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Is Human Capital the Key to the IT Productivity Paradox?

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Abstract

Unlike previous analyses, we consider (i) that IT may affect productivity growth both directly and indirectly, through human capital interactions, and (ii) possible externalities in the use of IT. Examining, hypothetically, the statistical consequences of erroneously disregarding (i) and (ii) we shed light on the small or negative growth effects found in early U.S. studies, as well as the positive impacts reported recently. Our empirical analysis uses a 14-industry panel for Swedish manufacturing 1986-95. We find that human capital develop-ments made the average effect of IT essentially zero in 1986 and steadily increasing thereafter, and, also, generated large differences in growth effects across industries.

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1 Introduction

The IT productivity paradox was formulated by the Nobel laureate Robert Solow 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: "You can see the computer age everywhere but in the productivity statistics." [Solow (1987)]

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 have accounted for the development of communications equipment. We have kept the term IT, however, mainly for historical reasons but also because we find the term ICT somewhat artificial. After all, what is the use of information if it isn't communicated?

In empirical studies, the paradox has received support in analyses based on early (pre–1990) data for the U.S. or Canada. Mostly, the results show either very small or insignificant effects of IT on productivity growth; see, e.g., Harris and Katz (1991) and Parsons, Gotlieb, and Denny (1993). Even more disturbing, some studies have reported significantly negative effects; cf. Loveman (1988) and Berndt and Morrison (1995). A number of explanations to these counter-intuitive results have been suggested. Some of the most common ones are: the time required before the IT investments manifest themselves in increased productivity has been underestimated, the magnitude of the investments have been overestimated, measurement problems on both the input side and the output side have concealed the productivity effects.[1]

However, a couple of recent studies, using data extending to the end of the 1990's, have found productivity–increasing effects of IT. Oliner and 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:

[1] These and other explanations will be discussed in more detail in Section 2.

Oliner and Sichel claim that IT accounted for about two–thirds of the acceleration in labor productivity between the first and second halves of the 1990's.

Bresnahan, Brynjolfsson and Hitt (1999) take a different approach to resolving the paradox. Taking up the idea of capital-skill complementarity discussed by Griliches (1969) and Lucas (1990), they argue that too much attention has been paid to investments in hardware and software and too little attention has been paid to the human capital structure in the firms investing in IT. 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. Furthermore: 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 go further in exploiting the human capital connection. We make use of the endogenous growth model discussed by Barro and Sala-i-Martin (1999), where an externality is created through a combination of learning–by–investing and knowledge spillovers. Moreover, endogenous growth theory also provides us with an important insight with respect to the *form* of the relationship between human capital and productivity growth. As shown by Romer (1990) and Benhabib and Spiegel (1994) this theory implies that the *levels* of human capital and physical capital like, e.g., computers should be important in explaining the *rate* of productivity growth.

The empirical analysis is based on data for 14 industries in the Swedish manufacturing sector, observed annually 1986–1995. 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. some five years earlier than in the U.S. Otherwise, the developments in the two countries seems to have been qualitatively similar. The present analysis should be of relevance for the U.S., too.

The next section contains a review of some attempts to explain the IT productivity paradox. In Section 3 we try to reconcile the different explanations by means of a stylized model. Section 4 describes the data that we have used in the empirical analysis. Our results are provided in Section 5 and conclusions in Section 6.

2 Literature review: attempts to explain the paradox

For brevity, we will here only provide a very condensed list of some explanations to the IT productivity paradox that have been suggested in the literature.[2]

- *Investments in IT have really been massive only very recently.* 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 recent study by Oliner and Sichel (2000).

  It should be noted, however, that this explanation has nothing to say about the significantly negative effects established by, e.g., Loveman (1988) and Berndt and Morrison (1995)

- *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.

[2] For a more extensive discussion see, e.g., Triplett (1999). Also, see Gordon (2000), 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.

This explanation also points to the importance of (positive) externalities. As the knowledge about (how to exploit) IT becomes more wide-spread, this will speed up the rate of diffusion. The resulting increase in the number of people with access to IT will raise the benefits of IT accruing to individual users, which will accelerate diffusion even more. The importance of this spiralling effect has been especially notable in the 1990's, with the rapidly expanding use of email and the Internet.

- *Mismeasurement of outputs.* According to this explanation, the use of IT has increased the quality of existing products and services and created lots of new goods, neither of which are (fully) captured in the official statistics. This has led to a downward bias in the measured output growth effects; see, e.g., Brynjolfsson (1993). Still, it is essential to point out, like Lee and Barua (1999) do, that efficiency related gains in the production of the "old" goods should still be accounted for by conventional output measures. Thus, while mismeasurement of output certainly is part of the puzzle it cannot resolve it entirely.

  A second problem, discussed by Siegel (1997), is that economic fluctuations can introduce a wedge between "true" and reported output prices, thereby creating a bias in measured output volume. This problem can be overcome by conditioning productivity growth upon a business cycle indicator.

- *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 as they included equipment not ordinarily associated with IT like, e.g., typewriters and accounting machinery.[3] On the other hand, the often noted difficulties to adjust for quality increases

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

in IT price indexes implies a tendency to underestimate the volumes of IT investments.[4] 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.

- *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 1980s. 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.

- *Lack of organizational changes accompanying the IT investments.* Brynjolfsson and Hitt (2000) argue that in order to exploit the full potential of IT the technology has to be combined with changes in work practices such as, decentralization and decreased vertical integration. They point out, however, that often such changes can only be captured by firm-level case studies.

- *No account has been taken of the complementarity between IT and skilled workers.* Although the capital-skill complementarity hypothesis was put forward already by Griliches (1969), the connection between IT and human capital has almost invariably been disregarded in assessments of the possible productivity-enhancing effects of IT.[5] Presumably, this is primarily due to lack of data.

[4] Much of the estimation of IT price indexes has focussed on price indexes for computers. For a hedonic approach to this problem, see Berndt, Griliches and Rappaport (1995).

Observing that IT involves non-computer equipment, too, Lee and Barua (1999) have turned upside down the argument about how the quality adjustment problem 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. While valid with respect to the early definitions of IT that involved many items whose IT character could be questioned and which, accordingly, did not undergo equally rapid quality increases as computers, this criticism is probably much less valid today.

[5] However, complementarity between IT and skilled workers has been documented in studies of

However, by matching two different data sets Bresnahan, Brynjolfsson and Hitt (1999) 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.[6]

From this brief review it is clear that there are rather diverse results on the connection between IT and growth, and that the explanations for these findings are rather diverse, too. Our next step is to formulate a simple model that can reconcile the different results and discriminate between some of the suggested explanations.

3 A stylized model

In order to highlight some of the features of previous analyses that we believe are of special importance, we consider a stylized version of the model that we use in our empirical analysis. One purpose with this section is to show that it is possible within a simple framework to account for the fact that the effects of IT on growth seem to have changed over time. Another, is to show that such a framework allows an assessment of the relative merits of some of the explanations suggested in Section 2.

Our stylized model captures three features:

1. The connection between IT and human capital; a link that has been largely ignored in most previous studies. By treating human capital as an omitted variable in the earlier studies, we can easily relate them to our analysis.

2. Measurement error in the IT variable(s).

labor demand, see, e.g. Berman, Bound and Griliches (1994) and Autor, Katz and Kreuger (1998).

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

3. Positive externalities in the use of IT, arising through learning–by–investing and knowledge spillovers [Barro and Sala–i–Martin (1999, Ch. 4)].

One issue that is not included in this list is the problem of output measurement error. From an analytical point of view, output measurement error is much less problematic than input measurement error. While the latter can be both negative and positive, the error in measured output can safely be assumed to imply that output is underestimated. Since IT should also have positive effect on output as recorded by conventional output measures [Lee and Barua (1999)], abstracting from output error should primarily affect the level of growth. The qualitative nature of the relation between IT and growth should not be much affected.

The second source of output measurement error considered in Section 2, economic fluctuations, will be taken care of in the econometric analysis. However, as the corresponding adjustment merely amounts to adding a control variable to the productivity growth equation it does not add anything to the discussion here.

Our simple model will be based on the maintained hypothesis that information technology and human capital are complements. As noted above, this notion has received empirical support in the study of Bresnahan et al. (1999).

Denote by g_t the rate of growth in total factor productivity in a given industry in period t and denote by IT and HC measures of information technology and human capital, respectively. We assume that the "true" model is

$$g_t = \beta_o + \beta_{1t} IT_{t-1} + \beta_2 \left(IT \times HC\right)_{t-1} + u_t \qquad \text{where} \qquad \beta_2 > 0. \tag{1}$$

The interpretation of the coefficient β_{1t} depends on the specification of the IT variable. In a traditional growth accounting context IT would measure the growth rate in information technology. In that case β_{1t} would be interpreted as a measure of the "excess return" to IT; see, e.g., Siegel (1997). The reason is that investments in IT, weighted by ex ante rental prices, are already included in the rate of productivity growth, g_t.

Here, we rather think of IT as a measure of the *level* of IT capital which, together with the *level* of human capital, HC, determines the rate of productivity growth, as suggested by Romer (1990). However, with respect to the theoretical results below, this distinction is immaterial. Those results only concern the sign of β_{1t} which under both specifications should be positive if IT enhances productivity growth.

The maintained hypothesis is manifested in the positivity constraint on the coefficient for the interaction variable, $(IT \times HC)$. As noted in point 1, this kind of variable has mostly been omitted in earlier analyses.

The IT and $IT \times HC$ variables are lagged one period. There are two reasons for this. First, IT and human capital are not likely to affect productivity growth momentarily, but with some delay. Secondly, by considering the previous period's IT and HC we do not have to account for the fact that the choice of inputs as well as the choice of output is really endogenous; lagging IT and HC we can treat them as predetermined variables.

The effect of the interaction term $IT \times HC$ is to make the influence of IT on productivity growth conditional on the sector's human capital:

$$\frac{\partial g_t}{\partial IT_{t-1}} = \beta_{1t} + \beta_2 HC_{t-1} \,. \tag{2}$$

Thus, the effect of IT on productivity growth is increasing in human capital. Note, however, that the total effect on growth need not be positive, provided that β_{1t} is negative and sufficiently large in magnitude.

For simplicity, the disturbances, the u_t, will here be assumed to be independently and identically distributed. In Section 5, we will take into consideration that the disturbances are likely to be differently distributed across industries.

To account for measurement error in the IT variable, we assume that observed IT, IT^*, is given by:

$$IT_t^* = IT_t + w_t \tag{3}$$

where w represents pure measurement error that is uncorrelated with IT i.e. $E(w) = 0$, $Var(w) = \sigma_w^2$, and $Cov(IT, w) = 0$. Moreover, we take w to be uncorrelated with HC and u, as well and, finally, u and w to be uncorrelated. We thus have:

$$Cov(w, IT) = Cov(w, IT \times HC) = Cov(u, w) = 0. \tag{4}$$

Next, note that there is a subindex t on the parameter β_1. This indicates that this is a time-varying parameter. The reason for this assumption is that we want to capture the externality in the use of IT; cf. point 3 above.[7] We thus specify β_{1t} as a function, ψ, of the total use of IT in the economy as a whole:

$$\beta_{1t} = \psi\left[\left(PROD_{IT}^N + IMP_{IT}^N - EXP_{IT}^N\right)_{t-1}\right], \qquad \psi' > 0 \tag{5}$$

where $PROD_{IT}^N$, IMP_{IT}^N, and EXP_{IT}^N denote production, imports, and exports of IT at the national level, respectively.[8] This specification is motivated by the fact that, by definition, an externality is an effect which is not accounted for by individual firms. Accordingly, it will not be reflected in the capital rental prices involved in the computation of the rate of productivity growth, g_t.[9] As ψ is an increasing function, an increase in the externality will lead to a larger effect on growth.

Referring to the model discussed by Barro and Sala–i–Martin (1999), it is natural to relate the specification (5) to the learning–by–investing mechanism. The other element of their model, knowledge spillovers, we can connect with the variable $IT \times HC$ and the corresponding coefficient β_2. Here, the natural association is networks:

[7] Siegel (1997) also tries to capture IT externalities, albeit in a more narrow sense, by means of a measure of the IT investments made by the industry's suppliers.

[8] The argument of the function ψ is introduced in lagged form, for the same reason that the variables IT and HC are entered lagged one period, cf. above.

[9] This, in turn, means that the rate of IT investment will be less than the socially optimal rate. As shown by Barro and Sala–i–Martin (1999, pp. 150–151) the social optimum can be obtained by the introduction of an investment tax credit. The income tax reduction in connection with the purchase of personal computers for private use that has been available in Sweden since 1998 can be seen as an investment tax credit of this kind.

employees working with computers tend to form networks with colleagues in other firms and organizations, networks which facilitate the transfer of knowledge in general and, in particular, information on how to exploit IT (more) efficiently.[10] Thus, while the primary function of the variable $IT \times HC$ is to account for complementarity between IT and human capital, the HC factor may also pick up an externality due to knowledge spillovers. We will not be able to distinguish the two empirically; both the complementarity effect and the externality should result in positive estimates of β_2.

Using the model described by equations (1) – (5), we will discuss three important issues that have arisen in connection with earlier studies, namely:

I. Can the negative effects of IT on productivity growth that have been found in several studies based on (U.S.) pre–1990 data be explained by measurement error in the IT variable, as argued by Lee and Barua (1999), or are they more likely to be indicative of a truly negative return to 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? Can this finding simply be explained by a late surge in IT investments, as argued by Oliner and Sichel (2000)?

III. If complementarity between IT and skilled labor is allowed for, like in Bresnahan et al. (1999), in order to trace indirect effects of IT that affect growth through human capital, what should one then expect will happen with the estimated direct effect?

To be able to discuss these points we need some preliminary results. To this end, assume that g_t is regressed on the observed IT variable, i.e. IT^*_{t-1}, using data for

[10] The literature on network economics is vast and rapidly growing. Possibly as a result of the mechanism that we are considering here, an updated bibliography can be found on the Internet at http://raven.stern.nyu.edu/networks/biblio_hframe.html

the pre–1990 period and post–1990 period, respectively. This implies that the measurement error in IT is ignored, that the variable $(IT \times HC)_{t-1}$ 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 value $\overline{\beta}_{1,\mathrm{I}}$ during the pre-1990 period and the value $\overline{\beta}_{1,\mathrm{II}}$ for the post-1990 period.

To derive the probability limits of the OLS estimates under the stated conditions, we apply a result from applied human capital theory, stated in Lam and Schoeni (1993).[11] This yields

$$\operatorname{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right) = \overline{\beta}_{1,\mathrm{K}} - \overline{\beta}_{1,\mathrm{K}} \cdot \lambda + \beta_2 \widehat{\theta}\,(1-\lambda)\,, \qquad \mathrm{K} = \mathrm{I},\ \mathrm{II} \tag{6}$$

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

$$\lambda \equiv \frac{Var\,(w)}{Var\,(IT^{*})}\,, \tag{7}$$

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

$$\widehat{\theta} = \frac{Cov\,(IT \times HC, IT)}{Var\,(IT)}\,, \qquad \widehat{\theta} > 0. \tag{8}$$

From (6) 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, caused by the leaving out 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 the sign of the true parameter $\overline{\beta}_{1,\mathrm{K}}$. If $\overline{\beta}_{1,\mathrm{K}}$ is positive then the MEB will be negative, and if $\overline{\beta}_{1,\mathrm{K}}$ is negative, the MEB will be positive.

Equation (6) can be used to derive upper and lower bounds on the probability limit of the OLS estimate $\widehat{\overline{\beta}}_{1,\mathrm{K}}$. These bounds are given in Table 1, for various assumptions about the true parameter and the magnitude of the omitted variable bias.

[11] Lam and Schoeni 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 schooling variable.

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

I)	$\overline{\beta}_{1,\mathrm{K}}>0$	$\Longrightarrow$	$0 \leq \mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right) \leq \overline{\beta}_{1,\mathrm{K}}+\beta_2\widehat{\theta}$
II)	$\overline{\beta}_{1,\mathrm{K}}<0$ and $\beta_2\widehat{\theta}>\lvert\overline{\beta}_{1,\mathrm{K}}\rvert$	$\Longrightarrow$	$0 \leq \mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right) \leq \overline{\beta}_{1,\mathrm{K}}+\beta_2\widehat{\theta}$
III)	$\overline{\beta}_{1,\mathrm{K}}<0$ and $\beta_2\widehat{\theta} < \lvert\overline{\beta}_{1,\mathrm{K}}\rvert$	$\Longrightarrow$	$\overline{\beta}_{1,\mathrm{K}}+\beta_2\widehat{\theta} \leq \mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right) \leq 0$

Note: The index K denotes either I or II

We can now consider issue I. As can be seen in Table 1, there is only one case in which the range of $\mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right)$ belongs to $\Re_{-}$, namely case iii). This case corresponds to a true effect that is negative *and* smaller than the lower bound of the range of $\mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right)$; this is so because the omitted variable bias, $\beta_2\widehat{\theta}$, is positive. There are thus good reasons to believe that a negative estimate corresponds to a truly negative effect. Furthermore, this conclusion is not changed if it is assumed that there is no measurement error. As the measurement error decreases, $\mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right)$ approaches the upper bound of the range but as this upper bound is equal to zero, the probability limit does not change sign even if the measurement error is eliminated altogether. We may thus conclude that while the presence of measurement error can affect the magnitude of the estimated effect it is very unlikely that it can explain its direction. Accordingly, from our viewpoint, Morrison's (1997) suggestion that overinvestment in IT during the latter part of the 1980's caused a negative effect on productivity growth seems more plausible than the claim made by Lee and Barua (1999) that the negative relation was due to measurement error.[12]

[12] Actually, Lee and Barua do not report any results showing the effects of measurement error only. They state that ".... the negative contribution of IT .... is attributable primarily to the choices of the IT deflator and modeling technique." However, they do not provide any assessment making it possible to disentangle the impacts of these two factors.

We next consider point II. While the findings by Oliner and Sichel (2000) do not provide an answer, simply because they do not attempt to explain the change in TFP growth, their results indicate what kind of explanation we should be looking for. Heavy investments in IT and falling prices of computers mean that IT is becoming available to an ever increasing number of people. This development will increase the positive externalities associated with the use of IT.

To formalize this point, we assume that $\overline{\beta}_{1,\mathrm{II}} > \overline{\beta}_{1,\mathrm{I}}$, in accordance with (5). However, this assumption is not sufficient to determine the sign of $\overline{\beta}_{1,\mathrm{II}}$. Above, we concluded that it is most likely that $\overline{\beta}_{1,\mathrm{I}} < 0$. Accordingly, $\overline{\beta}_{1,\mathrm{II}}$ may be negative, too, albeit closer to zero than $\overline{\beta}_{1,\mathrm{I}}$. Unfortunately, the sign of the estimate $\widehat{\overline{\beta}}_{1,\mathrm{II}}$ is not of much help here. In Table 1, we see that a positive range of $\mathrm{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{II}}\right)$ is consistent with both $\overline{\beta}_{1,\mathrm{II}} > 0$ and $\overline{\beta}_{1,\mathrm{II}} < 0$; cf cases i) and ii), respectively. However, going a step further enables us to discriminate between these two cases.

The additional step involves expanding the simple OLS regression by including a vector of proxy variables for the omitted variable, i.e. for $IT \times HC$. The point is that this will affect the estimate of $\overline{\beta}_{1,\mathrm{II}}$ differently, depending on the sign of the true parameter $\overline{\beta}_{1,\mathrm{II}}$. To demonstrate this, we provide the probability limit of the estimate of $\overline{\beta}_{1,\mathrm{K}}$ when proxy variables are included in the regression. We then compare this equation with equation (6) under different assumptions about the sign of $\overline{\beta}_{1,\mathrm{K}}$.

Denote the vector of proxy variables by $\mathbf{P}$, and the corresponding estimate of $\overline{\beta}_{1,\mathrm{K}}$ by $\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}$. Then

$$\begin{aligned}\mathrm{plim}\left(\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}\right) &= \overline{\beta}_{1,\mathrm{K}} - \overline{\beta}_{1,\mathrm{K}}\tfrac{\lambda}{1-R^2_{IT^*\times HC,\mathbf{P}}} \\ &\quad + \beta_2\widehat{\theta}\,(1-\lambda)\cdot\phi\left(IT^*, IT^*\times HC, \mathbf{P}\right)\end{aligned} \tag{9}$$

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 $0 < \phi(\cdot) < 1$.[13]

[13] Like (6), this equation draws on Lam and Schoeni (1993). They provide a similar expression to

Comparing (6) and (9) we note that

$$\overline{\beta}_{1,\mathrm{K}} > 0 \Longrightarrow \operatorname{plim}\left(\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}\right) < \operatorname{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right). \tag{10}$$

The implication (10) 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 $0 < \phi(\cdot) < 1$.

If, on the other hand, $\overline{\beta}_{1,\mathrm{K}} < 0$ then the effect of including proxy variables is ambiguous:

$$\overline{\beta}_{1,\mathrm{K}} < 0 \Longrightarrow \operatorname{plim}\left(\widehat{\overline{\beta}}_{(1,\mathrm{K})\cdot\mathbf{P}}\right) \lesseqgtr \operatorname{plim}\left(\widehat{\overline{\beta}}_{1,\mathrm{K}}\right). \tag{11}$$

The ambiguity is due to the fact that in this case the MEB and the OVB change in different directions. The MEB, which is positive in this case, increases, while the OVB, which is also positive, decreases.

Thus, by studying the effects of including proxy variables we should be able to gain additional information about the sign of the true parameter $\overline{\beta}_{1,\mathrm{II}}$. First, if the inclusion of proxies increases the estimate $\overline{\beta}_{1,\mathrm{II}}$ then, by (10), this is a strong indication that $\overline{\beta}_{1,\mathrm{II}}$ is *not* positive. On the other hand, if by adding proxies we decrease the estimate of $\overline{\beta}_{1,\mathrm{II}}$ then our results are consistent with $\overline{\beta}_{1,\mathrm{II}}$ being positive. To sum up: if $\overline{\beta}_{1,\mathrm{II}}$ is indeed positive, then the estimate of $\overline{\beta}_{1,\mathrm{II}}$ 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 last paragraph 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 negative, then

assess the effect on the estimated return to schooling when a proxy variable for the missing ability measure is included in the regression.

allowing for indirect effects through complementarity between IT and human capital will increase the estimated direct effect. If, on the other hand, the true direct effect is positive then allowing for indirect effects will decrease the estimated direct effect.

4 Data, variable definitions, and measurement issues

Our empirical analysis covers 14 industries in the Swedish manufacturing sector, observed annually over the period 1986–1995. Table 2 gives the industry codes. To indicate the relative size of the industries we also show their shares in manufacturing employment in the midpoint of the observation period. The data used are all part of the official statistics produced by Statistics Sweden and come from: the Swedish National Accounts (NA), the Employment Register (ER), the Labor Force Surveys (LFS), various Investment Surveys (IS) and the Trade Statistics (TS).The cross-sectional dimension of the data is a result of the most detailed break–down of IT investments provided in the IS. In the time series dimension, the starting point is given by the first year of the ER. The end point is the result of a change in the

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

Industry code	Industry	Employment share 1991, %
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 elswhere 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 classificarion system used here is very close to the ISIC codes.

industrial classification system, making it impossible to extend the time series beyond 1995.

4.1 The growth rate in total factor productivity

The variable whose variation we seek to explain is annual changes in rate of growth in total factor productivity (TFP). The TFP growth rate has been computed by means of a Törnqvist index.

Denoting the volume of gross output by Y and the volume of input i by X_i, the TFP growth rate g, is defined according to

$$g_t \equiv \Delta \ln TFP_t = \Delta \ln Y_t - \Delta \ln X_t \qquad t = 1986, ..., 1995 \tag{12}$$

where Δ is the difference operator, defined such that $\Delta \ \ln Z_t \equiv \ln Z_t - \ln Z_{t-1}$. To avoid excessive notation when we consider aggregate input in more detail, we suppress industry indexes here.

The growth in aggregate input is computed as a weighted average of the growth rates in individual inputs:

$$\Delta \ln X_t = \sum_{i=1}^{8} \overline{w}_{i,t} \Delta \ln X_{i,t},. \tag{13}$$

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

$$\overline{w}_{i,t} = \frac{1}{2}\left(\frac{P_{i,t-1}X_{i,t-1}}{\sum_{k=1}^{n} P_{k,t-1}X_{k,t-1}} + \frac{P_{i,t}X_{i,t}}{\sum_{k=1}^{n} P_{k,t}X_{k,t}} \right), \tag{14}$$

where P_i is price of input i.

The eight inputs considered are

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.

These variables will be described below.

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

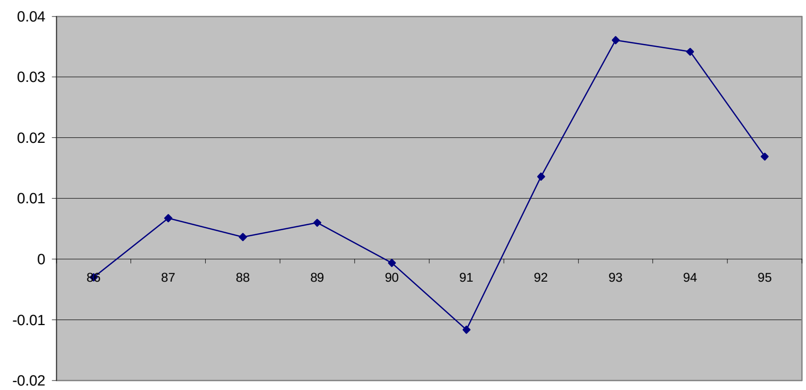


Figure 2: The industry variation around the weighted average. All observations lie within the bounds given by the dashed lines.

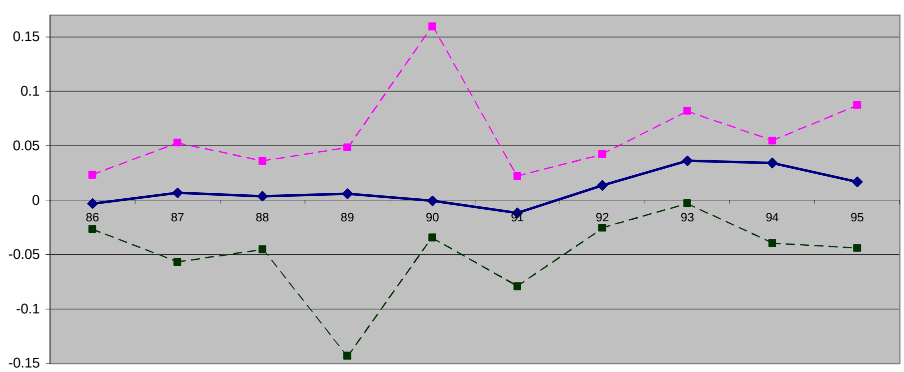


Figure 1 shows how the industry-weighted average of TFP growth rates has evolved over time. Each industry is weighted by its employment share, i.e. its share in $L = L_1 + L_2 + L_3 + L_4$. It can be seen that there is a marked difference between the latter half of the 1980s and the first half of the 1990's. While the period 1986–1990 showed low but stable growth, the growth rates during the 1991–1995 period were much higher, on average, and also more volatile. Figure 2 shows, however, that the variation around the weighted averages is smaller in the 1991–1995 period than during 1986–1990. It thus seems like the higher average growth rates in the first half of the 1990s correspond to a general tendency, rather than just being the result of high growth rates in some large industries.

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. This is true – during the years 1992–1994 Sweden went through the deepest trough since the depression in the 1930s and the restructuring that took place in its wake should definitely account for part of the high productivity growth rates. We will, however, control for the business cycle; cf. Section 4.5.

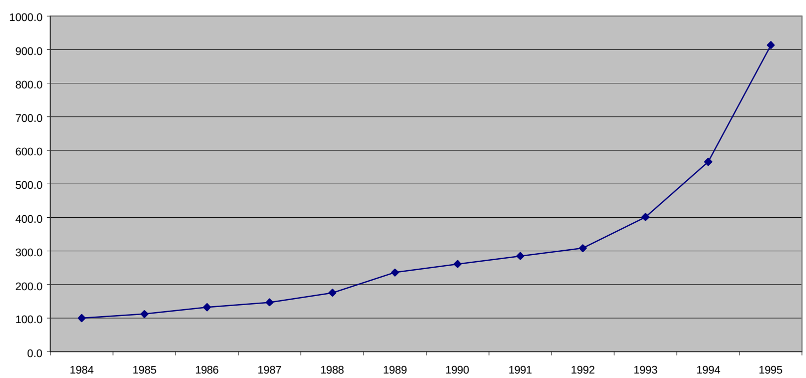
4.2 Measures of IT equipment and IT use

Following, e.g., Berndt and Morrison (1995), we use the share of computers in the total capital stock as our measure of IT equipment. In so doing, we also account for the point raised by Oliner and Sichel (2000) that the effects of the IT investments are likely to depend on the fraction that these investments make up of total investments. To avoid simultaneity bias due to the endogeneity of investments (cf. the discussion in Section 3) we relate the computer capital stock share in year $t-1$ to productivity growth in year t, i.e. we relate $(K_C/K)_{t-1}$ to g_t, where the subindex C denotes computers.

A more detailed discussion of what is covered by computer investments and how the share of computers in the total capital stock has evolved over time is given in the next subsection.

The index of the total use of IT, $TUIT$, discussed in connection with (5), includes both computers & peripherals, and communication equipment. The data on production, imports, and exports are all in fixed (1991) prices and thus measure the volume development of IT. The time path of the $TUIT$ index is shown in Figure 3.

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



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.

In the regressions we also include $TUIT$ with a one year lag, again to avoid endogeneity problems.[14]

4.3 Capital stocks

The capital stocks have been constructed by means of the national accounts (NA) and the investment surveys (IS) conducted by Statistics Sweden. The NA provides capital stocks on equipment and structures, computed according to the Perpetual Inventory method. By means of data on computer investments from the IS we have

[14]This means that the dramatic increase in the index between 1994 and 1995 will not affect the estimated parameters.

broken down the equipment capital stock into K_C, the computer capital stock, and K_M, the stock of non-computer equipment.[15]

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. For the manufacturing sector as a whole, the investments for use in the production process were 3–4 times as large as those for office use, in the late 1980s and early 1990s.

Table 3: Gross investment shares in Swedish manufacturing

Industry	Computers			Equipment			Structures		
	1984	1989	1993	1984	1989	1993	1984	1989	1993
3100	3.0	7.8	14.9	66.2	65.7	56.6	30.9	26.5	28.5
3200	3.4	8.3	16.5	81.8	57.1	52.5	14.8	34.6	31.1
3300	2.7	32.2	24.1	73.2	40.9	53.9	24.1	26.8	22.0
3400	3.5	10.3	23.3	79.4	72.9	62.4	17.1	16.8	14.3
3500	2.2	9.5	26.6	79.3	70.8	48.1	18.5	19.7	25.3
3600	1.7	11.0	17.4	81.3	65.9	71.9	17.0	23.1	10.7
3700	2.0	23.7	21.5	84.1	64.2	74.7	13.9	12.2	3.8
3810	8.1	25.4	28.6	64.0	51.4	54.9	27.9	23.2	16.5
3820	12.3	19.5	38.8	60.1	68.7	54.5	27.5	11.8	6.7
3830	14.6	17.1	70.0	70.7	68.5	15.8	14.7	14.4	14.2
3840	7.2	15.9	67.4	69.5	55.4	27.0	23.3	28.7	5.6
3850	16.9	12.2	23.1	68.1	75.4	65.0	14.9	12.4	11.9
3860	1.8	3.7	8.2	55.4	79.1	79.0	42.8	17.1	12.9
3900	2.5	6.8	17.0	78.4	83.4	78.3	19.1	9.8	4.7
3000	5.6	15.8	34.7	72.7	63.3	49.0	21.7	21.0	16.3

Table 3 shows that the share of computer investments in total investments increased dramatically already in the end of the 1980s. In most industries the investment shares of computers doubled between 1984 and 1989 and in two, 3300 = Saw Mills & Wood Products and 3700 = Basic Metals, the increase was more than 10-fold.

The relative increase continued into the 1990s. In 1993, ten of the 14 industries had at least doubled their computer investment shares, compared to 1989. In the two industries where the increases were the largest, 3830 = Electrical Machinery and

[15] For details on the computations of the computer capital stocks and the corresponding capital rental prices (used in the construction of the endogenous variable), see Gunnarsson and Mellander (1999).

3840 = Transportation, computers accounted for more than $\frac{2}{3}$ of total investments in 1993.[16]

In the accumulation of computer investments into computer capital stocks we have assumed a constant rate of depreciation of $\frac{1}{3}$. The rate of depreciation for computer capital should exceed that of other types of equipment capital. As the average rates of depreciation in the NA are between 16 and 21 percent for equipment capital *including* computers, $\frac{1}{3}$ does not seem like an unreasonable choice. The shares of computers, non-computer equipment and structures in the total capital stock are given in Table 4.[17]

Table 4: Capital stock shares in Swedish manufacturing

Industry	Computers			Equipment			Structures		
	1985	1990	1994	1985	1990	1994	1985	1990	1994
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

It can be seen that, because of the high rates of depreciation for computers, the

[16] Berndt and Morrison (1995) [BM] provide a table for a similar break-down of gross investments in the U.S. manufacturing sector, during the period 1976–86. The shares they report for the end of that period are mostly considerably higher than the corresponding shares given in Table 2, not only in 1985 but in 1990 as well. We believe that the high shares in BM are due to a "too wide" definition of computer equipment; cf. the discussion about mismeasurement of inputs in Section 2. This conjecture is supported by the claim in Oliner and Sichel (1994) that computers only made up 2 percent of the capital stock in the non-farm business sector as late as 1993. If that claim is correct, the 26 percent share of computers in total capital that BM report for the manufacturing sector already in 1986 must be too high.

[17] The capital stocks for year t are defined for January 1 in that year. Accordingly, the years of investment considered in Table 3 constitute the last additions to the stocks considered in Table 4 below.

development of the computer capital stock shares is not as spectacular as that of the investment shares.[18] Still, the dramatic increase in investment shares between 1984 and 1989 is matched by an almost equally impressive increase in the computer capital stock shares between 1985 and 1990. As a consequence of the large build–up of the IT capital stocks during the end of the 1980s, the increase in the IT investment shares between 1989 and 1993 had rather modest effects on the development of computer capital stock shares between 1990 and 1994, however.

It is quite clear from Table 4, there is a lot of variation across industries in our IT measure, the computer capital stock share. This is important because the relatively short period covered by our data makes cross-sectional variation crucial in our empirical analysis.

4.4 The human capital data

The human capital variables have been constructed by means of the Swedish Employment Register (ER) and the Labor Force Surveys (LFS).

The ER contains data on, i.a., the number of employees by industry, their level of education and fields-of-study, age, sex, and immigrant status, as well as their yearly earnings. The LFS provides information on work hours per week, by industry and sex, enabling an approximate conversion of the number of employees into full-time equivalents.[19]

Employment is like investments endogenously determined. Thus, in our regressions, the human capital variables are also lagged one year, relative to productivity growth. Table 5 provides cross-classifications of labor for the entire manufacturing sector, by

[18] Comparing, again, with Berndt and Morrison (op.cit., Table 2), we find that our computer capital stock shares differ even more from theirs, than did the investment shares. The reason is that the depreciation rates they used for computer equipment were considerably lower than the rate that we have used here.

[19] The approximate nature of the conversion is due to the fact that the LFS does not contain data on work hours by level of education. As a result, we can only capture that part of the variation in the work hour distributions across levels of education that stems from differences in gender compositions.

level of education and fields-of-study, for the years 1985, 1990 and 1994. The table corresponds to weighted averages of the corresponding cross-classifications for each industry, where the weights are given by employment shares.

Table 5: Employment shares in Swedish manufacturing, by level of education and fields–of–study, 1985, 1990 and 1994.

1985:

Level of education	Field-of-study			$\sum$
	Engineering	Business administration	"other"	
< 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
$\sum$	0.31	0.10	0.59	1

1990:

Level of education	Field-of-study			$\sum$
	Engineering	Business administration	"other"	
< 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
$\sum$	0.37	0.12	0.51	1

1994:

Level of education	Field-of-study			$\sum$
	Engineering	Business administration	"other"	
< 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
$\sum$	0.41	0.13	0.47	1

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

It should be noted that in the empirical analysis we employ cross-classifications like those in Table 5, but which differ both with respect to industry and year.

To be able to account for human capital in a broader sense, we will also consider data on 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. Thus, if (specific) skills acquired in the workplace are more important for productivity than (general) computer skills acquired in school, then the relation between age and productivity growth should be positive instead.

4.5 Control variables

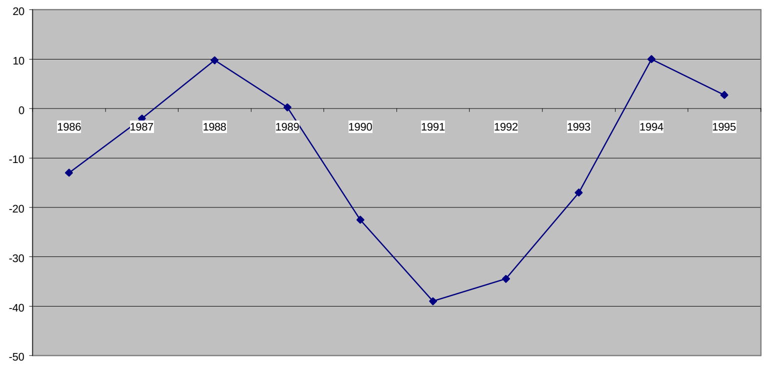
To account for cyclical variations in TFP growth, we have used a business cycle indicator, BCI, for the Swedish manufacturing sector. It weighs together data on orders, stocks of finished goods, and expected production.[20] The development of the BCI over the period studied is shown in Figure 4.

Comparing Figure 4 with Figure 1, we see that the BCI captures the turning points in TFP growth quite well. However, the BCI cannot explain the relative magnitudes of productivity growth at different points in time. In particular, it does not capture that, on average, TFP growth was much higher during 1991–1995 than during 1986–1990.

Following, e.g., Berndt and Morrison (1995) we control for changes in capital not caused by computer investments by means of the share of non-computer equipment in

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

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



the total capital stock, K_M/K. Since, $K_C/K + K_M/K + K_S/K \equiv 1$, we fully control for the capital structure by including both K_C/K and K_M/K in the regressions.

Among the control variables we also include the shares of females and immigrants, respectively, in the work force.

Gender might be important for two, different, reasons. First, as pointed out by Weinberg (2000), computers have created a lot of job openings for women that weren't available before, by replacing physically demanding blue-collar jobs by jobs that require computer knowledge. Second, as discussed by Lindbeck and Snower (2000), modern work organizations are to an increasing extent characterized by multi-tasking. To the extent that women are better suited to multi-tasking than men – a hypothesis for which there is ample anecdotal evidence – this development should favor firms with a large female labor share.

Regarding immigrants the direction of causality is more ambiguous. On the one hand, it could 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 report results for simplistic growth equations of the type discussed in the beginning of Section 3, i.e. equations taking no account of human capital. These regressions will enable us to check the validity of the theoretical analysis and to make comparisons with results in earlier studies. We will also use one of these regressions as a benchmark when we assess the empirical importance of our study. That is to say, we will see what the extended regressions (in Section 5.2) add in terms of explanatory power and if they relate to the benchmark regressions as predicted in Section 3.

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

First, in our reported regressions, we follow Romer (1990) in that the *rate* of productivity growth is explained by (ratios of) *level* variables. Similar to Benhabib and Spiegel (1994), initial estimations within the standard growth accounting framework, using growth rates as explanatory variables, usually yielded insignificant results.

Second, 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 and Griliches (1994) and Kahn and Lim (1998). The motivation for the WLS procedure can be found in the latter paper: if we want to know what forces shaped the economy over a historical episode it makes sense to weigh large industries more heavily, and, more important, it is reasonable to assume the data for small industries to be noisier than the data for large industries, which can be taken into account by assuming that the standard errors of the residuals are inversely proportional to employment.

We model industry-specific effects stochastically, by WLS. Alternative estimations that we have carried out show that this specification fits the data much better than deterministic industry–specific effects, i.e. industry dummy variables.

Third, the (contemporaneous) business cycle indicator, BCI, and the (lagged) share of non-computer equipment capital in the total capital stock, K_M/K, are always included as control variables in the regressions. As noted earlier, the inclusion of the BCI is a partial correction for output measurement error. The motivation for the share K_M/K is that it has been found to be an important control variable in other studies, e.g., Berndt and Morrison (1995).

Fourth, throughout the empirical analysis we disregarded possible measurement error in the IT variable, because we lack information on this issue.

Finally, in the regressions where we account for the externality in the use of IT by means of the function $\psi\left[\left(PROD_{IT}^N + IMP_{IT}^N - EXP_{IT}^N\right)_{t-1}\right]$ that was discussed in Section 3 we implement it in the simplest possible way, namely by specifying

$$\psi\left[\left(PROD_{IT}^N + IMP_{IT}^N - EXP_{IT}^N\right)_{t-1}\right] = \gamma \cdot TUIT_{t-1},$$

where γ is parameter, assumed positive, and $TUIT$ is the index described in Section 4.2.

5.1 Preliminary regressions, excluding human capital variables

The first point made in Section 3 was that the negative effects of IT on productivity growth reported in some U.S. studies using early (pre–1990) data were not likely to be mere statistical artifacts. Rather, they are most likely indications of truly negative effects, possibly arising because of (relative) over-investment in IT.

What, then, can be said of the Swedish manufacturing sector in this respect? To answer this question, we estimated the following equation for the first half of the period that we study:

$$\begin{aligned} \text{1986-90:} \quad g_{ht} &= -\underset{(1.696)}{0.0349} + \underset{(1.445)}{0.0003} \cdot BCI_t + \underset{(2.405)}{0.0830} \cdot (K_M/K)_{h,t-1} \\ &\quad - \underset{(0.141)}{0.0076} \cdot (K_C/K)_{h,t-1} \qquad R^2 = 0.18 \end{aligned} \tag{15}$$

where absolute values of t–statistics are in parentheses. The effect of IT, i.e. the coefficient of $(K_C/K)_{h,t-1}$ 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.

Estimation of the same equation for the first half of the 1990s yields entirely different results:

$$\begin{aligned} \text{1991-95:} \quad g_{ht} &= -\underset{(2.370)}{0.0864} + \underset{(4.257)}{0.0006} \cdot BCI_t + \underset{(3.205)}{0.1817} \cdot (K_M/K)_{h,t-1} \\ &\quad + \underset{(2.666)}{0.1954} \cdot (K_C/K)_{h,t-1} . \qquad R^2 = 0.48 \end{aligned} \tag{16}$$

However, in accordance with the discussion in Section 3, to be able to draw the conclusion that the underlying "true" parameter is indeed positive we have to show that the estimated effect decreases when a proxy variable for the interaction between IT and human capital is added to the regression. Using the interaction between K_C/K and the share of labor that has tertiary education within the field of engineering, TE/L, we obtain:

$$\begin{aligned} \text{1991-95:} \quad g_{ht} &= -\underset{(2.084)}{0.0793} + \underset{(4.060)}{0.0006} \cdot BCI_t + \underset{(3.048)}{0.1756} \cdot (K_M/K)_{h,t-1} \\ &\quad + \underset{(0.682)}{0.2906} \cdot [(TE/L) \times (K_C/K)]_{h,t-1} \qquad (17) \\ &\quad + \underset{(1.245)}{0.1385} \cdot (K_C/K)_{h,t-1} \qquad R^2 = 0.49 \end{aligned}$$

The inclusion of the IT and human capital interaction variable decreases the estimated (direct) effect of IT, thus strengthening the conclusion that IT has had a positive effect on productivity in the 1990s.

While the direct effect decreases markedly, the change in the total effect is much smaller. The total effect is given by: $0.1385 + 0.2906 \cdot (TE/L)$. Substituting the values in Table 5 for (TE/L), i.e. 0.06, 0.08, and 0.10, we obtain total effects of 0.1559, 0.1617, and 0.1675 in the years 1985, 1990, and 1995, respectively.

Finally, we will estimate the specification (15) for the whole period, although we already know that the assumption of a constant effect of IT is not supported by the data. The reason why we, nevertheless, run this regression is that we will use it as a benchmark against which to evaluate the regressions in the next section.

The outcome of the estimation is quite interesting:

$$\begin{aligned} \text{1986-95:} \qquad g_{ht} = & -\underset{(4.620)}{0.0846} + \underset{(3.340)}{0.0004} \cdot BCI_t + \underset{(5.151)}{0.1588} \cdot (K_M/K)_{h,t-1} \\ & + \underset{(4.295)}{0.1763} \cdot (K_C/K)_{h,t-1} \cdot \qquad R^2 = 0.27. \end{aligned} \tag{18}$$

The noteworthy result is that the coefficient for $(K_C/K)_{h,t-1}$ is quite close to the one obtained when the sub-period 1991–95 is considered; cf. (16). This means that by ignoring the externality we vastly over-estimate the effect of IT on productivity growth during 1986–90.

A second conclusion is that in a regression ignoring human capital effects a lot of variation in TFP growth remains to be explained; as can be seen from (18) only 27 percent of the variance in productivity growth is accounted for.

5.2 Incorporating the effects of human capital

Human capital will enter the regressions in two ways: explicitly through interaction variables involving human capital measures and implicitly through the externality in IT use. As discussed in Section 3, the latter effect will partly be accounted for by the index measuring the total use of IT and partly be included in the effects measured by the human capital interactions.

From an econometric point of view, multicollinearity is an important consideration in the present context. The more variables involving IT measures that we include in the regression the more multicollinearity we will get. To obtain precise estimates we will try to keep the number of interaction variables down and/or impose constraints on the coefficients.

For the same reason, we will only include human capital variables through the interaction variables. We will thus disregard direct, or first order, effects of human capital although such effects are suggested by the analyses in Romer (1990) and Benhabib and Spiegel (1994). As an alternative that is less demanding on degrees of freedom, we will check for the importace of direct effects of human capital by means of (non-nested) tests investigating whether human capital variables alone can explain the development of productivity growth rates.Another concern is the specific formulation of the human capital variables.

Concerning the specific formulation of the human capital variables, theory does not provide much guidance. We have, therefore, tried to use specifications that are amenable to policy analysis.

The effect that we are interested in is given the partial derivative of total factor productivity growth with respect to the share of computers in total capital:

$$\frac{\partial g_{ht}}{\partial \left(K_C/K\right)_{h,t-1}} = \sum_{i=1}^{m} \widehat{\theta}_i \cdot X_i \tag{19}$$

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

$$Var\left[\frac{\partial g_{ht}}{\partial \left(K_C/K\right)_{h,t-1}}\right] = \sum_{i=1}^{m} X_i^2 \cdot Var\left(\widehat{\theta}_i\right) + 2\sum_{i=1}^{m}\sum_{j>i}^{m} X_i X_j Cov\left(\widehat{\theta}_i \widehat{\theta}_j\right) \tag{20}$$

As the variance computation is a bit complicated we will, to begin with, merely consider the individual terms in (19), implying that we only have to consider the corresponding $t-$ ratios.

In Table 6, five alternative regressions are reported. In column I, we have included the direct effect of IT and indirect effects through human capital, which here is accounted for by educational levels only.

Table 6: Growth regressions allowing for externalities in the use of IT and complementarity between IT and human capital.

Dependent variable: g_{ht}	I	II	III	IV	V
Control variables:					
Constant	-0.0568 (2.709)	-0.0274 (1.249)	-0.0142 (0.612)	-0.0205 (0.803)	-0.0225 (1.226)
BCI_t	0.0028 (2.503))	0.0002 (2.077)	0.0003 (2.369)	0.0002 (2.000)	0.0002 (2.000)
$\left[\frac{K_M}{K}\right]_{h,t-1}$	0.1280 (3.677)	0.0737 (2.012)	0.0411 (0.993)	0.0504 (1.100)	0.0547 (1.753)
Direct effect of IT:					
$\left[TUIT \times (\frac{K_C}{K})_h\right]_{t-1}$	0.0004 (3.614)	0.0001 (0.773)	0.0001 (0.548)	4.4E-6 (0.034)	
Indirect effects of IT through human capital:					
$\left[\frac{\#Tertiary}{\#(Upper\ sec.+Tertiary)} \times \frac{K_c}{K}\right]_{h,t-1}$	0.6201 (2.160)	0.6815 (2.285)	0.4316 (1.296)		
$\left[\frac{\#Tertiary\ Engineers}{\#(Upper\ sec.+Tertiary\ Engineers)} \times \frac{K_c}{K}\right]_{h,t-1}$				0.8480 (2.388)	0.8779 (5.289)
$\left[\frac{\#Tertiary\ Business\ adm.}{\#(Upper\ sec.+Tertiary\ Bus.\ adm.)} \times \frac{K_c}{K}\right]_{h,t-1}$				-0.9451 (1.630)	-.8324 (2.383)
$\left[\frac{\#Tertiary\ "Other"}{\#(Upper\ sec.+Tertiary\ "Other")} \times \frac{K_c}{K}\right]_{h,t-1}$				1.1925 (0.977)	.8779 (5.289)
$\left[\frac{\#Upper\ sec.}{\#(9\ years+Upper\ sec.)} \times \frac{K_c}{K}\right]_{h,t-1}$	0.3717 (1.622)	0.3760 (1.862)	0.4542 (2.203)	0.9731 (2.688)	.8779 (5.289)
$\left[\frac{\#9\ years}{\#(<9\ years+9\ years)} \times \frac{K_c}{K}\right]_{h,t-1}$	-1.0130 (2.902)				
$\left[\frac{\#16\text{-}29\ year\ olds}{\#(16\text{-}29+50\text{-}74\ year\ olds)} \times \frac{Kc}{K}\right]_{h,t-1}$		-0.8569 (3.013)	-1.0948 (3.449)	-1.4997 (2.742)	-1.2593 (5.877)
$\left[\frac{\#Females}{\#Workers} \times \frac{K_c}{K}\right]_{h,t-1}$			0.4679 (1.645)	-0.0568 (0.108)	
$\left[\frac{\#Immigrants}{\#Workers} \times \frac{Kc}{K}\right]_{h,t-1}$		0.6946 (0.521)	1.2200 (0.896)	1.1696 (0.607)	
R^2	0.378	0.402	0.414	0.439	0.437

Note: Absolute values of t-statistics in parentheses

The direct effect contributes to the partial derivative (19) by the amount $0.0004 \cdot TUIT_{t-1}$ and is highly significant. As expected, an increase in the total use of IT raises the effect of IT on productivity growth.

The first of the indirect effects is equal to $0.6201 \cdot \frac{\textit{\# Tertiary}}{\textit{\# (Upper sec. + Tertiary)}}$. The ratio measures the share of the number of workers with tertiary education in the number of workers with at least upper secondary education. Again, the result is in accordance with prior expectations: an increase in the human capital among the workers with upper secondary education, through university studies, will enhance the productivity growth induced by an increase in computers' share in total capital.

The second indirect effect is defined similarly to the first. It involves the share of workers with upper secondary education among workers with either 9 year (compulsory) education or upper secondary education. The estimated effect equals $0.3717 \cdot \frac{\textit{\# Upper sec.}}{\textit{\# (9 years + Upper sec.)}}$ and is almost significant at the 10 percent level.

With respect to the third indirect effect, an unexpected and very significant estimate is obtained, namely $-1.0130 \cdot \frac{\textit{\# 9 years}}{\textit{\# (< 9 years + 9 years)}}$.. According to this result, substituting workers with 9 years of education for workers with less than 9 years of schooling should have a negative effect on the change in productivity growth. This does not seem plausible. It should be noted, however, that in assessing the effects of skill upgrading we do not control for differences in age and experience. This turns out to be important with respect to this particular result.

Since 1962, 9 years of schooling is the minimum level in Sweden. Accordingly, older individuals predominate among workers with less than 9 years of schooling. For example, for manufacturing as a whole, almost 60 percent were at least 50 years old and close to 95 percent were at least 40 years of age.[21] This means that a large part of the variation in the ratio $\frac{\textit{\# 9 years}}{\textit{\# (< 9 years + 9 years)}}$ is caused by individuals with less than 9 years of schooling going into retirement and being replaced by young individuals that

[21] Cf. Mellander (1999).

have just finished 9 year compulsory school. To a large extent the changes in this ratio thus reflect changes in the age distribution. Such changes might have negative effects, because employees with long work experience are replaced by individuals without work experience. On the other hand, the youngsters, while lacking work experience, have experience from IT during their school years which possibly make them contribute to productivity growth more than the older workers they replace.

To investigate the relative strengths of these two effects, $\frac{\text{\# 9 years}}{\text{\# (< 9 years + 9 years)}}$ was regressed on the ratio $\frac{\text{\# 16 – 29 year olds}}{\text{\# (16 - 29 + 50 - 74 year olds)}}$, supposed to roughly reflect the replacement of workers in the rightmost 15 year age interval in the age distribution by workers in the corresponding leftmost age interval.[22] The result of this regression was:

$$\begin{aligned} \frac{\text{\# 9 years}}{\text{\# (< 9 years + 9 years)}} &= \underset{(26.189)}{0.9989} \cdot \frac{\text{\# 16 – 29 year olds}}{\text{\# (16 - 29 + 50 - 74 year olds)}} \\ &\quad - \underset{(5.320)}{1.8488} \cdot \frac{\text{\# Immigrants}}{\text{\# Workers}}, \qquad R^2 = 0.99 \end{aligned} \tag{21}$$

As the coefficient for $\frac{\text{\# 9 years}}{\text{\# (< 9 years + 9 years)}} \times \frac{K_C}{K}$ in Table 6, column I, is negative, the positive coefficient for $\frac{\text{\# 16 – 29 year olds}}{\text{\# (16 - 29 + 50 - 74 year olds)}}$ in (21) implies that, with respect to growth impacts, the negative effect of lost work experience outweighs the addition of workers with high "IT content" in their basic education, at least during the period under study.

In the regression we have also included the share of immigrants among the workers. The reason is that immigration is the only way in which the numbers of workers with less than 9 years of schooling can increase. This variable is significantly negative. Referring, again, to the negative coefficient for the ratio $\frac{\text{\# 9 years}}{\text{\# (< 9 years + 9 years)}} \times \frac{K_C}{K}$ in Table 6, column I, this means that the share of immigrants appears to have a positive

[22] In Sweden the postulated age of retirement in manufacturing is 65. During the period of study, the average actual age of retirement was between 63 and 64. However, if the employer and the employee were in agreement, the employee could continue to work beyond 65. This is the motivation for including individuals up to 74 years of age.

effect on the change in the rate of growth. As discussed in Section 4.4, the sign of the immigrant effect is not clear, *a priori*. According to this result the positive effect from influences from other cultures seems to outweigh problems in communication, due to immigrants having imperfect knowledge of the host country language.

From the R^2 in (21) it is obvious that it is impossible to separate the effects of $\frac{\#\ 9\ years}{\#\ (<9\ years\ +\ 9\ years)}$, on the one hand, and $\frac{\#\ 16\ -\ 29\ year\ olds}{\#\ (16\ -\ 29\ +\ 50\ -\ 74\ year\ olds)}$ and $\frac{\#\ Immigrants}{\#\ Workers}$, on the other hand. Henceforth, we will, therefore, use the latter two variables instead of the former. Comparison of columns I and II in Table 6 shows the effect of this change. The main difference is that the direct effect becomes much smaller and statistically insignificant. This is in line with the discussion in Section 3, predicting that inclusion of additional human capital variables should decrease the estimated direct effect. Another noteworthy result is that the contribution of the immigrant share to the change in productivity growth is not significant. The primary reason for this is that there is very little variation in the immigrant share, giving rise to multicollinearity between the immigrant share and the intercept in the growth equation.

Column III differs from column II only in that the share of female workers has been added. This share is barely significant at the 10 percent level.

However, the gender effect does not seem to be genuine but, rather, a reflection of gender differences with respect to fields–of -study. This conclusion can be drawn by comparison of columns III and IV of Table 6. In column IV the variable $\frac{\#\ Tertiary}{\#\ (Upper\ sec.\ +\ Tertiary)}$ has been disaggregated according to field–of–study. This change makes the female share insignificant.

A somewhat counter–intuitive finding in column IV is the result that increasing the share of business administrators with tertiary education has a negative impact effect on the change in productivity growth. However, an explanation for this result can be found in Murphy et al. (1991). They claim that when talented people become entrepreneurs they improve the technology and thus affect productivity and income growth in a positive way. But talented people can also become rent-seekers in which case they just redistribute wealth and harm the growth potential of the economy in the sense that they leave fewer resources for more productive activities.

Murphy et. al. (op. cit) proxy the talent allocated to entrepreneurship and the talent allocated to rent-seeking by the college enrollment levels in engineering and law, respectively, and study their implications for growth. They find that engineers and lawyers affect growth directly and indirectly (through correlation with other variables) in a positive and a negative way, respectively.

Our results in column IV are in line with the indirect effects on growth obtained by Murphy et al. (op. cit.). As the category business administrator includes lawyers we can think of the effect of the share of business administrators with tertiary education as an indirect measure of the effect of rent-seekers.[23] Thus, consistent with the predictions of Murphy et al we find positive effects of engineers (entrepreneurs) on growth and negative effects of lawyers (rent-seekers).[24]

The results reported in column V constitute our preferred model. This specification has been obtained by subjecting the model in column IV to a composite hypothesis, namely:

(i) zero constraints on the coefficients for $\left[TUIT \times \left(\frac{K_C}{K}\right)_h\right]_{t-1}$, $\left[\frac{\#Females}{\#Workers} \times \frac{K_C}{K}\right]_{h,t-1}$, and $\left[\frac{\#\ Immigrants}{\#\ Workers} \times \frac{K_C}{K}\right]_{h,t-1}$,

(ii) equality of the coefficients for $\left[\frac{\#\ Tertiary\ Engineers}{\#\ (Upper\ sec.\ +\ Tertiary\ Engineers)} \times \frac{K_C}{K}\right]_{h,t-1}$, $\left[\frac{\#\ Tertiary\ "Other"}{\#\ (Upper\ sec.\ +\ Tertiary\ "Other")} \times \frac{K_C}{K}\right]_{h,t-1}$ and $\left[\frac{\#\ Upper\ sec.}{\#\ (9\ years\ +\ Upper\ sec.)} \times \frac{K_C}{K}\right]_{h,t-1}$.

[23] Indirect in the sense that they measure the effects on growth from the interacion between those with tertiary education on the one hand and computers on the other hand.

[24] Independent evidence in Mellander and Skedinger (1999) points in the same direction; they show that in the mid 1990s wage premia for university education were much higher among business administrators than among engineers, in seven European countries, in spite of a university degree in engineering requiring more years of study. A possible interpretation of this result is that the university wage premium for business administrators is "too high" relative to the corresponding premium for engineers.

As indicated by the negligible difference in R^2 between columns IV and V, this hypothesis cannot be rejected at any reasonable level of significance. That (ii) cannot be rejected is quite interesting. It means that it does not matter whose skills are increased — the positive effect on growth will be same.

In the end, we thus end up with a model containing only six parameters, which explains almost 44 percent of the variation in the rate of total factor productivity growth across industries and over time! This is quite remarkable. It is also a very clear improvement over the four–parameter benchmark model (18) which only explains 27 percent of the variation in the productivity growth rates.

Comparing the model in column V of Table 6 with the benchmark model (18), we see that the improvement has been achieved by replacing the share of computers in total capital, K_C/K, by interaction variables involving this same share and different human capital indicators. In this sense, human capital certainly seems to be the key to the IT productivity paradox.

However, while these results clearly show that the human capital variables are essential, one might wonder about the importance of the computer capital share, $\mathrm{K_C/K}$. Is this variable really essential, too, or can the human capital variables do the job by themselves? To check this, we have performed non-nested tests of whether $\mathrm{K_C/K}$ should be included in the growth equations or not. The test we have used is the one proposed by Davidson and MacKinnon (1981). As this test cannot be directly applied in the context of linear constraints of the kind that we have imposed in column V of Table 6, we have only tested the specifications I - IV.[25] The results of the test are reported in Table 7.

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, Ha, corresponds

[25] As shown by Pesaran and Hall (1998), it is not overly difficult to formulate 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 IV and V in Table 6 are very close we have not taken the trouble to perform the generalized test on specification V in Table 6.

to when $K_C/K = 1$ in the Table 6 regressions. In none of the tests can the null be rejected at any standard level of significance.

Table 7: Test statistics for non-nested tests of the presence of K_c/K in the growth equation; critical value at 1% significance level = 2.34

	Model specification			
	I	II	III	IV
H_o: include K_c/K H_a: exclude K_c/K	0.10	0.26	0.94	0.84
H_o: exclude K_c/K H_a: include K_c/K	2.97	3.31	3.74	4.16

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.

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 in each one of the tests.

These results provide strong support for the notion that it is the interaction between IT capital, as measured by K_C/K, and human capital that drives our results, rather than just the human capital variables. That the outcomes of non-nested tests are as clear as in this case is not very common; often the tests produce inconsistent results (reject both of the null hypotheses) or inconclusive results (reject neither).

The benchmark model specifies the effect of marginal increases in computers' share of capital to be constant, while our model allows these effects to vary both over time and by industries. This is illustrated in Figures 5a–c, showing the distributions of the partial derivatives (19) across industries at three points in time, 1986, 1991 and 1995. The precision in these estimates has been calculated according to (20).

Note that the vertical axis in the figures measures the effects in percentage points. 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 have been weighted according to 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 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.

At each point in time, there is considerable spread across industries. Among the three years covered by Figure 5a–c, the largest variation is found in 1986.In that year the spread is 0.46 percentage points, the range being given by a negative effect of -0.12 percentage points in 3840 = Transportation and a positive effect of 0.34 percentage points in 3860 = Shipyards.[26] In 1991 and 1995 the spread is considerably smaller – about 0.30 percentage points in both years.

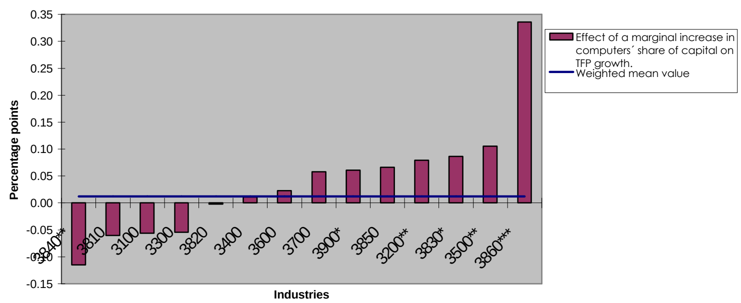
The upper range of the 1995 estimates is quite high: for five industries the point estimates are 0.25 or higher, indicating that 1 percent increase in computers' share in total capital increases the rate of TFP growth by $\frac{1}{4}$ of a percentage point or more.

In line with our findings, a comparison of Figure 5 and Table 4 shows that the industries that had the largest increases in the shares of computers in total capital

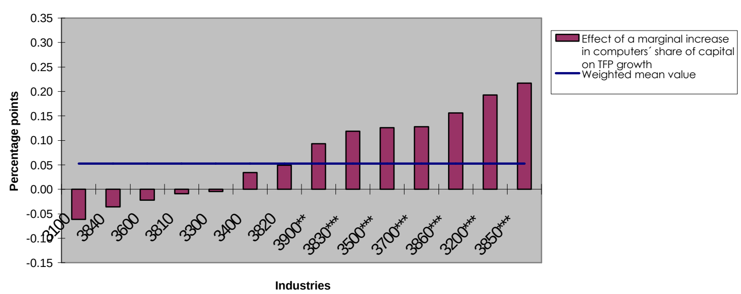
[26] The shipyards rank very high in 1991 and 1995, too. Since the Swedish shipyards have undergone major structural changes since the mid 70's and have been facing severe problems with low and, sometimes, negative profits this industry could be seen as a potential outlier. To check this, we reestimated the model given by column V in Table 5, 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.

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

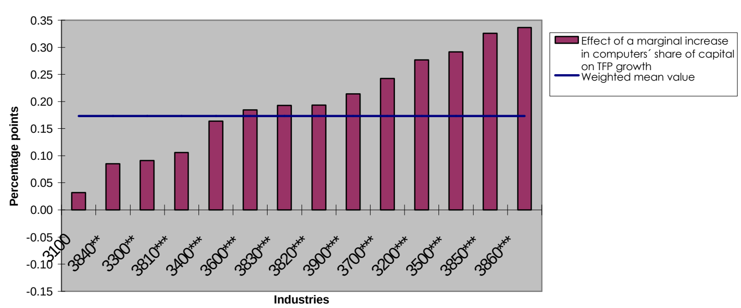
a:1986



b:1991



c:1995



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

do not coincide with 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 4. These investments did not result in top-ranking marginal effects of IT in either 1991 or 1995, however; see Figure 5. Similarly, the doubling of the computer capital stock share in 3830 = Electrical Machinery between 1990 and 1994 only resulted in a marginal effect of IT on growth that was about equal to the average effect across all industries; again compare Figure 5.

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), the effects of computer investments were essentialy zero outside the IT-producing industries and the industries producing durable manufacturing goods, in the U.S. 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 = Transportation, except shipyards (essentially automobiles). On the other hand, there are several industries outside this group recording large positive effects like 3200 = Textiles and 3500 = Chemicals.

6 Summary and conclusions

Our principal conclusion from this study is the following: Yes, 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.

With respect to the negative effects of IT on growth reported in studies based on early (pre–1990) data for the U.S.[27], we conclude that these results are likely to be indicative of a truly negative effect as suggested by Morrison (1997), rather than the consequence of measurement error, as argued by, e.g., Lee and Barua (1999).

The positive connection between IT and productivity growth that has been found in studies based on more recent U.S data[28] is in our theoretical analysis attributed to positive external effects in the use of IT, arising through learning–by-investing and knowledge spillovers, as in Barro and Sala–i–Martin (1999, Ch. 4). These external effects are assumed to be increasing in the total use of IT, implying that over time, as more and more IT capital is accumulated, the growth effects of IT increase, going from negative to positive.

To check the validity of the model, we carry out a preliminary empirical analysis where we regress productivity growth on IT, measured as the share of computers in total capital, but where we do not account for human capital.

Running the regression on panel data for 14 Swedish manufacturing industries over the period 1986-90, we obtain a negative estimate of the effect of IT on productivity growth. This estimate is small in absolute value and statistically insignificant. However, the theoretical analysis tells us that, nevertheless, the result indicates that IT had a truly negative effect on growth during this period. Thus, it seems like Morrison's (op.cit.) result of overinvestment in IT in U.S. manufacturing is applicable to the Swedish manufacturing sector, too.

In contrast, a regression covering the period 1991–95 generates a large positive estimate of the direct effect of IT on growth. The theoretical analysis tells us that if the true effect of IT was indeed positive during this period, then this estimate should decrease if indirect effects of IT are allowed for, through interaction between human

[27] See, e.g., Loveman (1988) and Berndt and Morrison (1995).

[28] Cf. Oliner and Sichel (2000).

capital and IT. This prediction is verified by the data.

Having thus established that the qualitative nature of the relationship between IT and growth in Sweden seems to have been similar to that experienced by the U.S. and that complementarity between IT and human capital may be important in explaining this relation, we proceed with the actual empirical analysis.

For comparative purposes, we first run a simple regression, omitting human capital, for the whole period, 1986–95. The resulting estimated direct effect is statistically significant and equal to 0.18, implying that a 1 percent increase in computers' share of total capital will increase productivity growth by 0.18 percentage points. Thus, by running the regression on data for the entire period we obtain a result which conceals that the effect of IT on growth has varied strongly over the period. As expected, the model does not fit the data very well; only about $\frac{1}{4}$ of the variation in total factor productivity growth is explained.

Next, we include several interaction variables, involving the product of the IT measure and various human capital indicators. The theoretical analysis predicts that accounting for indirect effects of IT in this way will reduce the estimated direct effect. This is precisely what happens – as successively more detailed information on human capital is introduced the direct effect finally vanishes altogether. In the process, control variables measuring the shares of females and immigrants among the workers become insignificant, too.

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 rates. 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 high–skilled workers is confirmed. For workers whose education lie within a common field of study, the indirect effects of IT on growth are higher the higher the share among these workers with university education. The pattern is the same at lower levels of education, where workers cannot be separated by fields of study but only by level of education. Somewhat surprising, the hypothesis that marginal skill upgrading has the same effect across different fields of study and different levels of education cannot be rejected.

The only exception to the complementarity relation between IT and skilled labor concerns workers within the field of business administration. For these, skill upgrading from upper secondary to university education is estimated to have a negative impact on productivity growth. We interpret this result as evidence of the presence of rent-seeking behavior among business administrator, which has a detrimental effect on growth, in the spirit of Murphy et al. (1991).

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

Due to the presence of the human capital variables, our simple model is able to account very well for the increase over time in the growth–enhacing effect of IT, that was postulated in our theoretical analysis (and verified by our preliminary empirics). 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 inclusion of the human capital variables also allows the effects of IT to vary across industries. Our results clearly show that this is a very important feature.

The variation across industries is substantial, although slightly decreasing over time. In 1986 the IT growth effects were distributed over the interval [–0.11, 0.34], corresponding to a spread of 0.46 percentage points. In 1991 and 1995 the corresponding intervals were [–0.05, 0.11] and [0.04, 0.34]. From the latter interval it can be inferred that in 1995 marginal increases in computers' share of capital were positive in all industries. For several of these, the effects were remarkably high; in five industries 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 this result, we find that the industries were the (relative) increases in computer capital have been particularly large are not the same 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.

With respect to policy considerations, one conclusions is immediate from the complementarity between IT and skilled labor: measures to promote increased use of IT should be followed up by measures promoting skill upgrading.[29] Our results actually

[29] It is interesting to note that Swedish policies actually seem to be moving in this direction. Since 1998 there has been a tax rebate on the purchases of computers for private use, in order to promote wide-spread use of IT. Currently, the government is investigating the possibilities to implement tax–rebated personal "competence accounts", by means of which individuals can save for further education of their own choice.

show that, in general, upgrading skills at a given level of IT (i.e. share of computers in total capital) has a much stronger growth–enhancing effect than increasing IT investments at a given human capital structure. The latter effect is the one that we have discussed above; as noted these are seldom above 0.25.

To consider the former effect, i.e. the effect of skill upgrading, assume that among engineering workers the share with university education is increased by 1 percent. According to our estimates this will increase growth by 0.88 percentage points. The same effect can be obtained by similar human capital increases in the other categories of workers considered, except for the business administrators.

Another policy implication concerns early retirement. Our results indicate that measures aimed at facilitating early retirement among older workers, in order to make more room for labor market entrants, can be (strongly) harmful for growth.[30]

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. Another highly interesting extension is to carry out a similar analysis with respect the service sector where the effects of IT on growth might well be quite different from those in manufacturing.

[30] Policies of this kind were tried in Sweden during the late 80s and early 90s.

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