambda)^{v} \tag{2}$$

X_J in the above equation is a quality-weighted number of machines with new machines given greater weight than old machines, reflecting the newer technology embodied in them. Here $X_{K_{vt}}$ is the amount of capital built in year v (of vintage v) that is still in use at time t, and λ represents the rate of embodied technical progress, i.e. the quality of new machines improves at λ percent a year. Nelson´s approximation formula of equation (2) is written in the following way[15]:

$$X_{Jt} = \mathrm{B}(1+\lambda)^{t} X_{K_t} (1+\lambda(G_0 - G_t)) \tag{3}$$

where $X_{K_{vt}}$ is gross capital stock at time t and G_t and G_0 its average age at times t and 0, respectively. The above simplification involves a single moment of the age distribution of capital and replaces an equation involving the full distribution of vintages.

In its continuous version, Nelson´s approximation formula can be written as:

$$X_{Jt} = \mathrm{B}' e^{\lambda t} X_{Kt} e^{-\lambda G_t} \tag{4}$$

where $B' \approx 1$. Taking the log of the above expression gives the following equation:

$$\ell n X_{Jt} = \ell n X_K + \lambda t - \lambda G_t \tag{5}$$

[14] In the analysis to follow for the rest of Section 4.1., I do not consider the rates of depreciation. Those will be taken into account though, when estimating the model.

[15] Nelson (1964) reports that his tests show that the approximation is very good.

Equation (5) will be used in order to incorporate the effects of embodied technical change of computer equipment capital into the production function. This equation has a very intuitive explanation. When the age distribution of the capital stock is not changing over time the rate of growth of the quality-adjusted capital stock is represented by the first two terms. The third term provides an adjustment when the age distribution is changing. A given age distribution determines a given difference between average quality and the quality of new capital. If each old machine were one year older, the difference between average quality and new quality would be larger by λ. More generally the change in the gap between average quality and the quality of new equipment is approximately equal to $-\lambda G_t$.

4.2 The production function

The translog production function, which is a second-order Taylor´s series approximation in logarithms to an arbitrary production function, [Christensen et al. (1973)] will be used in the analysis. This functional form will enable us to incorporate the effects of embodied technical change into our model by making use of equation (5). It is further a flexible functional form, because it does not place any a priori restrictions on substitution possibilities among the factors of production. It allows some factors of production to be substitutes and others to be complements.

I will consider eight inputs: four different categories of labor, L_1, L_2, L_3, L_4, computer equipment capital, X_C, non-computer equipment capital, X_M, structure capital, X_S, and intermediate goods, X_{IG}. All of them are treated as variable inputs.[16]

The production technology is represented by the following constant returns to scale translog production function:

$$\ell nQ = \ell n\alpha_0 + \alpha_T \ell nt + \sum \alpha_i \ell nX_i + \sum b_{it} \ell nX_i t + \tfrac{1}{2} \sum\sum b_{ij} \ell nX_i \ell nX_j \tag{6}$$

where $i, j = L_1, L_2, L_3, L_4, J, M, S, IG$, and $b_{ij} = b_{ji}$

[16] Treating all inputs as variable and, thus, optimally adjustable within one year greatly simplifies the formulation and estimation of the model. Admittedly, the assumption can be questioned with respect to structure capital but this is not an input of primary interest here.

Disembodied technical change is both (Hicks-) neutral and non-neutral in the above equation. Embodied technical change is incorporated in equation (6) through the computer equipment capital using a variant of equation (5), namely:

$$\ell n X_J = \lambda_C \left(t - G_t\right) + \ell n X_C \tag{7}$$

All input levels in (6) must be strictly positive, since otherwise $\ell n X_i$ or $\ell n X_i \to \infty$ and then output is not well defined.

Constant returns to scale imply the following restrictions:

$$\sum_j \alpha_j = 1,\ \sum_i b_{ij} = \sum_j b_{ji} = \sum_i \sum_j b_{ij} = 0 \text{ for } i, j = L_1, L_2, L_3, L_4, C, M, S, IG$$

The marginal products of the inputs are denoted as follows:

$$\frac{\partial Q}{\partial X_i} \equiv f_{X_i} = \frac{Q}{X_i}\left(\alpha_i + b_{it}t + b_{ii}\ell n X_i + \sum_j b_{ij}\ell n X_j + b_{iC}\lambda_C\left(t - G_t\right)\right)$$

Here, λ_C denotes the rate of embodied technical change of computers. The second order derivatives are given by:

$$f_{X_iX_i} = \frac{Q}{X_i^2}\left(b_{ii} + \left(\alpha_i + b_{it}t + \sum_j b_{ij}\ell n X_j + b_{iC}\lambda_C\left(t - G_t\right) - 1\right)\left(\alpha_i + b_{it}t + \sum_j b_{ij}\ell n X_j + b_{iC}\lambda_C\left(t - G_t\right) - 1\right)\right)$$

$$f_{X_iX_j} = \frac{Q}{X_iX_j}\left(b_{ij} + \left(\alpha_j + b_{jt}t + \sum_j b_{ij}\ell n X_j + b_{jC}\lambda_C\left(t - G_t\right) - 1\right)\left(\alpha_j + b_{jt}t + \sum_j b_{ij}\ell n X_j + b_{jC}\lambda_C\left(t - G_t\right) - 1\right)\right)$$

where $i, j = L_1, L_{21}, L_3, L_4, C, M, S, IG$

Further, $\partial Q / \partial X_i > 0$ must hold, since the economic region of a linearly homogeneous production function is characterized by strictly positive marginal productivities. With reference to (6) we have:

$$M_{X_i} = \frac{\partial \ell n Q}{\partial \ell n X_i} = \frac{\partial Q}{\partial X_i}\frac{X_i}{Q} > 0 \tag{8}$$

As can be seen above, all output elasticities must be positive. Assuming further that input and product markets are competitive, the necessary conditions for profit maximization are $\partial Q / \partial X_i = P_i$, where P_i is the factor price of the ith input relative to the price of output Q. Substituting this relationship into (8) we obtain:

$$M_{X_i} = \frac{\partial Q}{\partial X_i}\frac{X_i}{Q} = \frac{P_i X_i}{Q} > 0 \tag{9}$$

In other words, the logarithmic marginal product of the *i*th input is equal to its share in total revenue. And, by constant returns to scale, the revenue share of input *i* equals its share in total costs.

When defining the partial elasticity of substitution between inputs, the most common measure is the Allen partial elasticity of substitution (AES. This measure defines the percentage change in the ratio of the quantity of two factors to the percentage change in their price ratio when all other factors are allowed to adjust to their optimal levels. The AES is given by:

$$\sigma_{ij} = \left(\sum_i f_i X_i / X_i X_j \right) / \left(|\bar{F}_{ij}| / |\bar{F}| \right) \tag{10}$$

where $|\bar{F}|$ is the determinant of the bordered Hessian and $|\bar{F}_{ij}|$ is the cofactor of F_{ij} in $\left|\bar{F}\right|$. The assumption of linear homogeneity of (6) assures that $\sum_i f_i X_i \equiv Q$.

The AES is related to the standard cross-price elasticity in the following way:

$$\eta_{x_i p_j} \equiv \frac{\partial X_i}{\partial P_j} \frac{P_j}{X_i} = AES_{x_i p_j} * s_j \tag{11}$$

where s_j is the cost share of factor j.

Although the Allen partial elasticity of substitution has been used extensively, it does not always measure the effect of greatest interest [see for eg. Thompson and Taylor (1995)]. One such instance is when the cost share of the variable of interest is very small. This is the case with computer equipment that we focus on here. Relatively small variations in the cost share will then induce sizable variations in the estimates of the Allen elasticity of substitution. Furthermore, as Chambers (1988) pointed out, expression (11) is ”the most compelling argument for ignoring the Allen measure in applied analysis. The interesting measure is $\left[\eta_{x_i p_j}\right]$- why disguise it by dividing it by a cost share? This question becomes all the more pointed when the best reason for doing so is that it yields a measure that can only be interpreted intuitively in terms of $\left[\eta_{x_i p_j}\right]$”.

For the abovementioned reasons I will only report the own- and cross price elasticities. Positive (negative) numbers of the cross price elasticities will indicate that the two goods are substitutes (complements).

4.3 The regression model

The stochastic version of the factor shares of my model can be expressed as follows:

$$M_{X_i} = \alpha_i + b_{it}t + \sum_j b_{ij}\ell n X_i + b_{iC}\lambda_c(t - G_t) + u_i \tag{12}$$

where α_i is a set of industry specific dummies, and $i, j = L_1, L_2, L_3, L_4, C, M, S, IG$. The disturbances in (12) can be attributed to a variety of forces, like, e.g., input markets that are not perfectly competitive, measurement errors, or random deviations from profit maximization on the part of firms.

The assumption of linear homogeneity of (6), together with the symmetry restrictions, makes it possible to limit our attention to the estimation of $M_{L_1}, M_{L_2}, M_{L_3}, M_{L_4}, M_M$, M_C, and M_{IG} only. This is because we are ensured that the parameter estimates of any seven of the eight equations in (12) will identify exactly all parameters of the production function.

Since the cost shares in (12) sum to unity at each observation, the parameter estimates must satisfy the following zero column sum restrictions:

$$\sum_i \alpha_i = 1,\ \sum_i b_{it} = 0,\ \sum_i \sum_j b_{ij} = 0,\ \sum_i b_{iC}\lambda_C = 0 \tag{13}$$

Furthermore, we impose symmetry since the partial derivatives must be symmetric in inputs in order for (12) to be interpretable as the logarithmic marginal productivities of a well-defined production function. Imposing symmetry implies the following restriction:

$$b_{ij} = b_{ji},\ \forall i, j \tag{14}$$

A potential problem in the estimation of the model is the fact that the translog does not satisfy monotonicity and quasi-concavity globally. Monotonicity of the translog requires the logarithmic marginal products to be positive for all inputs. Further, quasi-concavity implies that the bordered Hessian is associated with a negative definite quadratic form. It practice there is no unanimity of the minimum percentage of observations that should verify quasiconcavity and monotonicity so as to call a production function regular. The finding of acceptable regions satisfying the previously alluded properties is an empirical question.[17]

[17] We will return to this question in the discussion of the results.

Next, we consider some estimation problems. First, we have to consider the fact that the estimates b_{ij} and b_{ji} (*i* not equal to *j*) for any two equations of the system (12) will not generally be equal. Thus we cannot estimate a set of unique parameters by applying least squares to each equation individually. The imposition of the symmetry and linear homogeneity restrictions allows us to estimate the following alternative equation:

$$M_{X_i} = \delta_i + b_{it}t + \sum_j b_{ij}\ell n\left(\frac{X_j}{X_S}\right) + b_{iC}\lambda_C(t - G_t) + u_i \tag{15}$$

where $i, j = L_1, L_2, L_3, L_4, C, M, IG$

We can combine the above equations into a single regression equation of the following form:

$$A = B \times C + U \tag{16}$$

where A is a 7x1 vector, B is a 7x49 matrix, C is a 49x1 vector, and U is a 7x1 vector.

The disturbances in (15) are most likely correlated, because, e.g., deviations from profit maximization should affect all input demands. To yield more efficient parameter estimates one can use Zellner´s two-stage estimation procedure. This approach has also a potential problem, namely that the estimates obtained depend on the choice of the left out equation. One estimation procedure that does not suffer of this potential problem is maximum likelihood. Kmenta and Gilbert (1968) showed that iterative Zellner (IZEF) and maximum likelihood estimates are identical. Thus, by applying the IZEF method to equation (15) we obtain estimates that are asymptotic maximum-likelihood estimates and are therefore independent of which share equations we use.

As mentioned earlier the simplest way to capture disembodied technical change without running the risk to introduce edogeneity problem is to use a time trend. In general, however, the regression results will not be invariant with respect to the specification of the time trend. Here we employ index of the total use of IT in Sweden (TUIT) to capture disembodied technical change. For a given industry, this index should be exogenous, like a time trend. An advantage over the trend is that this index allows us to make a comparison between disembodied and embodied technical change that is associated only with computers. Equation (12) becomes:

$$M_{X_i} = \alpha_i + b_{it}TUIT + \sum_j b_{ij}\ell n\left(\frac{X_j}{X_S}\right) + b_{iC}\lambda_C(t - G_t) + u_i \tag{17}$$

where $i, j = L_1, L_2, L_3, L_4, C, M, S, IG$

In the estimation, 3 variants of equation (17) will be estimated. In the first one I will assume that there is only disembodied technical change. The second regression will present the case where all technical change is taken to be embodied and in the third regression I will allow for both embodied and disembodied technical change. In this way we will be able to establish if the omission of either one of the types of technical change will affect our results.

Since the primary interest of the current paper is not to estimate the rate of embodied technical change it will be set a priori to 0.15. This value of λ is chosen after considering a grid of values within the estimated range of rates of embodied technical change found in the production-based camp of literature on the quantification of embodied technical change mentioned in the literature review. The grid search revealed that the chosen value of λ maximizes the log likelihood function.

In the estimation of the system of input cost shares I will also include the production function in equation (6). That is:

$$\ell nQ = \ell n\alpha_0 + \alpha_T \ell nt + \sum \alpha_i \ell nX_i + \sum b_{it}\ell nX_i t + \tfrac{1}{2}\sum\sum b_{ij}\ell nX_i \ell nX_j \tag{18}$$

There are two reasons for including equation (18) in the estimation. The first is that it will make possible to identify the parameter α_T, which measures an important aspect of disembodied technical change, namely Hicks- neutral technical progress. The other reason for including (18) is that it adds degrees of freedom in the estimation and, thereby, increases the precision of the parameter estimates.

5. Results

In Table 5 I have only included the estimated parameters of the production function that relates to the effects of technical change for the inputs labor, computer and non-computer equipment capital.[18] Regression (I) corresponds to the case, where there is only disembodied technical change, measured by the TUIT variable.

[18] The rest of the estimates are provided in Appendix B.

As can be seen from Table 5 the yearly rate of neutral technical change is about 2% and highly significant. This result is in line with the estimates found in the studies by Mellander (1999) and Gunnarsson et al. (2001).

The estimates of disembodied skill-biased technical change are given by the $b_{it}'s$. As can be seen they are all significantly different from zero for the first three categories of labor, indicating that disembodied technical change should not be ruled out when estimating the effects of technical change. Further, we find support for the skill-biased technical change hypothesis. Technical change reduces the demand for workers with less than 9 years of education, and for those with 9 years of education while it increases the demand for those with upper secondary and tertiary education. The effects of technical change are increasing in magnitude when going from the lowest to the highest level of education for the first three categories of labor.

The estimates concerning disembodied technical change with respect to computer and non-computer equipment capital are positive and negative, respectively. The negative sign on b_{Ct} indicates that disembodied technical change has affected the demand for computers in a negative way compared to a weighted average of the effects of disembodied technical change for all the other inputs. An explanation to this finding can perhaps be found in Morrison (1997). In her paper, she found that in the U.S. there was ”overinvestment” in IT during the latter half of the 1980s. The natural interpretation of the term ”overinvestment” here is in a relative sense, i.e. that IT investments were too large compared to outlays on other factors of production, notably human capital. Possibly, a similar development took place in Sweden, too. If so, the fact that the stock of computer capital was too large at the beginning of the period, may well have led to a relative decrease in the demand for computers, especially when combined with the fact that disembodied technical change increased the demand for non-computer equipment.

The case where we have only embodied technical change is investigated in regression (II). In this case the estimates are all significantly different from zero except for the case of labor with upper secondary education. The results indicate that it is important to consider embodied technical change when estimating the effects of technical change. However, in regression (II) we do not find support for the skill-biased technical change hypothesis. It seems to be the case that embodied technical change is increasing the demand for workers with less than 9 years, 9 years of education and those with upper secondary education while decreasing that of workers with tertiary education. Thus, the opposite of what is true for disembodied technical change seems to be the case here. There is in the case of embodied technical change a sort of anti skill-biased technical change. That is to say that, embodied technical change seems to be more favorable to a worker the lower his/her level of the education.

A possible explanation of the found bias towards low skills can perhaps be found in Goldin and Katz (1996). As argued by them, manufacturing should be envisioned as having two distinct stages, namely: (i) a machine-installation and machine-maintenance segment, and (ii) a production or assembly portion. Skilled workers and capital are always complements in the machine-maintenance segment of manufacturing, creating workable capital. This capital is then used by unskilled labor in the production or assembly portion of manufacturing, where the creation of the final product occurs. "How the adoption of a technology alters the relative demand for skilled workers will depend on whether the machine-maintenance demand for skilled labor is offset by the production-process demand for unskilled labor." [Goldin and Katz (1996)]. For the industries studied during this particular 10-year period, ranging from the mid-80´s to the mid 90´s, it seems that embodied technical change was such that the machine-installation and machine-maintenance aspect was dominated by the production or assembly dimension.

The argument found in Goldin, and Katz can perhaps be strengthened by the following argument. In manufacturing the major part of computer capital consists of industry robots and computer numerically controlled (CNC) equipment. Unlike the case with a PC, the technical change embodied in this kind of capital may well reduce the need for skilled workers, rather than enhancing its productive capacity. In other words, the technical change embodied in the non-computer equipment capital may have taken over much of the sophisticated thinking previously needed from skilled workers. This might be even true with respect to the machine-installation and machine-maintenance portion of production previously run mainly by skilled labor. So, running and in many instances installing and maintaining this kind of new capital may not require the high skills needed by previous machines, but may be performed by less skilled labor. In new computer-based equipment, installation and maintenance are often very simple and self-instructive due to the use of routines created by means of computers.[19]

Table 5: Estimated parameters of technical change for labor, equipment capital and non-equipment computer capital.

	Regression I	Regression II	Regression III
α_T	0.02102***	---	0.01949***
	(0.00448)		(0.00448)
b_{L_1t}	-0.00093*	---	-0.00133**
	(0.00056)		(0.00056)
b_{L_2t}	-0.00043*	---	-0.00064*
	(0.00024)		(0.00025)
b_{L_3t}	0.001537**	---	0.001064
	(0.00075)		(0.00076)
b_{L_4t}	0.000019	---	0.000296
	(0.00063)		(0.00063)
b_{Mt}	0.002716***	---	0.003048***
	(0.00047)		(0.00048)
b_{Ct}	-0.00049***	---	-0.00106***
	(0.00014)		(0.00015)
$b_{L_1C} * \lambda$	---	0.00091***	0.00069***
		(0.00014)	(0.00015)
$b_{L_2C} * \lambda$	---	0.00034***	0.00028***
		(0.00007)	(0.00007)
$b_{L_3C} * \lambda$	---	0.00016	0.00014
		(0.0002)	(0.0002)
$b_{L_4C} * \lambda$	---	-0.0008***	-0.0007***
		(0.00017)	(0.00017)
$b_{MC} * \lambda$	---	-0.00035***	-0.0006***
		(0.00012)	(0.00012)
$b_{CC} * \lambda$	---	0.00069***	0.00079***
		(0.00005)	(0.00005)

Notes:
a)The absolute value of the standard errors,are given in the parentheses.
b)*,**, and*** denote significantly different from 0 at the 10%, 5%, and 1% level.

When it comes to the demand for computer and non-computer equipment capital embodied technical change had a positive effect on the former and a negative one on the latter. This is natural; with technical change being embodied, firms have to buy new computers in order to reap the benefits of technical change. The resulting relative

[19] This argument points to the importance of extending the present analysis to the service sector. In services the distinction between maintenance and production is irrelevant implying that the effects of embodied technical change may be different.

increase in the demand for computers may well lead to a relative decrease in the demand for equipment capital.

In equation (III) I include both embodied and disembodied technical change. The results are fairly stable as can be seen from Table 5. In general one can say that both embodied and disembodied technical change can be estimated separately by regressions (I) and (II), respectively. The omission of either one of the types of technical change, or the inclusion of both in the model, does not seem to affect our results.

In order to be able to say something about the relative magnitude of the skill-biases, the elasticities for disembodied and embodied technical change are calculated according to the formulas:

$$\varepsilon_{M_i,TUIT} = \frac{\partial M_i}{\partial TUIT}\frac{TUIT}{M_i} \quad \text{and} \quad \varepsilon_{M_i,t-G} = \frac{\partial M_i}{\partial (t-G)}\frac{(t-G)}{M_i}$$

where $i = L_1, L_2, L_3, L_4$ represents labor with education levels 1, 2, 3, and 4. The elasticities show how a 1% change in technical change (disembodied or embodied) affects the demand for the four different categories of labor respectively.

Table 6 displays the elasticities for the skill-biases for regression (III). [20] In the first part of the table, three industries 3300= Saw, Mills and Wood Products, 3400= Pulp, Paper and Printing and Publishing, and 3500= Chemical, Plastic Products and Petroleum, are investigated for the year 1993. Together, these three industries make up about 1/3 of the manufacturing sector, in terms of employment. There are no considerable differences between the effects of technical change on the different types of labor across the industries considered. An exception to this statement is perhaps the effects of disembodied and embodied technical change on labor with education level 4. The latter effects are about 70% higher for industry 3300 than for 3400 and 3500. When comparing the effects of the two types of technical change across the different types of labor we observe that the effects of embodied technical change are larger (in absolute value) than those of disembodied in three of the labor categories, namely those with education levels 1, 2, and 4.

[20] Being functions of estimated parameters, the elasticities are random variables. As the mappings from the parameter estimates to the elasticities are highly non-linear it is very difficult to compute standard errors for the elasticities, however. One simplification that would reduce the computations substantially would be to disregard the fact that the M_i's are functions of the estimated parameters. This simplification can be justified on the ground that the estimated cost shares fit the data very well and so are very close to the actual shares.

The second part of the table concerns industry 3500 for the years 1987, 1990 and 1993. We see that all effects increase in absolute value over time. When it comes to disembodied technical change, its negative effects on workers with education level 1 and 2 increase over time, and so does its positive effects on workers with education level 3 and 4. This means that in this case, the skill-biased technical change hypothesis is strengthened over time. As for embodied technical change, its positive effects on workers with education level 1, 2, and 3, and the negative effect on workers with education 4 also increase over time. The anti skill-biased technical change is strengthened over time. Also it seems that for labor of type 1, and 2, the effects of embodied technical change became larger than those of disembodied (in absolute value) only in year 1993.

Table 6: The elasticities of the skill-biases for regression III.

Year 1993:

	L1		L2		L3		L4	
Industry:	Disemb.	Embod.	Dis.	Emb.	Dis.	Emb.	Dis.	Emb.
3300	-0.032	0.042	-0.024	0.026	0.019	0.006	0.024	-0.137
3400	-0.038	0.049	-0.020	0.021	0.012	0.004	0.007	-0.042
3500	-0.046	0.059	-0.025	0.028	0.014	0.005	0.006	-0.033

Industry 3500:

	L1		L2		L3		L4	
Year:	Disemb.	Embod.	Dis.	Emb.	Dis.	Emb.	Dis.	Emb.
1987	-0.013	0.009	-0.008	0.005	0.005	0.001	0.003	-0.008
1990	-0.025	0.030	-0.015	0.015	0.009	0.003	0.004	-0.022
1993	-0.046	0.059	-0.025	0.028	0.014	0.005	0.006	-0.033

To sum up Table 6, one can say that the effects of embodied technical change seem to be larger (in absolute value) in general than those of disembodied technical change for the three industries considered here. One should note however that for at least industry 3500 this is a pattern observed only in the last year for labor with the two lowest levels of education. We should also mention here that the results provided in Table 6 are contingent upon our maintained assumption that the rate of embodied technical change is constant and equal to 15 percent per year.[21]. Finally, it should also be mentioned that elasticities of the skill-biases are very small in magnitude and range approximately between –0.01and 0.06.

[21] As noted above in Section 4.4 this rate of embodied technical change is determined by a grid search. However, the fact that it is taken to be constant over time, will imply that small variations in this rate will have only minor effects on the results.

Table 7: Elasticities of demand for labor, equipment capital and non-equipment computer capital.

Price Elasticity	Year 1993			Industry 3500		
	Industry 3300	Industry3400	Industry 3500	1987	1990	1993
$\eta_{L_1L_1}$	-2.72	-3.71	-14.64	-3.95	-4.91	-14.64
$\eta_{L_1L_2}$	-0.10	0.96	4.15	0.71	1.18	4.15
$\eta_{L_1L_3}$	1.52	-2.59	12.71	3.69	3.39	12.71
$\eta_{L_1L_4}$	0.55	6.11	0.09	-0.32	0.52	0.09
η_{L_1M}	-2.67	1.63	-8.91	-2.04	-2.11	-8.91
η_{L_1C}	0.06	-1.28	-0.64	-0.13	-0.31	-0.64
$\eta_{L_2L_2}$	-3.60	-2.22	-4.54	-2.75	-2.91	-4.54
$\eta_{L_2L_1}$	-0.15	1.04	4.80	0.96	1.47	4.80
$\eta_{L_2L_3}$	3.39	2.04	-1.20	1.58	1.15	-1.20
$\eta_{L_2L_4}$	0.65	-1.59	-0.32	-0.32	-0.25	-0.32
η_{L_2M}	-1.82	-0.43	2.43	0.12	0.44	2.43
η_{L_2C}	-0.02	0.33	0.14	-0.01	0.03	0.14
$\eta_{L_3L_3}$	-3.00	-3.68	-7.46	-4.94	-3.23	-7.46
$\eta_{L_3L_1}$	1.14	-1.01	4.89	1.78	1.44	4.89
$\eta_{L_3L_2}$	1.67	0.74	-0.40	0.56	0.39	-0.40
$\eta_{L_3L_4}$	-1.13	5.13	0.31	0.83	-0.14	0.31
η_{L_3M}	4.18	2.91	3.65	1.74	0.98	3.65
η_{L_3C}	-0.06	-0.94	0.38	0.19	0.31	0.38
$\eta_{L_4L_4}$	-0.90	-24.16	-1.63	-2.61	-1.45	-1.63
$\eta_{L_4L_1}$	1.83	5.23	0.05	-0.29	0.39	0.05
$\eta_{L_4L_2}$	1.41	-1.26	-0.16	-0.21	-0.15	-0.16
$\eta_{L_4L_3}$	-4.94	11.25	0.46	1.57	-0.25	0.46
η_{L_4M}	5.32	-10.08	0.04	-0.41	0.51	0.04
η_{L_4C}	-0.53	4.51	-0.17	-0.20	-0.24	-0.17

Next, I investigate the relationship between the different types of inputs. In particular I report the elasticities of demand for labor, equipment capital and non-equipment capital in Table 7.[22] Again, first for year 1993 for industry 3300, 3400 and 3500 and then for industry 3500 for the years 1987, 1990, and 1993. What interests me the most are the relationships between skilled labor – defined by the two highest levels of education – and computer capital on the one hand, and skilled labor and non-computer equipment capital, on the other hand. These relationships differ somewhat as can be seen from Table 7.

[22] The requirement that the production function be quasi-convex in inputs implies, inter alia, that all own-price elasticities of demand should be negative. Unfortunately, this condition often turns out to be violated for a large part of the observations. In this study, more than 50% of the own-price elasticities were of the expected negative sign, which is quite good, given the very rich parametrical structure of the model. As only observations with negative own-price elasticities lend themselves to meaningful interpretations only such results have been chosen for Table 7.

For all industries there seems to be a relationship of substitutability between non-computer equipment capital and workers with education level 3. When it comes to workers with education level 4 their relationship with non-computer equipment capital seem in general to be substitutability. Workers with education level 3 (those with upper secondary schooling) are complements with computer equipment capital in industry 3300 and 3400 while substitutes in industry 3500. Complementarity exists also between computers and workers with tertiary education except for the case of industry 3400. For industry 3500, this relationship becomes weaker over time. Also, by comparing the relationship between computers and workers with the two highest levels of education we notice that the degree of complementarity increases the higher the education level.
In general one can say that computer equipment capital and skilled labor are complements, while non-computer equipment capital and skilled labor are substitutes. Thus, when speaking about the relation of capital and skilled labor it is important to distinguish between different kinds of capital.

6. Summary and concluding remarks

The objective of this study has been to analyze how the skill mix in labor demand is affected by technical changes, on the one hand, and by the relation between capital and labor, on the other hand. To this end, detailed production data for 14 industries in the Swedish manufacturing sector 1985-1995 have been used to simultaneously estimate a translog production function and input demand equations derived from that production function.

The major distinction between this and previous studies is the modeling of technical change: both embodied and disembodied technical changes are explicitly allowed for, within the same formal framework. Coupled with very detailed information on both labor and capital, this feature enables a thorough investigation of the relationship between two hypotheses concerning labor demand, namely Griliches (1969) hypothesis of capital-skill complementarity and the hypothesis of skill-biased technical change launched by Berman, Bound, and Griliches (1994). The investigation has been inspired by the claim of Krusell et al. (2000) that, in the US, skill-biased technical change and capital-skill complementarity have been essentially one and the same thing, a claim which has been extended to Swedish conditions by Lindquist (2001).

To summarize the results, the model's 8-input structure will here not be considered at full length. We will limit our attention to two labor and two categories of capital. The labor categories are those that can qualify as skilled labor, workers with upper secondary education and workers with tertiary education. The two types of capital that we will discuss are computers and (non-computer) equipment. Even with this aggregate input structure the numbers of permutations become large when each of the inputs are combined with the two kinds of technical change, embodied and disembodied. To further limit the discussion, we will not consider the results for all of the 14 industries but focus on three industries for which the estimated production function satisfies most of the regularity conditions that follow from economic theory. The industries are the sectors 3300 = Saw mills and wood products, 3400 = Pulp and paper & printing and publishing, and 3500 = Chemicals, plastics, and petroleum. Together, these industries make up about a third of the employment in Swedish manufacturing.

Regarding the relationships between labor and capital, we find that in two of these three industries (3300 and 3500) the most skilled workers (with tertiary education) are complements with computers, but substitutes with equipment. In industry 3400 the pattern is reversed, i.e. tertiary educated workers are substitutes with computers and complements with equipment. What we learn from this is that not even with respect to the most well-educated category of workers and the most sophisticated type of capital, i.e. computers, is there a clear pattern of capital-skill complementarity. Moreover, our results for equipment capital tell us that the notion of capital-skill complementarity has to be qualified with respect to the type of capital considered: only in one of the three industries (3400) are tertiary educated workers and equipment capital complements.

Stepping down the skill ladder, we see that the differences between the two categories of capital seem to be more important than the differences between the two kinds of skilled labor: qualitatively, the relations between workers with upper secondary education and computers and equipment, respectively, are very similar to what we find for workers with tertiary education.

Turning to the impacts of technical change on the demands for skilled workers our primary result is that both embodied and disembodied technical change matter. This implies that the common approach in empirical analyses, i.e. to assume that all technical change is either disembodied or embodied in nature may result in misleading inferences.

Our results also show that the relative importance of embodied and disembodied technical change differs between workers with upper secondary education and workers with tertiary education. With respect to the former category disembodied technical change is more important for determining labor demand while embodied technical change dominates with respect to tertiary educated workers.

At this stage, an intermediate conclusion can be reached with respect to the claim put forward by Krusell et al. (2000) and Lindquist (2001): if one wants to make the argument that capital-skill complementarity is the explanation for skill-biased technical change, one has to qualify this argument carefully. There are two reasons for this conclusion, which relate to the necessary conditions for this argument to be valid. First of all, one necessary condition for the argument to hold is that skilled labor and capital really are complements. At best, this property is satisfied with respect to the very highest skilled workers and the most sophisticated capital, i.e. computers. Secondly, the other necessary condition, i.e. that there is only embodied technical change, does not hold with respect to our data. But, possibly it can be taken to be satisfied approximately with respect to the demand for the most skilled workers. In short, the empirical analysis in this study indicates that the explanation suggested by Krusell et al. (2000) may possibly be valid for university educated labor working with computers, but that it cannot be extended to other workers and other types of capital.

The abovementioned conditions are necessary but not sufficient when making the argument that capital-skill complementarity is the explanation for skill-biased technical change. An inspection of the estimated skill-biases further emphasizes the need for more nuance characterization of the relation between capital, skilled labor and technical change. This is so because our results show that with respect to most skilled category of labor the dominant skill bias in technical change – the one associated with embodied technical change – is *negative*. This result is in sharp contrast with previous studies which invariably have found the bias in technical change to be positive for the most highly skilled workers. Presumably, this difference is due to the much more general modeling framework used in this paper. [23]

[23] Consistent with this conjecture is that the (smaller) skill bias associated with disembodied technical change is positive with respect to tertiary educated workers, like in studies only allowing for disembodied technical change, see, e.g., Mellander (1999) and Lindquist and Skjerpen (2000).

One explanation for the finding of a negative skill bias for tertiary educated workers can be found in Goldin, and Katz (1996). They claimed that manufacturing should be envisioned as having two distinct stages, namely: (i) a machine-installation and machine-maintenance segment, and (ii) a production or assembly portion. Skilled workers and capital are always complements in the machine-maintenance segment of manufacturing, creating workable capital. That capital is then used by unskilled labor in the production or assembly portion of manufacturing, where the creation of the final product occurs. Embodied technical change seems to have been of the type favoring the production or assembly portion segment of manufacturing over the machine-installation and machine-maintenance portion, for the industries and the period studied. The above argument is strengthened even further if one assumes that a part of the machine-installation and machine-maintenance segment of production in the industries studied is probably run more and more by less skilled labor. This is because as the sophistication of the machines increases, they can perform many complex tasks previously done by skilled labor, in this way replacing the need for the thinking man. It should be noted though that this latter argument may well be invalid within a different setting and another time frame. Also, it is certainly conceivable that there are instances in which the argument explaining the negative high-skill bias in embodied technical change could be made in the opposite direction. What is worth noticing however is that it seems to be the case that not all kind of technical change is good for skilled labor in my case. The results seem also very stable in terms of the different specifications of the model used. The omission of either one of the types of technical change, or the inclusion of both in the model does not seem to affect our results.

In judging the results one should keep in mind that the rate of embodied technical change of computers is kept constant in our model. As mentioned before, computers have seen a remarkable quality improvement embodied in them. Keeping in mind Moore´s law, which tell us that the number of transistors on a chip doubles every 18-24 months, a perhaps more realistic assumption in our model would be one which allowed for advances in the rate at which technology improves. The determination of an appropriate improvement rate could however represent a new modeling challenge.

It should also be remembered that our study is based on data ending quite a few years back. An extension of the data set might as well show that the results have changed during recent years. One should also remember that our results concern the manufacturing sector. A study of the service sector should perhaps provide us with a different outcome and would be an interesting extension to the study outlined in this paper.

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Appendix A: Data description

The Swedish National Accounts (SNA) provides data on the industry level on capital stocks, labor and intermediate goods.

Data for two types of capital are provided by the SNA, namely equipment and structures. In order to obtain the IT capital stock, information provided in the yearly publications of the so-called *Investment Surveys* provided by Statistics Sweden have been used. These are aggregated over industries and provide information about computer investment for both office use and applications in production. For the estimation of the IT capital stock, the total gross investments of equipment, in current prices, is broken-down into computer and non-computer equipment. To compute IT investments in fixed prices, we have constructed an IT price index by means of Statistics Sweden data on imports of computers and peripherals, in current and fixed prices.

The disaggregation of labor into educational categories has been made possible by utilizing individual data from the Swedish Employment Register (SRE). This is an exhaustive register containing information by industry about workers, i.a. education, wage income and demographic characteristics. The labor data are adjusted for the incidence of part-time work by using industry-level information on the distribution on working hours by means of the Swedish Labour Force Survey (SLFS) provided in the SNA. In this way we obtain an approximation of the number of employees, provided by means of the SRE, into full-time equivalents. The approximation is due to the fact that the LFS does not contain data on work hours by level of education and thus only the part of the variation in the work hour distributions across levels of education that stems from differences in gender compositions, is captured.

The rental price for capital (K) is calculated according to the following equation:

$$P_{K,t} = P_{I,t-1}\left[r_{t-1} + \delta_K \frac{\left(P_{I,t/t-1}\right)^e}{P_{I,t-1}} - \left(\frac{\left(P_{I,t/t-1}\right)^e - P_{I,t-1}}{P_{I,t-1}} \right) \right]$$

where $P_{K,t}$ is the rental price at the beginning of period t, $P_{I,\ t-1}$, is the gross investment price index for period t-1, r_{t-1} is a long-term interest rate measured at the very end of period t-1 and $(P_{I,\ t/t-1})^e$ is the expected value of the investment price index for period t, given information about this index up to (and including) period t-1.

The P_I and the δ_K are provided in the SNA. The interest rate is measured by means of the nominal rate on Swedish long-term industrial bonds and $(P_{I,\ t/t-1})^e$ is implemented by means of a univariate Kalman filter.

The capital rental price for computers is also calculated according to the equation above. For the gross investment price index, an import price index for computers, normalized to 1.0 in 1991, is used. Since this price index can only be computed for the period 1985-1995, the expected investment price index is calculated by means of a fitted linear trend to the log-differences of the computer import price index. This method is used instead of the Kalman filter used for the other types of capital.

For the construction of the price indexes for labor, we use information on payroll taxes for white-collar and blue-collar workers from *Näringslivets Ekonomifakta*, a private Swedish statistical agency. The price indexes for labor of category i, where i=1, 2, 3, 4, are given by the wage-bill for this category, including payroll taxes, divided by the labor input.

Appendix B: Continuation of table 1- the rest of the estimated parameters.

	Regression I	Regression II	Regression III
$b_{L_1L_1}$	0.050516***	0.062395***	0.053939***
$b_{L_1L_2}$	-0.02004***	-0.01329***	-0.01728***
$b_{L_1L_3}$	-0.02301***	-0.03071***	-0.0221***
$b_{L_1L_4}$	-0.01437***	-0.02169***	-0.01883***
b_{L_1M}	0.010405***	-0.00023	0.005741**
b_{L_1C}	0.003394***	0.006064***	0.004614***
b_{L_1IG}	0.005264	-0.00401	0.003781
$b_{L_2L_2}$	0.045634***	0.044825***	0.045782***
$b_{L_2L_3}$	-0.01055***	-0.01189***	-0.01133***
$b_{L_2L_4}$	-0.00084	-0.00482**	-0.00242
b_{L_2M}	0.001572	-0.00022	0.001071
b_{L_2C}	0.00034	0.002269***	0.001843***
b_{L_2IG}	-0.01925***	0.02265***	-0.01971***
$b_{L_3L_3}$	0.142825***	0.147999***	0.14177***
$b_{L_3L_4}$	-0.01027*	-0.01211**	-0.01194**
b_{L_3M}	-0.01467***	-0.01029***	-0.01296***
b_{L_3C}	-0.0009	0.001068	0.000948
b_{L_3IG}	-0.10286***	-0.09916***	-0.10193***
$b_{L_4L_4}$	0.064618***	0.071889***	0.068454***
b_{L_4M}	0.009447***	0.016248***	0.011877***
b_{L_4C}	-0.00254**	-0.00534***	-0.00459***
b_{L_4IG}	-0.03555***	-0.02827***	-0.03331***
b_{MM}	0.024595***	0.018895***	0.025717***
b_{MIG}	-0.03505***	-0.02992***	-0.03529***
b_{MC}	-0.00338***	-0.00232***	-0.00403***
b_{IGIG}	0.215033***	0.223172***	0.213377***
b_{IGC}	-0.00641***	-0.00792***	-0.00648***

Essay IV

Employment and Allocative Efficiency in the Swedish IT-sector

1. Introduction

In this study we are going to try to shed some light on employment in the Swedish IT-sector during the period of 1993-2002. In this ten-year period of study the IT-sector was transformed from one of the fastest growing sectors in the economy to one of the most troubled one's. The "IT-bubble" burst sometime by the end of the year 2000 with a massive stock market crash affecting most companies related to IT and media. [1] Some of the reasons offered for this development were a large number of bad profitability reports that caused a sudden drop in the share values of companies related to IT and media, an over-establishment in the IT-sector and lower demand for IT-solutions [VA 020527; Augustsson (2006)).

Employment in the IT-sector received a lot of attention in the media the years before and after the burst of the bubble There were reports that the IT-sector experienced a shortage of workers with university education or some other type of IT-knowledge certification during the period prior to 2000 (URA 2000:8). After the downturn there were indications that the labor market for IT-workers underwent some changes (URA 2001:1, CS 020104). The general picture was that the new conditions lead to a decrease in the need to recruit new IT-personnel and that many workers within the IT-sector were also laid-off. However, according to some reports, the general perception of the labor market of the whole IT-sector undergoing a major crisis was

[1] For an extensive survey about the crash, see Augustsson (2006).

exaggerated.[2] By the end of 2002 there were reports that the labor market for most IT-professions was heading from the previous shortage to balance and in some instances to an excess supply of workers (URA 2001:1, 2001:9, 2002:1).

It should be kept in mind at this point that the shortage of IT-competence is not a phenomenon that appeared for the first time at the end of the 1990s. As mentioned in Bibby (2000), "The problem of IT sills shortage was identified over 30 years ago when the embryonic computer industry realized that it had to educate its customers in how to use its products and that there were no teachers or trainers available with the skills to do so". The Business Tendency Survey conducted by the Swedish national institute of economic research (NIER)[3] indicates the existence of shortages of workers in industries of the Swedish IT-sector from as far back as 1993. The fact that many firms experienced a shortage of qualified workers in the IT-area was also mentioned in a Swedish Government Proposition in 1996 (1995/96:125, p.34). Moreover, the shortage of IT-personnel was international: by the end of 1998 there were altogether, 510,000 unfilled jobs in the technology sector in the EU member states plus Norway and Switzerland (Bibby, 2000)).[4]

In order to be able to understand why the shortage of workers in the IT-sector has been persistent over the near past one has to first try to understand why information technology has been so widespread over this period. The speed of improvement of information technology over the period of our study has been amazing [Aspray and Freeman (1999)]. These improvements have helped information technology to successfully penetrate into virtually every sector of society. Further, the decrease in computer prices has made it possible to embed the new technology in many kinds of organizational and physical systems and has made IT products commodity items (op. cit.). As the demand for information technology-based products and services grew there was a corresponding persistent increase in the demand for skilled workers, possessing knowledge about IT.

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[2] According to a report by TCO (2002) employment in the IT-sector increased during 2001 although in more modest proportions than previous years. Also according to this report the crisis considered mostly the manufacturing part of the IT-sector. There were also several union reports that the unemployment for IT-consultants was relatively low in the beginning of 2001 (SD 010405).

[3] For more details see the data section.

[4] In the US, a rapport prepared by the trade association, Information Technology Association of America (ITAA), claimed that there were about 191,000 unfilled information technology jobs in 1997 due to a shortage of qualified workers (CW 970226).

Markets characterized by rapid sustained growth can prevent the labor market from clearing for a substantial period of time, due to the dynamics of market adjustment [Arrow and Capron (1959)]. An increase in the demand for labor will create a shortage of labor, in the sense of an excess of demand over supply. This will eventually lead to an increase in wages until the shortage is eliminated. The increase in the wages will not be instantaneous; there will be a lag in the response of wages. to a shortage. This is due to the fact that it takes time for the firm to recognize that a shortage exists at the current salary level and to decide upon the need for higher salaries and the number of vacancies at such salaries. It will also take some time for employees to recognize the salary alternatives available and to act upon this information and try to equalize salaries with outside offers. In the case of a steadily increasing demand, as the market price approaches the equilibrium price, the latter steadily moves away from the former. There will be a persistent shortage which will be the result of the failure of the wages to adjust upward as rapidly and by as large amounts as required to eliminate the excess demand, given the supply. Arrow, Capron (op. cit.) used this reasoning to explain the shortage of engineers and scientists in the 1950s but the same logic can be used in order to explain the labor market for the rapid growing information technology sector.[5]

The abovementioned shortages of skilled workers in the IT-sector most probably lead to inefficient use of workers compared to the other sectors of the economy since even if the firm wants to use an input efficiently, the firm will appear to be inefficient if that input is unavailable.[6]

It is possible that shortage of workers may have force some employers to fill positions with workers who are less than adequate qualified or under-skilled leading to poorer performance [Aspray and Freeman (1999)]. [7] Haskel and Martin (1993) argue

[5] Arrow and Capron claimed that there were some conditions in the engineer-scientist market which implied that there existed dynamic shortage in this market. Some of those conditions were that there was a very rapid increase in demand, that the elasticity of the supply with respect to price changes was expected to be small due to the length of time it takes to train new personnel. Also the fact that the market was heterogeneous made it hard for workers to evaluate information about wage changes and act upon them. In my view, all of these arguments apply to the IT-sector as well.

[6] An indication of the existence of inefficiencies in the IT-sector is the fact that the changed conditions within this sector lead in some instances to employment within this sector facing decreases in their nominal wages. There were several reports in the media about firms in the It-sector that were forced to lower the wages of their workers. (CS 011102; CS 020308; CS 021017; CS 020918).

[7] In Sweden, the shortage of formally educated people in the late 1990s seems to have been so severe that in their effort to secure the “IT-knowledge” needed for their companies many firms recruited workers with incomplete degree, lowered their competence demands, offered high salaries (GP 990226; CS

that skill shortages can reduce productivity in two ways. First, they claim that shortages increase the hiring cost per skilled worker, leading firms to substitute to less productive unskilled workers. Second, they leave the firm less able to bargain higher levels of effort from their workers.

Further, the unfulfilled need to hire new workers may have forced many firms to practice an extensive "overtime work" policy with respect to workers that were available. There were several media stories in Swedish press about how workers in the IT-sector were forced to overtime work (SD 021103; DN 010731; V 010920).

In this study we are going to investigate if the existence of a shortage of skilled labor in the IT-sector has caused allocative inefficiencies with respect to the utilization of labor with different levels of education. Allocative inefficiency arises when the input mix is not consistent with cost minimization due to the marginal productivity values of the firm´s inputs not being equalized with the prevailing factor prices.

The empirical analysis is carried out using data from 19 industries from the Swedish economy for the years 1993-2002. The method used is a parametric shadow cost function approach [see eg. Toda (1976), that allows for allocative inefficiency. The shadow prices are modelled as functions of labor shortage indicators obtained from surveys conducted by the NIER. The existences of inefficiencies will be investigated over time and compared to the extent of inefficiencies outside the IT-sector.

According to my knowledge, this is the first study checking for allocative inefficiency with respect to employment in the IT-sector. It is important to investigate the existence of allocative inefficiencies not only in order to be able to understand the IT-sector and its future, but also in order to be able to draw inferences about the future of other sectors.

The next section contains a short literature review. A description of the data is given in section 3 and in section 4 the set-up of the model is described. Section 5 contains the results and in the last section we have some concluding remarks.

000503), and recruited workers without suitable education but with some form of experience (GP 990226; CS 000503).

2. Methodology: a brief review

One approach to deal with allocative efficiency is to use a shadow profit or shadow cost function.[8] With this approach, one estimate parameters that measure allocative inefficiency by scaling either input quantities or input prices, obtaining shadow input quantities and shadow input prices respectively. Lau and Yotopoulos (1971) developed the shadow profit framework. They estimated a Cobb-Douglas technology and computed relative efficiencies for large and small firms. The relative efficiency of the two groups of firms was examined by testing the coefficient of the group dummy variable. The shadow profit framework was developed by amongst others, Atkinson and Halvorsen (1980), and Lovell and Sickles (1983).[9]

Toda (1976) developed the shadow cost function approach. He estimated a cost function by making the assumption that the observed ratio of the capital rental price and the wage was in a fixed proportion to the ratio of marginal productivities. His cost function was estimated for eight non-competitive branches of the Soviet manufacturing industries for the period 1958-71. Another application of the shadow cost function approach is that of Atkinson and Halvorsen (1984). They estimated a flexible functional form (translog) and provided input-specific estimates of allocative inefficiency. Their sample consisted of 1970 data for 123 privately-owned electric utilities. In a subsequent paper, Atkinson and Halvorsen (1986) investigated the effects of ownership type and regulation on the shadow prices for inputs in the electric utility industry. Both publicly- and privately-owned electric utilities were found to be cost inefficient. Allocative inefficiency parameters were modelled as a function of dummy variables. Atkinson and Halvorsen (1990) obtained both input and firm-specific allocative inefficiency parameters. Atkinson and Cornwell (1994) used panel data to measure allocative and technical efficiency for the major U.S. airlines. The utilization of data in which the number of time periods is large relative to the number of firms allowed them to estimate consistently the allocative efficiency parameters by treating them as fixed effects.

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[8] Another way of dealing with non-optimizing behaviour is the so-called error-component approach, used by, amongst others, Lovell and Schmidt (1979) and Greene (1980). The general idea of this approach is the attachment of error components to the first-order conditions for cost minimization. These kinds of models have been criticized on the ground that estimation within this framework depends on arbitrary and restrictive functional form and distributional assumptions [see Bauer (1990)].

[9] Since we will not follow this approach we will not discuss it further.

Later, time-varying parameters of allocative inefficiency have been modelled. Oum and Zhang (1995) used a time trend in one specification of allocative inefficiency and a time dummy variable in another. Atkinson and Cornwell (1998) use both a set of seasonal dummies and time dummies in their specification of allocative efficiency.

3. Data

In our empirical analysis we use data on 19 industries in the Swedish economy for the years 1993-2002.[10] The definition of the IT-sector in this study is comprised by the industries included in Table 1. [11, 12] Industries 30 and 32 belong to the manufacturing sector while industry 72 is part of the private service sector.

Table 1: The industries comprising the IT-sector and their employment shares in 1997.

Industry code	Industry	Employment shares I*, in percent	Employment shares II**, in percent
30	Manufacture of office machinery and computers	0.6	4.3
32	Manufacture of medical, precision and optical instruments, watches and clocks	5.6	38.5
72	Computer and related activities	8.4	57.2
	Total IT-sector	14.6	100.0

Note: The classification system used here is SNI92.
* : Shares of employment in total employment considered in the empirical analysis.
** : Shares of employment in the IT industries considered.

To measure output, we use data on value added provided by Statistics Sweden.[13]
Data on the capital stocks and investments are also from Statistics Sweden. The capital is divided into three categories, namely machines, structures and the rest of the capital.

[10] The cross-sectional dimension is determined by the availability of our shortage indicator.
[11] For a complete list of the industries constituting the non IT-sector and their employment shares see Appendix A.
[12] The definition of the IT-sector is narrower than that defined by OECD (2002). Except for the industries used in this study the OECD definition of the IT-sector includes the following classes: 31.3 (Manufacture of insulated wire and cable), 33.1 (Manufacture of medical and surgical equipment and orthopedic appliances), 51.43 (wholesale of electrical household appliances and radio and television goods), 51.64 (Wholesale of office machinery and equipment), 51.65 (Wholesale of other machinery, for manufacturing, trade and shipping), 64.2 (Telecommunications), and 71.33 (Renting of office machinery and equipment, incl. computers). Unfortunately, it was not possible to include these industries in the analysis due to data limitations.
[13] For the IT-sector the use of value added instead of gross output should not be of great importance. The difference between the two is that gross output includes intermediate goods. Intermediate goods are most important for industrial production where the use of raw materials, consumption goods, etc. is extensive. For the IT-sector the use of intermediate goods is most probably less extensive.

The rental price of capital, $P_{K_{i,j,t}}$ is estimated using the following equation:[14]

$$P_{K_{i,j,t}} = P_{I_{i,j,t-1}}\left[r_{t-1} + \bar{\delta}_{ij}\frac{\left(P_{I_{i,j,t/t-1}}\right)^e}{P_{I_{i,j,t-1}}} - \frac{\left(P_{I_{i,j,t/t-1}}\right)^e - P_{I_{i,j,t-1}}}{P_{I_{i,j,t-1}}}\right]$$

$$= P_{I_{i,j,t-1}}\left[r_{t-1} + \bar{\delta}_{ij}\frac{\left(P_{I_{i,j,t/t-1}}\right)^e - P_{I_{i,j,t-1}}}{P_{I_{i,j,t-1}}} + \bar{\delta}_{ij} - \frac{\left(P_{I_{i,j,t/t-1}}\right)^e - P_{I_{i,j,t-1}}}{P_{I_{i,j,t-1}}}\right]$$

where $P_{I_{i,j,t-1}}$ is the gross investment price index for the period *t-1,* r_{t-1} is the long-term interest rate, and $\bar{\delta}_{i,j}$ is the average depreciation rate for capital of type *i* in industry *j*. $\left(P_{I_{i,j,t/t-1}}\right)^e$ represents the expected value of the investment price index for period t, given information up to period t-1 and the difference $\left(P_{I_{i,j,t/t-1}}\right)^e - P_{I_{i,j,t-1}}$ measures the expected windfall profit (loss) that accrues to the owner of the capital asset through an increase (decrease) in the renewal cost.

The average depreciation rate is calculated over the period 1993-2003 according to the following formula:

$$\bar{\delta}_{i,j} = 1 + \frac{I_{i,j,t-1}}{K_{i,j,t-1}} - \frac{K_{i,j,t}}{K_{i,j,t-1}}$$

where $I_{i,j,t-1}$ is the gross investments in capital of type *i* in industry *j* during the period *t-1*. $P_{I_{i,j,t}}$ is calculated from investment data in current and fixed prices. The interest rate r is the yearly average of the long-term Swedish government bonds. $\left(P_{I_{i,j,t/t-1}}\right)^e - P_{I_{i,j,t-1}} \Big/ P_{I_{i,j,t-1}}$ is approximated by $\ln\left(P_{i,j,t}\right) - \ln\left(P_{i,j,t-1}\right)$.

Labor is divided into three categories, L_1, L_2, L_3, where the subscript reflects the following levels of education respectively: (1) up to 9 year compulsory school, (2) upper secondary school, and (3) tertiary and postgraduate education.

Figure 1 shows employment in the IT-sector by level of education for the years 1993-2002. As can be seen from the figure employment for the least educated workers has been low and fairly stable for the period. During the period of study there are quite dramatic changes in the employment of individuals with tertiary and postgraduate

[14] The following rental price formula is adopted from Gunnarson and Mellander (1999).

education, however. For these groups, employment increases rapidly between 1993 and the year 2000. In 2001, the year after the burst of the IT-bubble there is a slight moderation in the increase, followed by a decrease in 2002.

Figure 1: Employment in the IT-sector, 1993-2002.

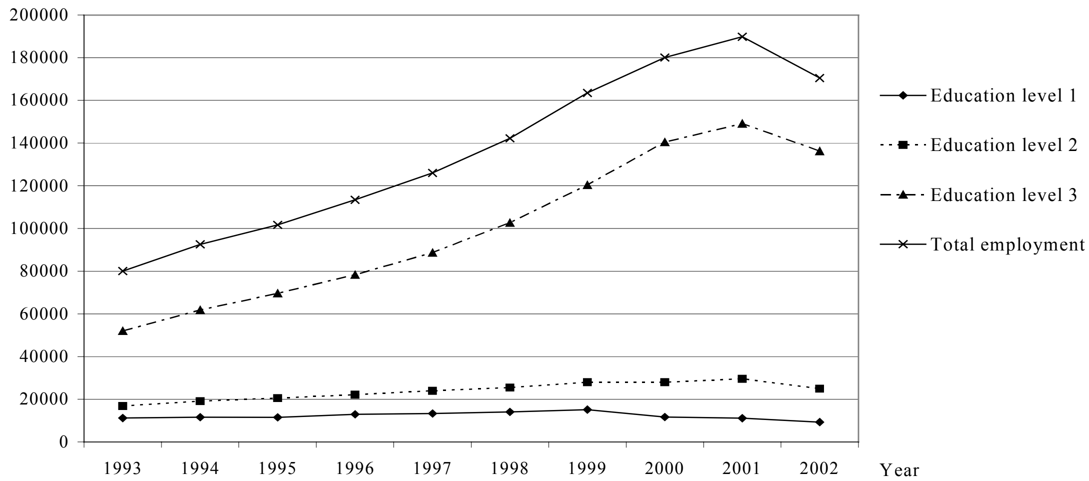


Figure 2 depicts the total employment in the non IT-sector over the same period. There are some noticeable differences compared to Figure 1 when it comes to employment with the two highest levels of education. First, employment in the non IT-sector of the most educated workers increases in more modest proportions during the period 1993-2000 compared to the IT-sector. Second, there is no marked downturn after the year 2000. Third, in the beginning of the period employment of those with tertiary and post graduate education (level 3) in the IT-sector is noticeably higher than employment of the two other education levels. This is not true for the non IT-sector where employment with education level 3 is lower than two other categories in 1993 and lower than employment with upper secondary education (level 2) up until 1996.

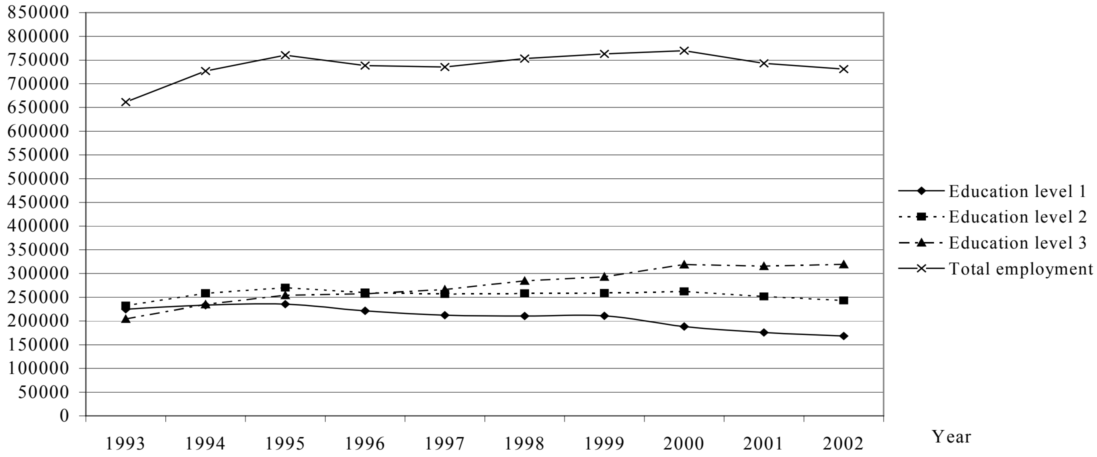
The price of labor, P_{L_i} is given by the following equation:

$$P_{L_i} = \frac{TW_i}{L_i} \qquad i = 1,2,3 \qquad (1)$$

where TW_i is the total wage-bill of category of labor *i*, while L_i denotes the number of workers. This specification is a measure of the total annual labor cost per worker. Unfortunately L_i does not take into account the number of hours worked and therefore does not capture overtime work. The wage-bill on the other hand, increases not only by increases in wages, but also by increases in overtime work.

The fact that our measure of the quantity of labour does not take into account hours worked is crucial to our analysis since as mentioned in the introduction overtime work is common in the IT-sector.

Figure 2: Employment in the non IT-sector, 1993-2002.



The development of the yearly average wage per employment in the industries comprising the IT-sector is depicted in Figure 3. Part a) of the figure provides the aggregate number, for all of the three industries. We see that after the year 2000 there are a relatively high increases in the wages for workers with upper secondary schooling and tertiary and postgraduate education, respectively. A possible explanation to these developments could be that as new conditions faced the IT-sector after the year 2000 many companies were forced to lay-off workers, most likely the least experienced who joined the personnel last. Those had probably relatively lower wages compared to the one´s remaining who were the most experienced and had been with the company a longer time thus having relatively high wages. These developments could have caused the average wage to increase in the years to follow.

Yearly wages by industry are provided in the lower part of Figure 3. As can be seen from these diagrams there is considerable variation across industries. For instance, wages are stagnating the last year in industry 30 while they in industry 72 are increasing after the year 2000. As noted in the previous paragraph, increases may reflect lay-offs of less experienced workers. Stagnating labor costs per employee, on the other hand, may be a consequence of a workforce that is unchanged in terms of individuals but where the average individual works less overtime.

Figure 3: Yearly average wage per employee in industries comprising the IT-sector and the industries comprising the IT-sector, 1993-2002.

Fig 3a) All industries comprising the IT-sector

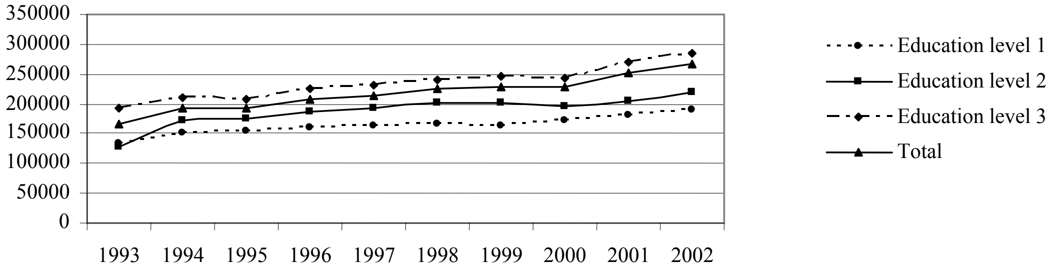


Fig 3b) Industry 30

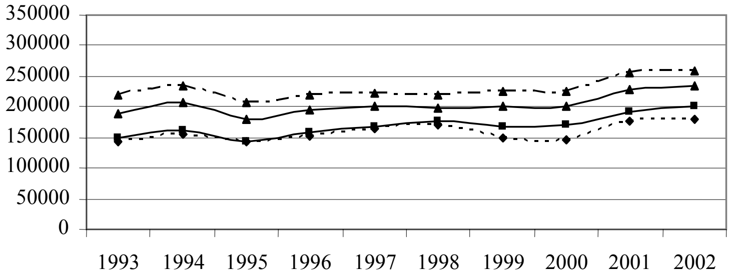


Fig 3c) Industry 32

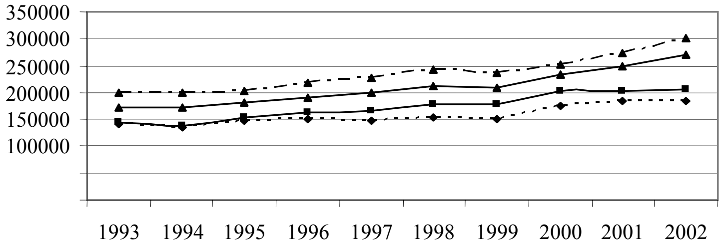
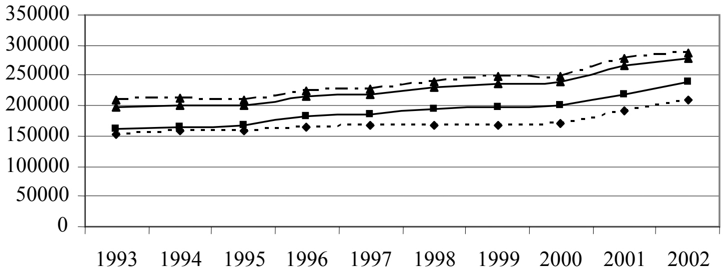


Fig 3d) Industry 72



Next, we turn to our measure of the shortage of workers, the shortage indicator (SI). [15] It is based on information obtained from the Business Tendency Survey conducted by the

[15] There are several ways in which a shortage of workers can be measured. As mentioned in [Aspray and Freeman (1999)] the most appropriate one is reliable up-to date vacancy data by occupation. General indicators of *potential* labor shortages are employment changes, unemployment rates and change in wage rates (op.cit). However, all of these measures provide only circumstantial evidence of a shortage, and for each indicator there are some reasons to question its validity (op.cit).

Swedish national institute of economic research (NIER). The question asked in the survey to the firms in industry 72 (Computer and related activities) is whether they experience a shortage of workers. For the rest of the industries the two questions were asked: whether the firm experiences a shortage of skilled workers on the one hand and a shortage of technical employees on the other hand. The answers are reported as the percentage of firms that answered that they had a shortage minus the percentage of firms that answered that they did not experience any shortage.[16,17] For the purpose of this study I have added the reported shortages of skilled workers and technical employees.[18]

The shortage indicators of the industries comprising the IT-sector are depicted in Figure 4. The general impression provided by the figure is that the industry as a whole seems to have suffered from a shortage of workers during most of our period of study. A common feature for all industries is that there was a sharp decrease in the reported shortage of workers after the year 2000. There has been large variation in the shortages for industries 30 (Manufacture of office machinery and computers) and 32 (Manufacture of medical, precision and optical instruments, watches and clocks). With respect to industry 72 (Computer and related activities), the shortage indicator has been more stable and consistently high prior to the year 2000.

The shortage indicators for the industries comprising the non IT-sector are shown in Table 2. As can be seen from this table there is great variation both over time and across industries. For some industries such as 20 (Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles) and 27 (Manufacture of basic metals) the indicator is fairly low and stable over time. Other industries such as 24 (Manufacture of chemicals and chemical products), 34 (Manufacture of motor vehicles, trailers and semitrailers) and 35 (Manufacture of other transport equipment) have experienced very substantial shortages in some years and a very small ones in other years.

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[16] The measure is seasonally adjusted and weighed by the size of the firms defined as the number of workers.

[17] A shortcoming of the shortage indicator is that it does not distinguish between workers with different skills, i.e., levels of education.

[18] An alternative specification would be one where the shortage indicators for skilled and technical workers where weighted, with weights being equal for the two categories of workers. This specification was tested in the empirical implementation of the model but did not affect the estimation of the allocative efficiency parameters.

Figure 4: Shortage indicator for the industries comprising the IT-sector, in percent, for the years 1993-2002.

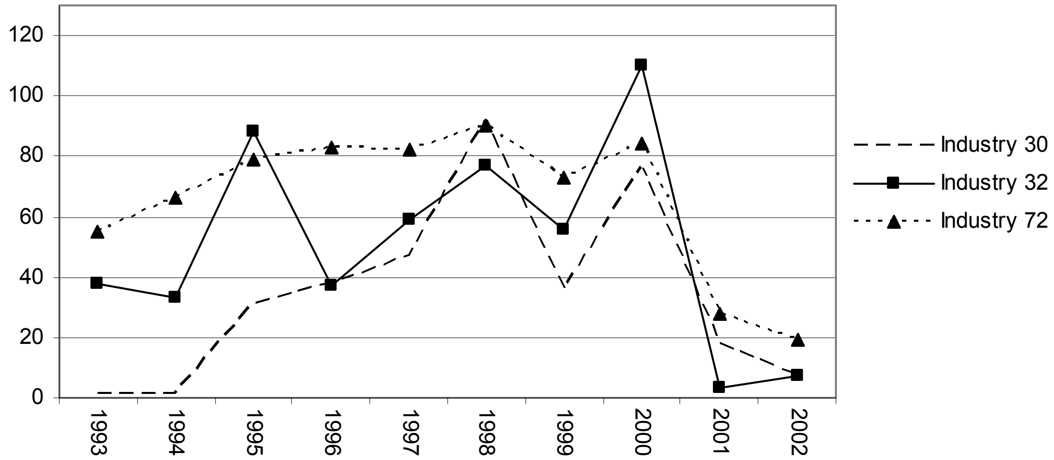


Table 2: Shortage indicator for the industries comprising the non IT-sector, in percent, for the years 1993-2002.

Year / Ind. Code	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
15[19]	2	6	12	10	11	12	27	38	28	34
17, 18, 19[20]	9	33	27	4	31	19	35	33	15	20
20	7	26	26	16	17	19	31	33	17	28
21	4	14	39	9	18	13	11	22	13	4
22	8	13	16	10	13	18	36	31	5	8
23	8	27	47	36	28	3	3	50	38	42
24	9	8	14	11	10	87	17	47	25	6
25	6	16	44	26	40	48	46	55	23	16
26	2	15	18	14	17	14	26	33	13	5
27	5	14	24	12	24	23	20	29	19	23
28	21	50	48	28	69	55	58	69	40	40
29	15	61	62	27	49	48	48	78	33	35
34	-2	87	68	0	56	40	84	72	30	12
35	9	7	57	64	69	72	57	67	49	24

[19] The available information concerns Manufacture of food, beverages and tobacco, which includes both industry 15 (Manufacture of food products and beverages) and 16 (Tobacco industry). Since industry 16 is a very small (in terms of employment shares) the shortage indicator concerning Manufacture of food, beverages and tobacco will be used as a proxy for industry 15 here.

[20] Information was only available for Manufacture of textile, clothing and leather products, which is the sum of industries 17(Manufacture of textiles), 18 (Manufacture of wearing apparel; dressing and dyeing of fur) and 19 (Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear).

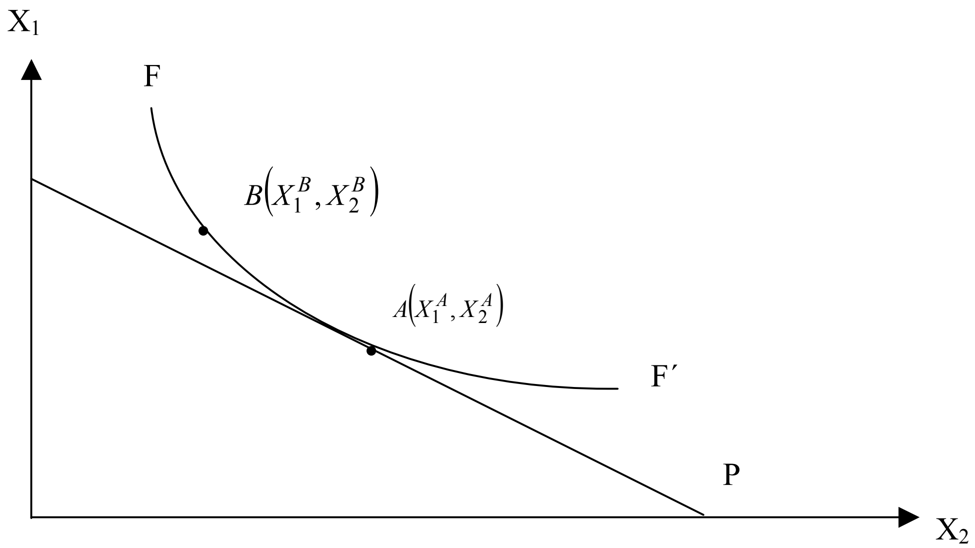
Comparing the shortage indicator in the IT- and non IT-sector we find that the average shortage indicator over the whole period of the non IT-sector is approximately 28 percent while that of the IT-sector is almost the twice as large, namely 51 percent. From this finding we can infer the existence of an extensive shortage of workers in the IT-sector compared to the non IT-sector in the period prior to 2000. After 2000 the shortage almost vanishes in the IT-sector while it seems that some industries in the non IT-sector still experience a shortage of workers.

4. The model

4.1 Conceptual framework

Figure 5 demonstrates how allocative inefficiency affects the production process.[21] Allocative *inefficiency* arises when the input mix is not consistent with cost minimization. The latter occurs when the marginal productivity values of the firm's are not equalized to the observed factor prices. Figure 5 illustrates the concept of allocative efficiency using a production process with two inputs, X_1, and X_2, and a single product Y.

Figure 5: The effect of efficiency improvements on production



[21] Technical inefficiency, the deviation of the firm's operation from the efficient production frontier, will not be considered in this paper.

The budget line P represents the price of input X_1 relative to X_2. The isoquant FF′ represents the production frontier. Allocative efficiency occurs if the inputs are combined so that their relative marginal products are equal to the corresponding relative prices. This is the case for point A but not for point B.

In the cost function framework, allocative efficiency can be measured in terms of production costs: a ratio of the minimum costs C, evaluated at point A, and the costs at the inefficient point, B, can be formed, i.e. $C\left(X_1^A, X_2^A\right) / C\left(X_1^B, X_2^B\right)$. This ratio will always belong to the half-open interval]0,1], where 1 represents efficiency. The model presented in the next section is going to be based on this conceptual framework.

4.2. Model specification

Allocative inefficiency will be modelled in terms of the parametric approach. A shadow cost function approach will be used. This approach allows for the existence of allocative inefficiency (inoptimal factor proportions) implying observed costs that are higher than minimum costs.

As Lau and Yotopoulos (1971) originally suggested, the shadow price for input i, P_i^S, can be approximated as follows:

$$P_i^S = k_i P_i \tag{2}$$

where P_i is the observed price for input *i*, and the price distortion[22], k_i, is input specific. The right-hand side of expression (2) can be interpreted as a first-order Taylor′s series expansion of an arbitrary shadow price function $g_i(P_i)$, which has the properties $\partial g_i(P_i)/\partial P_i \geq 0$, and $g_i(0) = 0$. A well-functioning input market would imply $k_i = 1$. In the case of $k_i \neq 1$ factor input markets are inefficient, causing excessive use of resources.

For analytical purposes, assume that firms minimize a well-defined but unobserved shadow cost function subject to unobserved shadow input prices:

$$C^S = C^S\left(Y, P^S\right) \tag{3}$$

[22] Throughout the paper the factor of proportionality between actual and shadow prices will be referred to as the price distortion.

Y is output and P^S is a vector of input-specific shadow prices. The shadow cost function is a generalization of the cost function which depend on shadow (internal to the firm) input prices rather than actual (market) input prices. By applying Shephard´s lemma the actual input demand functions can be derived from the shadow cost function:

$$\frac{\partial C^S}{\partial P_i^S} = X_i \tag{4}$$

The firm´s actual total cost then is

$$C^A = \sum_i P_i X_i = \sum_i P_i \frac{\partial C^S}{\partial k_i P_i} \tag{5}$$

$$i = L_1, L_2, L_3, K_M, K_S, K_R$$

where L_i denotes labor with educational level i = 1,2,3, K_M machinery capital, K_S structure capital and K_R other capital (the residual).To simplify the notation, we define the shadow cost share of input i as:

$$M_i^S \equiv \frac{k_i P_i X_i}{C^S} \tag{6}$$

From (6), we have

$$X_i = M_i^S C^S \left(k_i P_i\right)^{-1} \tag{7}$$

Substituting (7) in equation (5), actual total costs become:

$$C^A = C^S \sum_i k_i^{-1} M_i^S \qquad i = L_1, L_2, L_3, K_M, K_S, K_R \tag{8}$$

Taking logarithms

$$\ell n C^A = \ell n C^S + \ell n \sum_i k_i^{-1} M_i^S \tag{9}$$

As functional form for C^S, we employ the translog cost function, which provides a convenient second-order approximation to any arbitrary continuously twice-differentiable cost function [Christensen et al. (1973)].

$$\begin{aligned} \ell n C^S = {} & \alpha_0 + \alpha_Y \ell n Y + 1/2\, \alpha_{YY} \left(\ell n Y\right)^2 + b_t t + b_{tt} t^2 + \sum_i \alpha_{iY} \ell n Y \ell n\left(k_i P_i\right) \\ & + \sum_i \alpha_{it} t \ell n\left(k_i P_i\right) + \sum_i \alpha_i \ell n\left(k_i P_i\right) + 1/2 \sum_i \sum_j b_{ij} \ell n\left(k_i P_i\right) \ell n\left(k_j P_j\right) \end{aligned} \tag{10}$$

$$i, j = L_1, L_2, L_3, K_M, K_S, K_R$$

Imposing symmetry implies that $b_{ij} = b_{ji} \quad \forall i, j$. Linear homogeneity in input prices implies the following restrictions:

$$\sum_i \alpha_i = 1; \quad \sum_i b_{ij} = \sum_j b_{ij} = \sum_i \sum_j b_{ij} = 0 \quad \forall i, j; \quad \sum_i b_{it} = 0 \tag{11}$$

$$i, j = L_1, L_2, L_3, K_M, K_S, K_R$$

We also apply the following restrictions on the returns to scale properties of the technology:

$$\alpha_y = 1; \quad \alpha_{iY} = 0 \ \ \forall i \qquad\qquad i = L_1, L_2, L_3, K_M, K_S, K_R \tag{12}$$

The constraints (12), taken together with the fact that the parameter α_{yy} is unrestricted impy that the technology is homothetic, i.e. that there may be non-constant returns to scale but that these are independent of the input proportions.

Technical change is modeled in a very general way. Hicks-neutral technical change is allowed for, through the parameters b_t and b_{tt} in (10), as well as non-neutral technical change through the parameters b_{it}.

Using Shephard´s lemma we obtain the shadow cost shares,

$$M_i^S = \frac{\partial \ell n C^S}{\partial \ell n P_i^S} = \frac{k_o P_i}{C^S} \frac{\partial C^S}{\partial k_i P_i} = \frac{k_i P_i X_i}{C^S} = \alpha_i + \sum_j b_{ij} \ell n\left(k_j P_j\right) + b_{it} t \tag{13}$$

$$i, j = L_1, L_2, L_3, K_M, K_S, K_R$$

The actual cost function is obtained by substituting for $\ell n C^S$ from equation (10) and for M_i^S from equation (13) into equation (9). That is:

$$\begin{aligned} \ell n C^A &= \ell n C^S + \ell n k_i^{-1} M_i^S \\ &= \alpha_0 + \alpha_Y \ell n Y + 1/2\, \alpha_{YY} (\ell n Y)^2 + b_t t + b_{tt} t^2 + \sum_i b_{it} t \ell n(k_i P_i) \\ &\quad + \sum_i \alpha_i \ell n(k_i P_i) + 1/2 \sum_i \sum_j b_{ij} \ell n(k_i P_i) \ell n(k_j P_j) \\ &\quad + \ell n \left\{ \sum_i k_i^{-1} \left(\alpha_i + \sum_j b_{ij} \ell n(k_j P_j) + b_{it} t \right) \right\} \end{aligned} \tag{14}$$

$$i, j = L_1, L_2, L_3, K_M, K_S, K_R$$

The actual cost share of input i is

$$M_i^A = \frac{P_i X_i}{C^A} \tag{15}$$

Substituting for X_i and C^A using equations (7) and (8) respectively, we have

$$M_i^A = \frac{M_i^S k_i^{-1}}{\sum_i M_i^S k_i^{-1}} \tag{16}$$

Substituting for M_i^S from equation (13) we obtain

$$M_i^A = \frac{\left[\alpha_i + \sum_j b_{ij} \ell n\left(k_j P_j\right) + b_{it} t\right] k_i^{-1}}{\sum_i \left[\alpha_i + \sum_j b_{ij} \ell n\left(k_j P_j\right) + b_{it} t\right] k_i^{-1}} \tag{17}$$

Next we turn to the specification of the price distortions. Allocative efficiency is modelled in the following way:

$$k_i = \exp(\lambda_i SI_i)^{23} \tag{18}$$

Where, focusing on allocative efficiency with respect to semi-skilled and skilled-labor, we assume that k_i is equal to 1 for $i = L_1, K_M, K_S, K_R$.[24] The exponential specification of equation (18) guarantees the non-negative values of the price inefficiencies.

To estimate the equations given by (14) and (17), a classical additive disturbance term is added to each equation to be estimated, reflecting errors in shadow cost minimizing behaviour. The estimation is carried out using full information maximum likelihood (FIML) estimation. Since the cost shares sum to 1, we can drop one of the share equations.[25]

[23] The exponential formulation, previously used by, e.g., Kumbhakar and Bhattacharyya (1992) and Mellander (1993), guarantees that the price distortion parameter is negative. The exponent can be thought of as a first order MacLaurin series of a function *f* in *SI which has* the property that *f(0)=0,* implying allocative efficiency (*k=1)* for *SI* = 0.

[24] This restriction makes it possible to test for the absolute values of the k_i ´s

[25] The results are invariant to the equation dropped.

5. Results

In Table 2 we have included the estimates of the unrestricted and the restricted regression, the restricted regression corresponding to the case with no allocative inefficiencies.

Table 3: Regression results

Parameter	Restricted	Unrestricted	Parameter	Restricted	Unrestricted
b_{L1L1}	-0.0102	0.0083	b_{YY}	0.4182***	0.4235**
b_{L1L2}	0.0969*	0.0861*	b_t	-0.0427***	-0.0417***
b_{L1L3}	0.0055	-0.0095	b_{tt}	-0.0041	-0.0040
b_{L1M}	-0.0664	-0.0715	b_{L1t}	-0.0103***	-0.0105***
b_{L1r}	-0.0163	-0.0049	b_{L2t}	-0.0008	-0.0011
b_{L2L2}	0.0527	0.0584	b_{L3t}	0.0088***	0.0081***
b_{L2L3}	-0.0998***	-0.0838***	b_{Mt}	-0.0001	0.0010
b_{L2M}	0.0037	-0.0081	b_{Rt}	0.0043	0.0040
b_{L2R}	-0.0245	-0.0261			
b_{L3L3}	0.1565***	0.1921***	Allocative Efficiency parameters		
b_{L3M}	-0.0478	-0.0401			
b_{L3R}	-0.0013	-0.0300	λ_{L2NIT}		-0.0003
b_{MM}	0.1951***	0.2073**	λ_{L3NIT}		-0.0002
b_{MR}	-0.0081	-0.0131	λ_{L2IT}		0.0018
b_{RR}	0.0260	0.0469	λ_{L3IT}		-0.0098***

Note: *, **, *** denotes significantly different from 0 at the 10%, 5% and 1% level respectively.

In order to be able to choose between regression 1, the restricted model, and regression 2, the unrestricted model, we use a likelihood ratio test. The test statistic is computed as $-2\log\lambda$, where λ is the ratio of the maximum value of the likelihood function for the restricted equations to the maximum value of the likelihood function for the unrestricted equations. The test statistic is distributed asymptotically as chi-squared with degrees of freedom equal to the number of restrictions that we are testing. Since the test statistic is greater than the critical value of chi-square we conclude that the restricted model is not confirmed by our data.

A cost function is well-behaved if it is concave in input prices and if the input demand functions are strictly positive. The translog cost function does not satisfy these conditions globally and we must check for positivity and concavity at each observation. Positivity for the shadow cost function is satisfied if the fitted shadow cost shares are positive. We find that the positivity condition is satisfied for 99 percent of the observations. Concavity of the cost function is satisfied if the principal minors of the Hessian matrix, based on the parameter estimates, have the correct (alternating) signs. Concavity is verified for each industry for the years 1993, 1997 and 2002.

The low precision of some of the estimates presented in Table 3 is most probably a result of the rich parametrical structure of the model.

Next we consider the elasticities of demand, economies of scale, technical change and productivity growth for the unrestricted model[26] .

Regarding elasticities of demand, there is a substitute relationship between labor with education level 1 and labor with education levels 2 and 3. Labor with education levels 2 and 3 seem on the other hand to be complements. When it comes to the relationships between capital and labor, both pairwise complements and substitutes for are found, for labor at all levels of education. In accordance with the capital-skill complementarity hypothesis, complementarity relationships are more common, however, between capital and labor with the highest education.

Next we turn to returns to scale. We have increasing returns to scale on average for the years 1993-96, while they become almost constant on average for the period 1997-2000. For the years 2000 and 2001 the average economies of scale become slightly decreasing.[27]

The estimates of neutral technical change imply a downward shift in the cost function due to technical change – at about 4.5 percent per annum – but at a decreasing rate. Regarding non-neutral technical change, the estimates of the b_{it} indicates that technical change is skill-biased, favoring labor with tertiary and postgraduate education (level 3).

Productivity growth, which is a function of both technical change and returns to scale (cf. Appendix B), has on average been increasing steadily over time, at a rate around 4 percent per year for most of the years.

Next the price inefficiencies captured by the k_i of equation (18) are estimated. If $k_i = 1$, firms are price efficient in the use of input *i* given its market price. If $k_i > 1$,

[26] For the relevant formulas, cf. Appendix B.
[27] It should be noted here that output, *Y*, is normalized to unity in 1997 and that the estimated scale elasticity equals -0.4182×ln*y*. Accordingly, with output increasing over time, the estimated is quite natural.

firms under-utilize input *i* and if $k_i < 1$, firms over-use the input compared to a cost minimizing level given its market price.[28] Also an estimate of k_i less (greater) than one indicates that the marginal productivity of input *i* is less (more) than the effective prices firms face firms which implies that this input is being overpaid (underpaid). These sorts of non-optimal input use arise because the effective prices firms face are lower, in the case of $k_i > 1$, and higher in the case of $k_i < 1$ than the market prices. The further away the value of k_i is from unity, the higher the over (under)-utilization and overpayment (underpayment) of input *i*.

Further, it should be mentioned at this stage that in the empirical application we allow the λ_i in equation (18) to differ between the IT- and non IT-sector and also we we $SI_{L2} = SI_{L3}$ is valid. This specification allows us to estimate the yearly price distortions for the industries in the IT- and non IT-sector.

We first consider the inefficiencies for the industries in the non-IT sector, i.e. the. These are provided in Table 4.

Part a) of the table concerns labor with upper secondary schooling while part b) labor with tertiary and postgraduate education. In general we see from Table 4 that the values of $k_{is}{}'s$ do not differ over time, across industries and education levels. Most of them are approximately equal to one, meaning that there are no allocative inefficiencies. This implies that labor in the non IT-sector is efficiently allocated and paid according to the marginal productivity values. Thus, the shortages shown in Table 2 do not seem to have resulted in price distortions.

In Figure 6 the price inefficiencies of the IT-sector for labor with upper secondary schooling, K2, and labor with tertiary and postgraduate education, K3, are depicted. For labor with upper secondary schooling we see that the price inefficiencies are somewhat higher than one. Values above one imply under-utilization of this kind of labor, although the estimates do not differ significantly from one. This result does not reflect the fact that many firms within the IT-sector reportedly coped with the shortage of highly educated workers by lowering their competence demands and recruited workers

[28] These statements are contingent upon the maintained hypothesis of no allocative inefficiency prevailing in the use of the capital inputs and labor with the lowest level of education.

Table 4: The price distortions for the industries comprising the non IT-sector for:
a) Labor with upper secondary schooling

Ind. code \ Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
15	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
17	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99	1.00	0.99
18	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99	1.00	0.99
19	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99	1.00	0.99
20	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.99
21	1.00	1.00	0.99	1.00	0.99	1.00	1.00	0.99	1.00	1.00
22	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00	1.00
23	1.00	0.99	0.99	0.99	0.99	1.00	1.00	0.99	0.99	0.99
24	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	1.00
25	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00
26	1.00	1.00	0.99	1.00	0.99	1.00	0.99	0.99	1.00	1.00
27	1.00	1.00	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.99
28	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.99	0.99
29	1.00	0.98	0.98	0.99	0.99	0.99	0.99	0.98	0.99	0.99
34	1.00	0.97	0.98	1.00	0.98	0.99	0.98	0.98	0.99	1.00
35	1.00	1.00	0.98	0.98	0.98	0.98	0.98	0.98	0.99	0.99

b) Labor with tertiary and postgraduate education

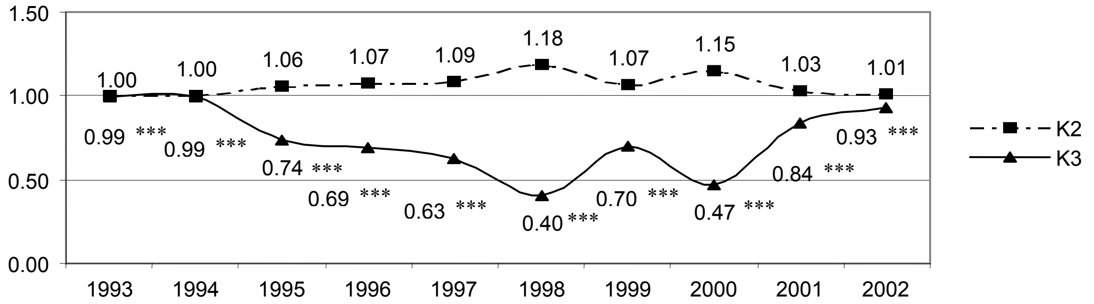
Ind. code \ Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
15	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
17	1.00	0.99	0.99	1.00	0.99	1.00	0.99	0.99	1.00	1.00
18	1.00	0.99	0.99	1.00	0.99	1.00	0.99	0.99	1.00	1.00
19	1.00	0.99	0.99	1.00	0.99	1.00	0.99	0.99	1.00	1.00
20	1.00	0.99	0.99	1.00	1.00	1.00	0.99	0.99	1.00	0.99
21	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	1.00	1.00
22	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.00
23	1.00	0.99	0.99	0.99	0.99	1.00	1.00	0.99	0.99	0.99
24	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.99	0.99	1.00
25	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.00
26	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00	1.00
27	1.00	1.00	0.99	1.00	0.99	0.99	1.00	0.99	1.00	0.99
28	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99
29	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99
34	1.00	0.98	0.98	1.00	0.99	0.99	0.98	0.98	0.99	1.00
35	1.00	1.00	0.99	0.98	0.98	0.98	0.99	0.98	0.99	0.99

Note: Values in part a) and b) are not significantly different than 1 at the 10%, 5% and 1% level.

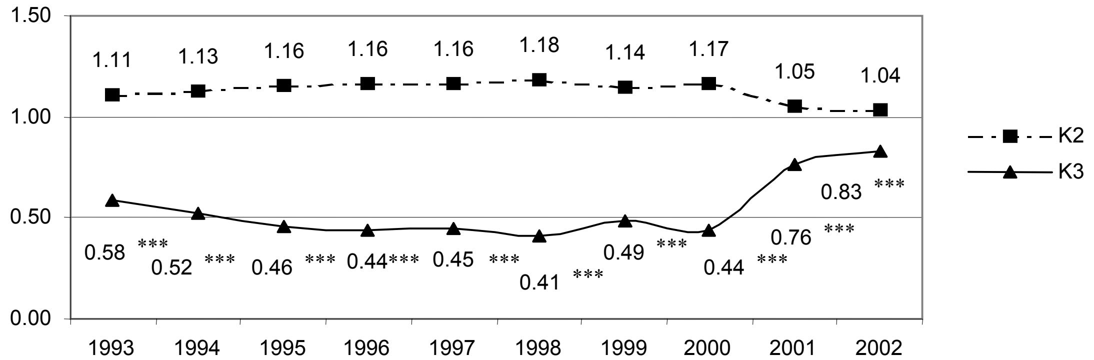
with incomplete degrees (GP 990226; CS 000503). If anything, it seems that the firms used too little labor of this kind.

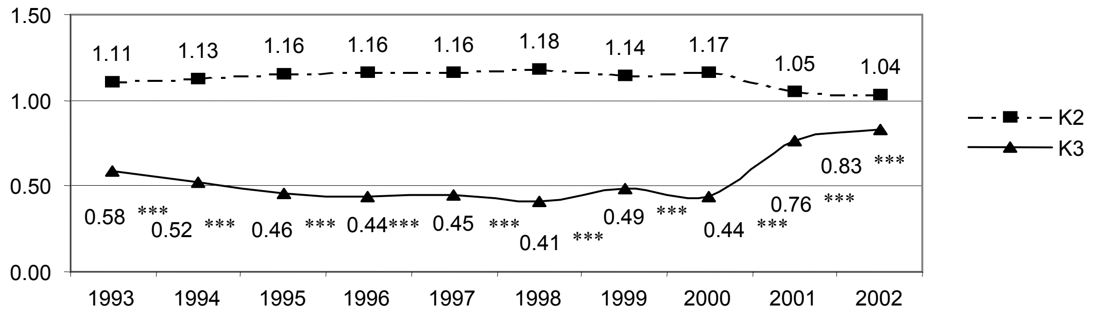
Figure 6: Estimated price inefficiencies for the IT-sector, 1993-2002.

Industry 30



Industry 32





Note: *, **, *** denotes significantly different from 1 at the 10%, 5% and 1% level respectively.

Labor with tertiary and postgraduate education seems to be over-utilized for most of the period and in all of the industries of Figure 4. In other words labor of this type is paid above its marginal productivity value.

The price distortions are highly volatile in industries 30 (Manufacture of office machinery and computers) and 32 (Manufacture of medical, precision and optical instruments, watches and clocks). When it comes to industry 72 (Computer and related activities) we notice that the allocative efficiency was stable and low for the whole period, prior to 2000. Also the price distortions in this industry are larger than those of the other two industries of the IT-sector in all but three years. On average the price distortions are approximately 0.74, 0.64 and 0.54 for industries 30, 32 and 72 respectively.

A common feature of all industries is that there was a sharp increase in allocative efficiency after the year 2000. This coincides with the time of the burst of the so-called ”IT-bubble” after which there was a reported decrease in the demand for workers in the IT-sector. The price distortions decreases and move closer to 1 for all industries at the end of the period indicating a decrease in over-utilization of labor with tertiary and postgraduate education. One explanation to this change could be that the burst of the bubble cause a sharp decrease in the amount of overtime worked.

Comparing Figure 4 and Figure 6 we notice that increases in the shortage indicator are mirrored by decreases in allocative inefficiency of labor with education level 3 and vice versa. The time pattern and the turning points of the shortage indicators and the price distortions of labor with tertiary and postgraduate education are very similar for each of the three IT industries.

Figure 6 can be interpreted as follows. Up to the year 2000 the industries in the IT-sector dealt with the shortage of workers by over –utilizing employees with tertiary and postgraduate education, through overtime work.[29] At the same time, they under-utilized workers with upper secondary schooling, by not trying to shift some less complicated tasks to these (formally) less skilled workers.[30] After the downturn around the year 2000, overtime among the most highly educated decreased, however, and, in parallel, the utilization of workers with upper secondary education increased. These changes lead to near efficient allocation of both worker categories.

While Figure 6 gives the impression that allocative inefficiency in the IT sector was quite substantial during the 1990s the ultimate evidence on the importance of the problem is how it affected total costs; cf the discussion in Section 4.1. Here we find

[29] As mentioned in the introduction, there are reports in the Swedish press that this was indeed the case in the case of some firms in the IT-sector.

[30] In other words, the claim of Haskel and Martin (1993) Aspray and Freeman (1999) that in the case of a shortage of workers companies may decide to settle for less qualified workers is not supported by our findings.

very small effects – the additional costs incurred by the inefficiency merely amount to a percent of the minimum total cost. What this result says is simply that allocative inefficiency with respect to (essentially) only one out of seven inputs will not matter very much for total costs.

6. Concluding remarks

This paper takes a closer look on the labour market of the IT-sector for the period 1993-2002. This includes the time before and after the burst of the IT-bubble. We have investigated if there are any allocative inefficiencies in the IT-sector caused by a shortage of workers within this sector. These inefficiencies have been investigated for two types of inputs and over time. The inputs considered are workers with upper secondary, tertiary and postgraduate education. We also compare if there are any particular differences in the efficient use of the abovementioned inputs in IT-sector and the non IT-sector. A panel data of 19 industries from the Swedish economy over the period from 1993 to 2002 is studied. In the empirical analysis we use a shadow translog cost function which allow us to explicitly take into account allocative inefficiency into our estimation. The deviation of shadow from actual input prices with respect to semi-skilled and skilled-labor, is assumed to be a function of a shortage indicator of workers obtained by Swedish national institute of economic research.

The results indicate that there are some important differences of the IT-sector compared to the non IT-sector when it comes to allocative inefficiency of labor input usage. The non IT-sector seem to efficiently utilize labor with upper secondary schooling, while there is over-utilization of this kind of labour in the IT-sector. When it comes to labor with tertiary education, the differences are more striking between the two sectors. While labor with tertiary and postgraduate education is well utilized in the non IT-sector there seem to be an extensive over-utilization of this kind of labor in all industries of the IT-sector. The only plausible for this finding is that labor of this kind was overused in terms of hours worked.[31]

The results suggest further that employment with tertiary and postgraduate education in the IT-sector seem to be overused and overpaid (compared to their

[31] Indications of the practice of overtime working in the IT-sector can be found in the Swedish press (SD 021103; DN 010731; V 010920).

marginal productivity value) during the whole period of study. The price distortions of labour with tertiary and postgraduate education are moving in exactly the opposite direction than the shortage indicator. This suggests that the shortage of the workers is causing inefficient use (over-utilization) of highly-skilled labor.

After the year 2000, when the burst of the so-called IT-bubble occurred and the reported shortage of workers in the IT-sector decreased, allocative efficiency improved significantly for all industries in the IT-sector. When it comes to the period prior to 2000, there is considerable variation over time of the allocative efficiency for industry 30 (Manufacture of office machinery and computers) and 32 (Manufacture of medical, precision and optical instruments, watches and clocks), while for industry 72 (Computer and related activities) allocative inefficiency has been consistently high. Also, over-utilization of labor with tertiary and postgraduate education seems to be larger on average in industry 72 compared to the other two industries of the IT-sector.

Figure 6 can be interpreted as follows. Up to the year 2000 the industries in the IT-sector dealt with the shortage of workers by over –utilizing employees with tertiary and postgraduate education, through overtime work.[32] At the same time, they under-utilized workers with upper secondary schooling, by not trying to shift some less complicated tasks to these (formally) less skilled workers.[33] After the downturn around the year 2000, overtime among the most highly educated decreased, however, and, in parallel, the utilization of workers with upper secondary education increased. These changes lead to near efficient allocation of both worker categories.

Overutilization of labor with tertiary and postgraduate education in the IT-sector should be viewed here as too much use of physical labor considering the reported shortage for this kind of labor. The only plausible explanation is that labour was over used in terms of overtime work considering our measure of the price of labour being the wage per employment.

When measuring impacts on cost of allocative inefficiency, we see that it is fairly similar both in the IT- and non IT-sector. The effects of the shortage on the cost have been negligible.

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[32] As mentioned in the introduction, there are reports in the Swedish press that this was indeed the case in the case of some firms in the IT-sector.

[33] Our findings do not support the claim of Haskel and Martin (1993) Aspray and Freeman (1999) that in the case of a shortage of workers companies may decide to settle for less qualified workers.

Concluding one could say that the shortage of workers seems mainly has affected workers with tertiary and postgraduate education in the IT-sector in the sense of having increased their overtime work. Firms seem have responded to the shortage of workers not by allowing parts of the work of the most educated to less educated workers (inferred by the under-utilization of labor with education level 2), but by encouraging overtime work of the most educated workers (inferred by the over-utilization of labour with education level 3). Further, firms in the IT-sector do not seem to have suffered in terms of higher costs induced by the inefficient use of workers with tertiary and postgraduate education.

This study is the only study as far as I know that investigates employment in the IT-sector. It is a step forward in understanding a little bit more about the IT-sector. Since this was, is and is going to be one of the fastest growing sectors in the economy, it deserves attention both when it comes to it's the past, present and future. The method in this paper is general and can also be used in order to investigate allocative inefficiencies in other sectors of the economy.

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Appendix A: The industries comprising the non IT-sector and their employment shares in total employment in 1997.

Ind. code	Industry	Employment shares I*, in percent
15	Manufacture of food products and beverages	10.3
17	Manufacture of textiles	1.2
18	Manufacture of wearing apparel; dressing and dyeing of fur	0.8
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	0.2
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles	5.2
21	Manufacture of pulp, paper and paper products	5.7
22	Publishing, printing and reproduction of recorded media	11.5
23	Manufacture of coke, refined petroleum products and nuclear fuel	0.2
24	Manufacture of chemicals and chemical products	4.3
25	Manufacture of rubber and plastic products	3.3
26	Manufacture of other non-metallic mineral products	2.5
27	Manufacture of basic metals	4.1
28	Manufacture of fabricated metal products, except machinery and equipment	11.8
29	Manufacture of machinery and equipment n.e.c.	12.9
34	Manufacture of motor vehicles, trailers and semitrailers	8.8
35	Manufacture of other transport equipment	2.6
	Total	85.4

Note: The classification system used here is SNI92.
* : Shares of employment in total employment of the industries used in the paper.

Appendix B: Elasticities, economies of scale, technical change and productivity growth

Following Berndt and Wood (1975) [34] the Allen partial elasticities of substitution can be calculated as follows:

$$\sigma_{ii} = \frac{b_{ii} + \left(M_i^S\right)^2 - M_i^S}{\left(M_i^S\right)^2}$$

[34] Berndt, E. R and D. O. Wood (1975): " Technology, Prices, and the Derived Demand for Energy", Review of Economics and Statistics, 57, pp. 259-68.

$$\sigma_{ij} = \frac{b_{ij} + M_i^S M_j^S}{M_i^S M_j^S} \qquad \text{for } i \neq j$$

where the M^S are the input cost shares. The price elasticities of demand $\left(E_{ij}\right)$ for factor the inputs follow directly from the elasticities of substitution:

$$E_{ij} = S_j \sigma_{ij}$$

If the value of the elasticity is positive (negative), then the inputs *i* and *j* are substitutes (complements).

Following Christensen et al. (1976), economies of scale are defined as:

$$SCE = 1 - \left(\frac{\partial \ln C}{\partial \ln Y} \right)$$

A positive (negative) value of *SCE* implies increasing (decreasing) returns to scale. If *SCE* is equal to zero, then we have constant returns to scale.

The measure of technical change (TECH) is given by:

$$TECH = -\left(\frac{\partial \ln C}{\partial t} \right)$$

A positive (negative) value of *TECH* implies technical progress (regression). If *TECH* is equal to zero, then we do not have any change in the technological level.

Following Caves et al. (1981) [35] the measure of Productivity growth (PGY) is calculated through multiplication of rate of technical change by the inverse of the elasticity of cost with respect to output:

$$PGY = -\frac{\left(\partial \ln C / \partial t\right)}{\left(\partial \ln C / \partial \ln Y\right)}$$

[35] Caves, D.W., L. R. Christensen, and J. A. Swanson (1981), "Productivity Growth, Scale Economies, and Capacity Utilization in U. S. Railroads, 1955-74", The American Economic Review, Vol. 71, No. 5.

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