The Impact of Computer Capital on the Demand for Heterogeneous Labor*

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Abstract

In this paper, a system of static and dynamic factor demand equations based on a variant of the generalized Box-Cox cost function nesting the translog, the generalized Leontief and the normalized quadratic functional form is derived and estimated. OCM capital and general capital are treated as quasi-fixed factors. Using panel data on 35 German industries, we find that OCM capital is complementary to all skill levels. In non-manufacturing industries, we find that an increase in general capital tends to reduce unskilled workers. Wage effects and substitution effects between different types of labor and material inputs play a minor role in explaining employment changes of highly skilled workers and medium-skilled workers but these effects are more important in explaining the demand for unskilled workers.

Keywords: skill-biased technological change, capital-skill complementarity

JEL Classification: J23, O33

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1. Introduction

The diffusion of information and communication technology (ICT) is often emphasized as one of the most important factors explaining the shift in labor demand towards skilled workers and away from unskilled workers (see among others, Autor, Katz and Krueger, 1998; Morrison-Paul and Siegel, 2001). During the 1980s and 1990s, the total stock of computing equipment grew rapidly as computer power exploded and prices of computers fell greatly (see Jorgenson, 2001). For the U.S., the total stock of quality adjusted computing equipment in constant prices grew rapidly with average growth rates between 20 and 30 percent per year (Jorgenson, 2001). German figures show similar tendencies.

Krusell et al. (2000) investigate the impact of technological change on the ratio of skilled labor wages to unskilled labor wages using U.S. time series data. The authors find that capital-embodied technological change alone can account for most of the variations in the skill premium over the last 30 years. A key element of the Krusell et al. (2000) analysis is the use of quality-adjusted prices for a number of durable equipment categories such as office and computing equipment including peripheral equipment and accounting machinery (OCAM), communication equipment, general industrial equipment and transportation equipment. There has been a strong decline in the relative price of equipment (ratio of the price index for capital equipment and the price index for consumption of non-durables and services) of about 7 percent per year and an associated strong increase in the stock of equipment. The results imply that technological change is driven by the cheapening of equipment relative to structures and that technological change leads to a change in the composition of the capital stock.

Furthermore, there have been many empirical studies that focus directly on the relationship between the demand for labor at different skill levels and computerization (for a survey of the literature see Chennells and Van Reenen, 1999). Two empirical approaches have been used to estimate the relationship between the computerization and labor demand. The first approach relates the change in the employment share of skilled labor to the ratio of an industry's initial ICT capital (or ICT investment) to its total capital (or total investment) (see Berman, Bound and Griliches, 1994). Alternatively, the change in the employment share of skilled labor is related to the change in ICT investment ratio (see Autor, Katz and Krueger, 1998). The second approach employs a complete system of input demands, i.e. not only a relative labor demand equation (see Morrison-Paul and Siegel, 2001; Fitzenberger, 1999; Ruiz-Arranz, 2001).

Using a number of different data sets for the U.S. on three- and four-digit industry level, Autor, Katz and Krueger (1998) extend previous work in a number of ways. First, they use different measures of skills (four educational qualification groups as well as different occupational groups), different measures of information technology as well as a longer time period. Second, the authors also consider non-manufacturing industries. Using three-digit industry data, Autor et al. (1998) find that the change in computer use (measured as the annual change in the fraction of workers using a computer at work) is positively related to the change in the employment share of college graduates and, to a lesser extent, to workers with at least two years of college. In contrast, the change in computer use is negatively related to the change in the employment share of high school graduates. The relationship between the change in computer use and the change in the employment share of workers with less than high school is not significantly different from zero. Furthermore, the authors suggest that the shift towards college-educated workers and away from high school-educated workers was greatest in industries that experienced the greatest rise in computer use. Finally, the authors find that computer investment can account for at least 30 percent of the increase in the non-production worker wage bill for the period 1959 −1989. Using similar approaches, Machin and Van Reenen (1998) find further support for the computer-skill complementarity. The authors use the proportion of workers using a computer at work as an index of computer use. Using two-digit manufacturing data for the U.S. and U.K., they find that the change in the cost share of non-production workers between 1986 and 1990 is positively related to the initial proportion of workers using a computer at work. Green, Felstead and Gallie (2000) investigate the impact of computer usage at work and other job features on the changing skills required of workers for the U.K.. The data are based on individual data of employed persons at three data points: 1986, 1992 and 1997. The authors find that the spread of computer usage is very strongly associated with the process of upskilling throughout the period. For France, Goux and Maurin (2000) find that the decline in the unskilled share of French employment is mainly due to the slackness of domestic demand for those industries with the highest proportion of unskilled workers. In contrast, the spread of computers (measured amongst others as the percentage of workers using a computer on the job) has little effect on the labor demand for both skilled and unskilled workers.

Based on a complete system of input demands, Morrison-Paul and Siegel (2001) investigate the impact of high-tech office and information equipment, R&D trade and outsourcing on heterogeneous labor demand. High-tech office and information equipment includes communications equipment, scientific and engineering instruments and photocopiers and related equipment in addition to office computing and accounting machinery. The authors estimate a seven equations input demand system derived from a generalized Leontief cost function with four educational qualification groups, energy and materials and an Euler equation for investment. Using U.S. two-digit manufacturing industry data, the authors find that the accumulation of high-tech capital explains 9 percent of the expanding employment of college graduates and 30 percent of the expanding employment of workers with some college experience for the period 1959-1989. Furthermore, Ruiz-Arranz (2001) extends the work of Krusell et al. (2000) by distinguishing between the effects of ICT capital and non-ICT capital. The author finds that ICT capital and skilled labour are strong complements and ICT capital is very substitutable to unskilled labour. However, the author does not find that non-ICT equipment is complementary to skilled labor. For Germany, Fitzenberger (1999) provides some evidence of the impact of computerization on labor demands for three types of labor (highly skilled, medium-skilled and unskilled workers) as well as materials. As neither OCM capital stock nor the price of OCM are available, Fitzenberger relies on the input coefficients (material inputs to total shipments) from the office machinery and computer industry and the electrical goods industry obtained from input-output tables as an indicator of embodied technological change. Using two-digit industry data for non-manufacturing industries for the period 1975-1990, he finds little evidence for skill-biased technological change in non-manufacturing industries. The finding of no significant impact of intermediate OCM inputs could be due to the fact that the material inputs from the OCM industries do not seem to be correlated with OCM investment.[1]

This paper presents new empirical estimates of the impact of OCM capital on the demand for heterogeneous labor. A four-equation input demand system with three types of labor and total intermediate materials as variable factors as well as two types of capital (OCM capital and general capital) as quasi-fixed factors is derived and estimated. Since functional forms are often data-specific and empirical results sensitive to the choice of the functional form of the cost function, elasticities are calculated using different flexible forms such as the generalized Box-Cox, the generalized Leontief, the normalized quadratic as well as the translog functional form. Furthermore, we combine the factor demand systems with a general

[1] The correlation coefficient between the change in OCM investment and the change in intermediate OCM inputs measured as annual average growth rates across non-manfacturing industries is -0.08 and not significantly different from zero.

dynamic adjustment process of each input factor. In particular, we estimate multi-equation error-correction models suggested by Anderson and Blundell (1982). As noted by Anderson and Blundell (1982), the advantage of these models is that it nests simpler dynamic specifications, such as the partial adjustment model as well as the static model or the model in first differences. To our knowledge, this paper presents the first application of a multi-equation error-correction model assuming a generalized Box-Cox functional form of the cost function. Workers are classified according to whether they have a university degree, a certificate from the dual vocational system including masters and technicians and workers without any formal degree. The data consists of panel data on 35 two-digit industries for the period 1978 −1994.

The paper proceeds as follows. Section 2 outlines the specification of both the generalized Box-Cox cost function, the normalized quadratic, the Leontief cost function and the translog cost function as well as the derived factor demands, while section 3 describes and summarizes the data. Section 4 presents the elasticities of the factor demand system as well as a decomposition analysis of the employment changes into output, capital and price effects. Section 5 concludes.

2. The empirical model

Most earlier work on the demand for heterogenous labor employs either the translog or the generalized Leontief cost function. The results of these studies, however, are difficult to compare because the different functional forms are not nested within a general functional form of the cost function. Therefore, an extension of Berndt and Khaled's (1979) Box-Cox cost function is considered here. This variant of a generalized Box-Cox cost function nests three different functional forms: (i) the translog cost function, (ii) the quadratic cost function and the generalized Leontief cost function. The generalized Box-Cox cost function can be written as:

$$c\left(p_{nt}, z_{nt}, a_n, \gamma\right) = \begin{cases} p'_{nt}\overline{x}_n \left(\gamma_2 C\left(P_{nt}, Z_{nt}; \alpha_{0n}\right) + 1\right)^{1/\gamma_2} & \text{for} \quad \gamma_2 \neq 0 \\ p'_{nt}\overline{x}_n \exp\left(C\left(P_{nt}, Z_{nt}; \alpha_{0n}\right)\right) & \text{for} \quad \gamma_2 = 0 \end{cases}, \tag{2.1}$$

where

$$C\left(P_{nt}, Z_{nt}; \alpha_{0n}\right) = \alpha_{Cn} + A_{pn}P_{nt} + A_z Z_{nt} + \frac{1}{2}P'_{nt}A_{pp}P_{nt} + P'_{nt}A_{pz}Z_{nt} + \frac{1}{2}Z'_{nt}A_{zz}Z_{nt}. \tag{2.2}$$

where the subscripts t and n denote time and industry, respectively. The technological parameters to be estimated are gathered in the vector $\alpha_n = (\alpha'_{0n}, \gamma_1, \gamma_2)'$, where α_{0n} entails all free parameters of α_{Cn}, A_{pn}, A_z, A_{pp}, A_{pz} and A_{zz}. Notice that subscript n characterizes parameters which are industry-specific. The vector of variable inputs is defined as $x_{nt} = (x_{hnt}, x_{snt}, x_{unt}, x_{mnt})'$ and the prices as $p_{nt} = (p_{hnt}, p_{snt}, p_{unt}, p_{mnt})'$, where the labor input x_{hnt} denotes the number of workers with a university degree, x_{snt} denotes workers with a certificate from the dual vocational system plus masters and technicians, x_{unt} low-skilled or unskilled workers and x_{mnt} total materials. Labor is measured in total workers (full-time equivalents). The net capital stock (excluding OCM capital), z_{ont}, and the OCM capital stock, z_{knt}, are the quasi-fixed factors.[2] Other explanatory variables entering the cost function are the level of production, z_{ynt}, and a time trend t. The two types of capital, output and time are regrouped in a vector $z_{nt} = (z_{knt}, z_{ont}, z_{ynt}, t)'$. Total variable costs are measured as the sum of labor costs and total materials: $c_{nt} = p'_{nt}x_{nt}$. The definition of Z, P and C will be amended later. Some restrictions are placed on the parameters in order for the Hessian of the cost function to be symmetric in P and Z for the number of parameters to be parsimonious:

$$\iota'_4 A_{pn} = 1,\ A_{pp} = A'_{pp},\ A_{zz} = A'_{zz}, A_{pz} = A'_{zp}, \iota'_4 A_{pp} = 0,\ \ \iota'_4 A_{pz} = 0, \qquad (2.3)$$

where ι_4 denotes a (4×1)-vector of ones. The components P_j and Z_j of the vector P and Z are transformations of the corresponding variables p_{jnt} and z_{jnt}:

$$Z_{jnt} = \begin{cases} \dfrac{z_{jnt}^{\gamma_1}}{\gamma_1} & \text{for} \quad \gamma_1 \neq 0 \\ \ln z_{jnt} & \text{for} \quad \gamma_1 = 0 \end{cases}, \quad j = k, o, y, \qquad (2.4)$$

$$P_{jnt} = \begin{cases} \dfrac{(p_{jnt}/\theta'_n p_{nt})^{\gamma_1}}{\gamma_1} & \text{for} \quad \gamma_1 \neq 0 \\ \ln (p_{jnt}/\theta'_n p_{nt}) & \text{for} \quad \gamma_1 = 0 \end{cases}, \quad j = h, s, u, m. \qquad (2.5)$$

The two parameters γ_1 and γ_2 capture the way that variables z_{jnt}, and p_{jnt} are transformed by the Box-Cox transformations. Note that in (2.4), the transformation is not applied to the time trend but only to general capital, OCM capital and

[2] An alternative possibility would be to model variable costs with computer capital as a variable input and general capital as a quasi-fixed input.

output. The (4×1) vector θ_n is equal to $\overline{x}_n / \overline{p_n}' \overline{x}_n$,where $\overline{p}_n$ and $\overline{x}_n$ are fixed levels of prices and quantities, so that $\theta_n' p_{nt}$ corresponds to a Laspeyres price index for total variable costs. Note that both functions P_j and C are homogeneous of degree zero in prices, so that the multiplicative term $\overline{p}'\overline{x}$ appearing in the Box-Cox function (2.1) ensures that the cost function is linearly homogeneous in prices.

The translog, the normalized quadratic as well as the generalized Leontief functional form are nested within the generalized Box-Cox specification and are obtained as special cases, for $\gamma_1 \to 0$, $\gamma_2 \to 0$ for $\gamma_1 = 1$, $\gamma_2 = 1$ and $\gamma_1 = 0.5$, $\gamma_2 = 1$, respectively (see Koebel, Falk and Laisney, 2001). These restrictions are directly imposed in the cost function. For example, the normalized quadratic cost function as special case of a generalized Box-Cox cost function can be written as:

$$\begin{aligned} c\left(p_{nt}, z_{nt}; \beta_n\right) &= p_{nt}' B_{pn} + \frac{1}{2} \frac{p_{nt}' B_{pp} p_{nt}}{\theta_n' p_{nt}} + p_{nt}' B_{pz} z_{nt} \\ &\quad + \theta_n' p_{nt} \left(\beta_{0n} + z_{nt}' B_z + \frac{1}{2} z_{nt}' B_{zz} z_{nt} \right), \end{aligned} \tag{2.6}$$

where the subscripts t and n denote time and industry, respectively.[3]

The generalized Leontief can also be formulated as a special case of a generalized Box-Cox cost function (see Koebel et al., 2001):

$$\begin{aligned} c\left(p_{nt}, z_{nt}; \beta_n\right) &= \sqrt{\theta_n' p_{nt}} \left(p_{nt}^{1/2}\right)' B_{pn} + \frac{1}{2} \left(p_{nt}^{1/2}\right)' B_{pp} p_{nt}^{1/2} + \sqrt{\theta_n' p_{nt}} \left(p_{nt}^{1/2}\right)' B_{pz} z_{nt}^{1/2} \\ &\quad + \theta_n' p_{nt} \left(\beta_{0n} + \left(z_{nt}^{1/2}\right)' B_z + \frac{1}{2} \left(z_{nt}^{1/2}\right)' B_{zz} z_{nt}^{1/2} \right). \end{aligned} \tag{2.7}$$

The translog cost function can also be formulated as a special case of a generalized Box-Cox cost function. After the restrictions on the Box-Cox parameters ($\gamma_1 \to 0$, $\gamma_2 \to 0$) are imposed in the Box-Cox cost function a variant of the translog cost function is obtained (see Koebel et al., 2001):

$$\begin{aligned} c\left(p_{nt}, z_{nt}; \beta_n\right) &= \beta_{0n} + \left(\ln p_{nt}\right)' B_{pn} + \left(\ln z_{nt}\right)' B_z + \frac{1}{2} \left(\ln p_{nt}\right)' B_{pp} \left(\ln p_{nt}\right) \\ &\quad + \left(\ln p_{nt}\right)' B_{pz} (\ln z_{nt}) + \frac{1}{2} \left(\ln z_{nt}\right)' B_{zz} (\ln z_{nt}). \end{aligned} \tag{2.8}$$

For the different functional forms of the cost function, a system of optimal input demands $x^* \left(p_{nt}, z_{nt}; \beta_n\right)$ is obtained by the application of Shepards' lemma

[3] The relationship between the matrices A and B is described in Koebel et al. (2001).

$(x^* (p_{nt}, z_{nt}, \beta_n) = \partial c^*/\partial p_{nt})$. Then the system of four-input demand equations is divided by the output level:

$$x_{nt}/y_{nt} = x^* (p_{nt}, z_{nt}, \beta_n) / y_{nt} + e_{nt}, \tag{2.9}$$

where e_{nt} denotes a residual vector that has zero mean and a constant variance matrix and that is uncorrelated with the explanatory variables. The static quadratic and generalized Leontief factor demand system can be estimated by linear SUR with fixed effects. The translog factor demand system and specified as a special case of the Box-Cox cost function as well as the Box-Cox factor demand system have to be estimated by non-linear SUR. Note that the inclusion of industry dummies may not be sufficient to allow for heterogeneity across industries. For this purpose, we split the 24 manufacturing industries into durables and non-durables.

Since the existence of adjustment costs may lead to a delay in the adjustment of factors to changes in output and prices, a dynamic specification of the factor demand system may fit the data better than a static model. Therefore, the factor demand system derived from the different cost functions can be combined with a general dynamic adjustment process of each input factor. In particular, we employ the general dynamic approach suggested by Anderson and Blundell (1982). The advantage of the GECM is that it nests a variety of dynamic specifications, such as the partial ECM, the partial adjustment model or the static model with or without a first-order autoregressive error term. The GECM of the four-equation system can be written as:

$$\begin{aligned} x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} &= D_1 \left(x^*_{nt}/y_{nt} - x^*_{n,t-1}/y_{n,t-1} \right) \\ &\quad + D_2 \left(x^*_{n,t-1}/y_{n,t-1} - x_{n,t-1}/y_{n,t-1} \right) + \varepsilon_{nt}, \end{aligned} \tag{2.10}$$

where both matrices $D_1 (4 \times 4)$ and $D_2 (4 \times 4)$ entail the unknown parameters reflecting departure from the long-run model. The vector ε_{nt} is assumed to have zero conditional mean and a constant conditional variance.

The complete model consists of 64 free parameters plus industry dummies which have to be estimated on the basis of 35×17 observations. Several less general dynamic models are nested within the GECM. If the matrix D_1 is diagonal, the GECM is reduced to the partial ECM. It is reduced to the simple ECM if both D_1 and D_2 are diagonal. The different dynamic specifications will be estimated by non-linear SUR. Starting values will be provided by the static models.

Furthermore, the GECM is reduced to the static model with an autoregressive error term if D_1 is the identity matrix I_4 and $D_2 = I_4 - R$, where $R (4 \times 4)$ is the serial correlation matrix:

$$x_{nt}/y_{nt} = x^*_{nt}/y_{nt} - R\left(x^*_{n,t-1}/y_{n,t-1} - x_{n,t-1}/y_{n,t-1}\right) + \varepsilon_{nt}. \tag{2.11}$$

The model written in first differences is obtained if $D_1 = I_4$ and $D_2 = 0$:

$$x_{nt}/y_{nt} - x_{n,t-1}/y_{n,t-1} = x^*_{nt}/y_{nt} - x^*_{n,t-1}/y_{n,t-1} + \varepsilon_{nt}. \tag{2.12}$$

Finally, the short- and the long-run model coincide if $D_1 = D_2 = I_4$:

$$x_{nt}/y_{nt} = x^*_{nt}/y_{nt} + \varepsilon_{nt}, \tag{2.13}$$

at the exception that the residual terms ε_{nt} are now serially uncorrelated, which was not necessary the case in (2.9).

There are two important issues about the estimation of the dynamic specification using panel data. First, it is well-known that in models which are linear in parameters, the fixed effects estimator with lagged dependent variables generates biased estimates. As proved by Nickell, the bias increases in the magnitude of the adjustment coefficients and decreases with the time dimension of each cross-section. This criticism also applies to the present non-linear GECM context where $x_{n,t-1}/y_{n,t-1}$ and ε_{nt} may be correlated. Judson and Owen (1999), however, find that the bias mainly concerns the coefficients of the lagged endogenous variables. Since this paper focuses on capital and price elasticities rather than on the adjustment parameters, this issue is neglected here.

A second problem is the potential non-stationarity of the data. The time series dimension is quite large with 17 years for each industry. We do not apply panel unit root tests for two reasons. First, the time series dimension may still be too small to apply panel unit root tests. Second, given the fact that most of the variables are input-output ratios as well as relative prices, stationarity of the series is a plausible assumption. In this case, the error-correction model can still be used to distinguish between long-run and short-run effects.

The key elasticities are the long-run elasticities of the demand for labor at different skill levels with respect to the quantity of OCM capital, z_o, and non-OCM capital, z_k:

$$\epsilon\left(x^*_j, z_i\right) = \frac{\partial x^*_j}{\partial z_i}\frac{z_i}{x^*_j}, \tag{2.14}$$

where $j = h, s, u$, respectively and $i = k, o$, respectively. The main hypothesis to be tested is that unskilled labor is a substitute for OCM capital but highly skilled workers are complementary to OCM capital. A positive sign indicates a complementary relationship. A weaker form of computer capital skill complementarity states that unskilled workers also benefit from the increase in the OCM capital stock; however, the effect is much lower than the impact of OCM capital on skilled or highly skilled workers.

3. Data and descriptive statistics

The data sample used consists of panel data on 35 German industries for the period 1978 −1994. The basic data source are the National Accounts. From 58 industries, we selected a subset of 54 industries. The public sector as well as agriculture are excluded. Data availability reduces the sample to 35 industries. Data sources for wages and employment by different educational qualifications are described in Falk and Koebel (2001). Wages are measured as average annual salaries (plus fringe benefits and non-wage labor costs) paid to full-time workers and are calculated from the IABS. One drawback of this database is that earnings for university graduates are topcoded. In general, earnings of highly skilled workers can be calculated from the wage and salary statistics. This database, however, is limited in coverage, in particular for some non-manufacturing industries (for instance other market services). For these industries, we assume that the ratio of earnings between medium-skilled and highly skilled workers is similar to the corresponding ratio in the trade, transport and financial intermediation sector.

Investment in office machinery and computers (OCM) is taken from the IFO capital flow tables provided by the IFO institute (see Faust et al. 1999). These series are available for the western part of Germany for the period 1970 -1994 and including East Germany since 1995. In Germany, OCM investment data are defined by ownership rather than by the use of new computer equipment. OCM investment includes mainframes, personal computers, direct access storage devices, printers, terminals, tape drives, storage devices, office machinery equipment and photocopiers and related equipment. In the U.S., by contrast, photocopiers and related equipment are not included into the category office machinery and computers. In a broad sense, high-tech capital can be defined as "Information Processing Equipment" (IPE), consisting of communications equipment, scientific and engineering instruments, photocopiers and related equipment (see Morrison, 1997, Morrison-Paul and Siegel, 2001). Note that both OCM and IPE investment do not include software development, maintenance or related services. In recent years, software and related services have often been included into IT capital (see

Jorgenson, 2001).

In order to obtain OCM investment in constant prices, nominal investment must be deflated by an investment deflator for OCM equipment. Unfortunately, hedonic price deflators for OCM investment or the output of the OCM industry do not exist for Germany (Deutsche Bundesbank, 2000). For personal computers, some work is carried out by Moch (2001). He estimates quality-adjusted price indices for personal computers for the period 1985 to 1994 and finds that the prices of personal computers adjusted for exchange rate movements are declining as fast as in the U.S.. To deflate nominal investment, we employ the U.S. Bureau of Economic Analysis's (BEA's) price index for OCAM equipment adjusted for exchange rates movements, which partly uses hedonic techniques to correct for quality change. The use of the current exchange rates to convert foreign prices into local currency can be criticized. Alternatively, purchasing power parities for the OCM industry can be employed. However, they are difficult to construct. Another important criticism to the application of U.S. price indices to other countries is that the composition of products may differ between countries. Van Ark (2001) suggests that the U.S. deflator for OCM investment may lead to an exaggeration of the price decline, since computer hardware production in the U.S. mainly consists of PCs and semiconductors, whereas computer production in the EU is more dominated by the production of peripheral equipment. In order to overcome this problem, we also experiment with the French quality-adjusted price index of OCM equipment (including photocopiers) to deflate nominal OCM investment.[4] In addition, the share of office machinery in total OCM may also differ across countries. A priori, one may expect that the share of office machinery equipment in total OCM equipment is very small. Information on the composition of OCM investment, however, is not available - only information on sales of OCM. Unreported results show that the share of office machinery in total sales of the OCM industry is around 10 percent. Similar tendencies can be observed for the U.K.[5]

Price indices for OCAM equipment are taken from the NIPA Table 7.8 published by the U.S. Bureau of Economic Analysis (BEA). Separate price indices are available for computers and peripheral equipment, office and accounting equipment and photocopiers and related equipment. Starting from 1985, BEA has used hedonic price indices for computer equipment to deflate its national accounts output and investment data (BEA, 2001, Whelan, 2000). It provides estimates for the

[4] I would like to thank N. Mulder (CEPII) for providing us with the French price index of OCM equipment.

[5] Personal correspondence with Mary O'Mahony.

quality-adjusted price index of computers and peripheral equipment for the period 1966 -2000. The measured decline is 16.3 percent per year for computer and peripheral equipment for the period 1970 -1999. In contrast, the prices of office and accounting equipment and photocopiers and related equipment increased by 1.2 and 2.5 percent over the period 1970 to 1999, respectively. This indicates that the official price deflators for these types of durable equipment may understate the true price decline. Indeed, Jorgenson (2001) and Krusell at al. (2000) argue that quality-adjusted deflators are restricted to few items (i.e. computers and peripheral equipment) and that deflators for other types of equipment probably understate the decrease in prices.

The decrease in the prices of OCAM equipment was accompanied by an investment boom and a change in the composition of OCAM investment. In the U.S., the share of computers and peripheral equipment in total OCAM equipment plus photocopiers and related equipment increased from 47 percent in 1970 to 84 percent in 2000 (both in nominal terms). In order to aggregate the three different price indices a Törnquist price index is constructed. The change in the Törnquist price index, $\Delta P/P_{t-1}$ can be written as:

$$\frac{\Delta P_t}{P_{t-1}} = \sum_{i=1}^{3} \frac{\Delta p_{it}}{p_{i,t-1}} \frac{1}{2}(s_{i,t} + s_{i,t-1}) \tag{3.1}$$

where $\frac{\Delta p_{it}}{p_{i,t-1}}$ is the annual growth rate of the three product groups in year t and the $s_{i,t}$ is the nominal investment share of the three product groups in year t. Three different U.S. price indices are constructed: (i) price index of OCAM equipment (without photocopiers and related equipment) adjusted for exchange rate movements, and (ii) price index of OCAM plus photocopiers and related equipment adjusted for exchange rate movements, (iii) price index of OCAM plus photocopiers and related equipment adjusted for exchange rate movements using PPP between the German mark and the U.S. dollar.

Figure 1 in appendix shows the movements of the resulting deflators expressed in German marks for the period 1970 to 1991. Figure 2 in appendix contains the development of the corresponding deflators for the period 1991 to 1999. Table 1 summarizes the evolution of the different deflators. We also include the French OCM investment deflator (adjusted for exchange rate changes) and the German deflator for OCM investment as well as the producer price index for the OCM industry. Both the U.S. and the French price index of OCM equipment rapidly declined and this decline accelerated in the second half of the 1990s (see Figure 1 and 2). The U.S. price index falls between 7.2 and 9.6 percent per year between the

Table 1: Average annual changes in different price indices of OCM equipment

investment deflators, all adjusted for exchange rate changes	'70-'91	'91-'99
U.S. deflator of OCAM investment (BEA)	−9.6	−16.3
U.S. deflator of OCAM investment (Jorgenson & Stiroh '95)	−10.2	n.a.
French deflator of OCM investment (INSEE)	−8.4	−10.0
U.S. deflator of OCAM + photocopiers (BEA)	−7.2	−13.2
U.S. deflator of OCAM + photocopiers (adj. using PPP)	−6.0	−14.9
German producer prices of the OCM industry	−1.2	−4.4
German implicit deflator of OCM investment	0.7	−0.8

Notes: Average annual percentage rates of growth. Price indices are converted to DM using current exchange rates. The U.S. price indices are constructed using the Törnquist formula. OCAM is defined as office, computing and accounting machinery. Source: U.S price indices: BEA, Table 5.8, 7.8.; Statistical Office Germany; INSEE; own calculations.

period 1970 to 1991 depending whether or not photocopiers and related equipment are included (see Table 1). Note that the decline in the U.S. price index of OCAM equipment is consistent with the corresponding price index presented in Jorgenson and Stiroh (1995). The decline accelerated over the period 1991 to 1999 with growth rates ranging between 13 and 16 percent per year. The French price index of OCM equipment converted in German marks fell by 10 percent per year for the period 1991 to 1999 (see Table 1). Furthermore, the choice of the conversion method appears to be less important. The decline in the price index based on PPP rates to convert U.S. dollar price in German marks is very close to the price index based on current exchange rates. In Germany, by contrast, the implicit deflator of office machinery and computer equipment slightly increased for the period 1970 to 1985, remained stable over the period 1986 to 1994 and then began to slightly decline in 1995. It is obvious that the German investment deflator of OCM equipment is not appropriate to deflate nominal OCM investment in nominal prices into constant prices. The official producer price index for the office machinery and computers industry also seems not very reasonable. Table 1 shows that the decline is 1.2 percent per year between the period 1970 −1991 and about 4.4 percent per year between the period 1991 to 1999 (see also Schreyer, 2001).

The OCM capital stock is constructed using the perpetual inventory method. Here, the U.S. depreciation rate is used to construct the OCM capital stock.

Fraumeni (1997) reports a depreciation rate of office, computing, and accounting machinery of about 0.2729 for the years before 1978 and 0.3199 from 1978 onwards. These rates are high and they are higher than the implicit depreciation rates based on the German national accounts. The initial OCM capital stock is assumed to be equal to the OCM investment in constant prices in 1970 divided by the depreciation rate. General capital is obtained by subtraction of OCM capital from total capital. Figure 3 in appendix shows the evolution of the OCM capital stock in total manufacturing using different deflators for OCM investment. Based on the U.S. deflator and the French deflator, the average growth rates of the OCM capital stock across manufacturing industries range between 20.4 and 22.4 percent per year. Since the investment deflator is falling quickly, much of the measured real growth rate of the OCM capital stock may actually be attributable to the deflator. The general conclusion is that the change in the OCM capital stock is not sensitive to the choice of the deflator except for the German deflator. Based on the German deflator the growth rate of the OCM capital stock is about 10 percent per year.

Table 2 presents summary statistics on the average annual change in quantities and factor prices for 24 manufacturing and 15 non-manufacturing industries over the period $1978 - 1994$. The OCM capital stock in constant prices grew at a faster rate than all other inputs. Over the period $1978 - 1994$, the OCM capital stock increased by 21 percent per year in manufacturing and 23 percent per year in non-manufacturing industries (unweighted means based on 24 and 15 industries, respectively). For the U.S. economy, Jorgenson (2001) reports that, measured in nominal terms, the stock of all IT assets (computers, communication and software) combined accounts for 4 percent of the domestic capital stock in 1999, while the share of computer hardware capital is less than 1 percent. Based on a broader definition of OCM capital, Morrison (1997) finds that in U.S. manufacturing the share of high-tech equipment increased from 3 percent in 1976 to 15 percent in 1991.

4. Empirical results

The parameters of the four-input demand system assuming a Box-Cox or a translog functional form are estimated using non-linear *SUR* on panel data. Note that the quadratic factor demand system and the generalized Leontief factor demand system are linear in parameters. The complete static model assuming a generalized Box-Cox functional form of the cost function consists of 32 free parameters plus

Table 2: Average annual changes in input quantities and factor prices

	mean	s.d.	min	max	mean	s.d.	min	max
	manufacturing				**non-manufacturing**			
	% change in input quantities and output							
highly skilled labor, x_h	3.6	1.9	−1.6	7.5	5.0	3.4	−2.2	11.5
skilled labor, x_s	0.1	1.6	−3.7	3.5	1.4	2.1	−2.5	4.1
unskilled labor, x_u	−3.9	1.6	−7.2	−0.2	−2.7	3.0	−9.3	1.8
total materials, x_m	1.6	1.7	−1.4	5.7	2.6	2.3	−0.5	7.8
general capital, z_k	0.4	2.1	−3.9	4.6	2.3	2.6	−3.4	7.2
OCM capital, z_o	20.6	1.9	15.4	24.2	23.0	3.7	17.7	30.5
gross output, z_y	1.0	1.8	−2.4	5.4	2.6	2.6	−1.1	7.6
	% change in factor prices							
highly skilled labor, p_h	4.5	0.2	4.0	4.9	4.4	0.2	4.1	4.8
skilled labor, p_s	4.2	0.3	3.7	4.9	4.3	0.5	3.8	5.1
unskilled labor, p_u	4.5	0.3	3.9	5.1	4.6	0.5	3.7	5.3
total materials, p_m	2.1	0.9	0.4	3.5	2.5	1.2	−0.1	4.1

Notes: Average annual percentage rates of growth for 24 and 15 industries over the period 1978-1994. We calculate the OCM capital stock using the U.S. depreciation rate. OCM investment is deflated by the U.S price index of OCAM equipment plus photocopiers adjusted for exchange rate changes. Source: Statistical Office Germany, IFO capital flow tables, Federal Labor Office, U.S. BEA: Table 7.8., own calculations.

the Box-Cox parameters γ_1 and γ_2 and 4×35 parameters for industry dummies which have to be estimated on the basis of $35 \times 17 \times 4$ observations. 32 additional parameters have to be considered in the generalized error-correction model (GECM). For the partial error-correction model and the simple error-correction model, 20 and 8 adjustment parameters have to be estimated. In order to allow for heterogeneity across industries we estimate separate factor demand systems for the manufacturing sector and the non-manufacturing sector. The static factor demand system is also estimated for the durable manufacturing sector and non-durable manufacturing sector in order to allow for a different production technology across manufacturing industries.

Table 3 contains the estimates of the Box-Cox parameters γ_1 and γ_2 for the separate estimation samples. For the manufacturing sector, we also provide estimates of γ_1 and γ_2 obtained from the PECM. In most cases, the Box-Cox parameters γ_1 and γ_2 are either significantly different from zero or significantly different from one. Note that γ_1 ranges between .13 and .33 indicating that both the GL and TL functional form are more appropriate in explaining the data than the normalized quadratic functional form.

Table 3: Estimates of the Box-Cox parameters

	γ_1	γ_2
static factor demand system		
non-durables	0.33 (14.60)	0.02 (0.17)
durables	0.20 (7.57)	0.30 (2.29)
total manufacturing	0.24 (12.80)	0.00 (0.01)
non-manufacturing	0.13 (3.47)	1.02 (8.05)
dynamic factor demand system		
total manufacturing[a]	0.25 (7.43)	0.08 (2.54)

Notes: t-values in parentheses. Estimation period is 1978-1994. The number of observations are 17×12 for durables, 17×12 for non-durables and 17×24 for total manufacturing and 17×11 for the non-manufacturing sector. [a]Estimates are based on the PECM.

Table 4 contains the values of the log-likelihood function obtained from the different functional forms of the cost function. For the panel of West German manufacturing industries, the values of the log-likelihood function obtained from the different static factor demand systems are $6,071.0$ for the factor demand system assuming a generalized Box-Cox functional form, $5,962.7$ for the translog factor demand system, $5,743.4$ for the quadratic factor demand system and $5,930.4$ for the factor demand system assuming a generalized Leontief functional form (see Table 4). A likelihood ratio test indicates that the Box-Cox parameters (γ_1 and γ_2) are jointly significant at the 5 percent level in all cases (see Table 4). For non-manufacturing industries, the log-likelihood values are $2,506.4$ for the factor demand system derived from the generalized Box-Cox function, $2,478.1$ for the translog factor demand system, $2,424.5$ for the quadratic factor demand system and $2,481.3$ for the factor demand system assuming a generalized Leontief

Table 4: Log likelihood values of the factor demand system based on different estimation samples and different functional forms

	log-likelihood values				LR-test		
	Box-Cox (BC)	translog (TL)	normalized quadratic (NQ)	generalized Leontief (GL)	TL vs. BC	NQ vs. BC	GL vs. BC
	static factor demand system						
non-durables	$3,189.6$	$3,086.0$	$3,065.9$	$3,140.3$	207.2^{*}	247.4^{*}	98.6^{*}
durables	$3,058.8$	$3,052.7$	$2,921.4$	$3,029.5$	12.2^{*}	274.8^{*}	58.6^{*}
manufacturing	$6,071.0$	$5,962.7$	$5,743.4$	$5,930.4$	216.6^{*}	655.2^{*}	281.2^{*}
non-manuf.	$2,506.4$	$2,478.1$	$2,424.5$	$2,481.3$	56.6^{*}	163.8^{*}	50.2^{*}
	dynamic factor demand system						
manufacturing	$6,946.4$	$6,923.6$	$6,862.3$	$6,903.3$	45.6^{*}	168.2^{*}	86.2^{*}
non-manuf.	$3,160.4$	$3,100.9$	$2,965.1$	$2,987.4$	110.0^{*}	390.6^{*}	346.0^{*}

Notes: The five percent critical value of the LR-test is 5.99. See Table 3.

functional form. For the non-manufacturing sector, the null hypothesis that the Box-Cox parameters (γ_1 and γ_2) are jointly not significantly different from zero can also be rejected at the five percent level. Similarly, for the dynamic specifications (GECM for manufacturing and SECM for non-manufacturing) the translog, the normalized quadratic and the generalized Leontief functional form are rejected at the five percent significance level. Unreported results show that the log likelihood value of the generalized error-correction model assuming a generalized Box-Cox functional is lower than the log likelihood value of the translog functional form. The lower log likelihood value of the factor demand system assuming a generalized Box-Cox functional form may indicate that the global maximum is not achieved. Note that in some cases it may be difficult to achieve the global maximum since the dynamic factor demand system assuming a Box-Cox functional form is highly non-linear in parameters. The factor demand system specified as partial error-correction model or simple error-correction model produces more reliable estimates.

Elasticities based on static factor demand models

In this section, we report elasticities obtained from estimating the static factor demand system. To conserve space, we present only the elasticities of factor demand obtained from the generalized Box-Cox functional form. Table 5 provides the elasticities of factor demand for the manufacturing sector based on split sample estimates distinguishing between durables and non-durables. The results of the LR test for the null of identical parameters across industries show that the pooled model can be rejected. The LR test is calculated as $2 \times ((3,189.6 + 3,058.8) - 6,071.0) = 354.8$, where $6,071.0$ is the log-likelihood value of the pooled model and the first two log-likelihood values correspond to the log-likelihood values of the two split sample regressions. Under the null hypothesis, this test statistic is chi-squared distributed with 34 degrees of freedom (there are $2 \times 34 - 34 = 34$ slope parameters which may be different in the split regressions). The five percent critical value is 48.32 which is much lower than the empirical value of 354.8. Table 6 provides the elasticities of factor demand for the non-manufacturing sector.

Elasticities were calculated at the midpoint data in 1986. Because the results for different industries are too voluminous to discuss in detail, we decided to report only the median elasticity as well as the t-statistic of the corresponding median elasticity. The elasticities of the different educational qualification groups with respect to OCM capital as well as general capital are given in row five and six of Table 5 and Table 6. A positive sign indicates a complementary relationship, whereas the negative sign indicates that the two inputs are substitutes. Output elasticities and the impact of time are provided in row seven and eight of Table 5 and Table 6. Own-price and cross-price elasticities of factor demand are given in the upper panel of Tables 5 and 6. Here a positive sign indicates that two inputs are substitutes.

For manufacturing industries, the results indicate that an increase in the OCM capital stock is increasing the demand for highly skilled workers as well as the demand for medium-skilled workers. Contrary to expectation, we find a positive impact of the OCM capital stock on the demand for unskilled workers. Based on split sample estimates, the median elasticity of OCM capital stock with respect to highly skilled workers is about 0.13 and highly significant (see Table 5). The elasticities of the OCM capital stock with respect to medium-skilled workers and unskilled workers are 0.04 and 0.14, respectively and are also highly significant.

The median elasticity of general capital with respect to university graduates is about 0.90 and highly significant (see Table 5). The impact of general capital on both medium-skilled workers and unskilled workers is also positive and significant at five percent level but somewhat lower than the impact of capital on university graduates ($\varepsilon_{x_s^* z_k} = 0.47$ and $\varepsilon_{x_u^* z_k} = 0.08$). This indicates that the impact of general capital (non-OCM capital) on employment is increasingly positive with

Table 5: Elasticities of factor demand obtained from the static generalized Box-Cox cost function based on split sample, **manufacturing**

$\epsilon_{x_i^*,p_j}$	x_h^*	x_s^*	x_u^*	x_m^*
	price elasticities			
p_h	$\boxed{-0.30}$	0.02	−0.04	−0.00
	(−0.61)	(0.45)	(−2.70)	(−1.17)
p_s	0.05	$\boxed{-0.21}$	0.00	0.05
	(0.45)	(−5.47)	(0.00)	(5.07)
p_u	−0.48	0.00	$\boxed{-0.29}$	0.06
	(−2.68)	(0.00)	(−4.03)	(4.26)
p_m	−0.22	0.20	0.37	$\boxed{-0.11}$
	(−1.15)	(5.71)	(6.74)	(−6.90)
$\epsilon_{x_i^*,z_j}$	output, capital and time elasticities			
general capital, z_k	0.90	0.24	0.08	0.10
	(4.96)	(5.74)	(2.86)	(3.38)
OCM capital, z_o	0.13	0.04	0.14	−0.01
	(4.64)	(2.74)	(4.39)	(−0.69)
output, z_y	0.12	0.43	0.55	0.91
	(0.67)	(6.68)	(17.28)	(26.37)
time, t	0.008	−0.003	−0.063	0.005
	(2.01)	(−0.89)	(−9.09)	(1.47)

Notes: The number of observations is 408. The estimation period is 1978-1994. The median value of the elasticities is evaluated at 1986 data. t-values in parentheses. Price homogeneity is imposed for each industry but does not necessarily hold for the median elasticities

the skill level ($\varepsilon_{x_h^* z_k} > \varepsilon_{x_s^* z_k} > \varepsilon_{x_u^* z_k}$). This is consistent with a weaker form of the capital-skill complementarity hypothesis. Furthermore, output elasticities for medium-skilled workers and unskilled workers are positive and significant with a higher output elasticity for unskilled workers than for medium-skilled workers ($\varepsilon_{x_s^* z_y} = 0.55 > \varepsilon_{x_u^* z_y} = 0.43$). The demand for highly skilled workers, however, seem to be rather independent of changes in output. Turning to the price elasticities of factor demand, we find that the own-price elasticities are significantly different from zero and negative, except for the own-wage elasticity of highly skilled workers.

For non-manufacturing industries, we also find a significantly positive impact of OCM capital on the employment of university graduates (see Table 6). The impact of OCM capital on medium-skilled workers is also positive and somewhat larger than the impact of OCM capital on highly skilled workers. Contrary to what is expected, we also find a large and positive effect of OCM capital on

Table 6: Elasticities of factor demand obtained from the static **generalized Box-Cox** cost function, **non-manufacturing**

$\epsilon_{x_i^*,p_j}$	x_h^*	x_s^*	x_u^*	x_m^*
		price elasticities		
p_h	-0.48	0.08	0.18	-0.02
	(-1.91)	(0.80)	(0.53)	(-2.82)
p_s	0.64	-0.39	0.29	0.09
	(0.81)	(-6.37)	(0.90)	(3.10)
p_u	0.28	0.08	-1.00	0.07
	(0.64)	(1.05)	(-3.02)	(4.07)
p_m	-0.34	0.18	0.64	-0.17
	(-2.27)	(3.53)	(0.92)	(-6.50)
$\epsilon_{x_i^*,z_j}$	capital, output and time elasticities			
general capital, z_k	1.17	0.47	-0.32	-0.00
	(7.05)	(6.41)	(-2.75)	(-0.01)
OCM capital, z_o	0.07	0.09	0.15	0.06
	(2.35)	(4.05)	(4.57)	(2.48)
output, z_y	-0.19	0.00	0.71	0.90
	(-1.35)	(-0.05)	(7.92)	(15.25)
time trend, t	-0.010	-0.016	-0.040	-0.010
	(-1.48)	(-3.66)	(-6.11)	(-1.82)

Notes: The number of observations is 187. See Table 5.

the demand for unskilled workers. Furthermore, an increase in general capital is reducing the demand for unskilled workers on the one hand and is increasing the demand for medium-skilled workers and highly skilled workers on the other hand. The elasticity of the employment of unskilled workers with respect to general capital is -0.32 compared to the elasticity of general capital with respect to highly skilled workers and medium-skilled workers of about 1.17 and 0.47, respectively (see Table 6). This is consistent with the hypothesis of capital-skill complementarity, which states that unskilled workers and capital are substitutes while skilled workers tend to be complements.

Elasticities based on dynamic factor demand models

Estimations results for the static factor demands presented above are partly hampered by serially correlated errors. This may suggest that the underlying static models are dynamically misspecified. We therefore present the long-run elasticities of the factor demand model based on dynamic factor demand models. The estimation period is 1979 −1994 because of the inclusion of variables in first differences. As expected, in all cases the LR-Test of the null hypothesis that the adjustment parameters are jointly equal to zero can be rejected. Table 7 shows the long-run elasticities of the partial error-correction model assuming a generalized Box-Cox functional form of the cost function for the manufacturing sector.

Table 7: Long-run elasticities of the dynamic factor demand model, **manufacturing** (based on the PECM-BC)

$\epsilon_{x_i^*,p_j}$	x_h^*	x_s^*	x_u^*	x_m^*
		price elasticities		
p_h	$\boxed{0.09}$ (0.32)	−0.01 (−1.27)	−0.01 (−1.14)	0.00 (1.38)
p_s	−0.15 (−1.42)	$\boxed{-0.18}$ (−4.07)	−0.10 (−1.79)	0.02 (4.28)
p_u	−0.13 (−1.42)	−0.05 (−1.46)	$\boxed{-0.21}$ (−2.60)	0.02 (3.42)
p_m	0.13 (1.66)	0.22 (6.04)	0.32 (6.27)	$\boxed{-0.04}$ (−4.10)
$\epsilon_{x_i^*,z_j}$	capital, output and time elasticities			
z_k	0.80 (7.11)	0.43 (6.78)	0.23 (3.05)	0.61 (7.23)
z_o	0.11 (2.03)	0.11 (5.48)	0.15 (6.40)	0.11 (3.78)
z_y	0.07 (0.76)	0.15 (2.21)	0.31 (3.73)	−0.20 (−1.96)
t	0.021 (3.42)	−0.025 (−6.88)	−0.053 (−7.91)	−0.024 (−4.79)

Notes: The number of observations is 456. See Table 5.

Again, we find a positive effect of OCM capital on any of the different types of labor. When looking at the static factor demand, this pattern also becomes apparent. The median elasticities of OCM capital with respect to highly skilled workers, medium skilled workers and unskilled workers are, 0.11, 0.11 and 0.15, respectively. Furthermore, we find evidence of capital-skill complementarity. The median elasticity of general capital with respect to university graduates is about 0.80 and highly significant. The impact of general capital on medium-skilled and unskilled workers is also positive but somewhat lower than the impact of general capital on university graduates. Finally, we can see that material inputs can be substituted for both unskilled workers and medium-skilled workers. In particular, the substitution possibilities are dominated by the substitutability between unskilled workers and materials. As expected, own-wage elasticities for medium-skilled and unskilled workers are negative and significant. For non-manufacturing industries, the results for the dynamic model appeared to be less satisfactory and are not reported here.

Sensitivity of the OCM elasticities with respect to the deflator of OCM investment

Table 8: Elasticities of employment with respect to OCM capital based on different deflators of OCM investment, **manufacturing** (obtained from the static Box-Cox)

OCM elasticities:	French deflator	German deflator
based on PECM		
$\epsilon_{x_h^* z_o}$	0.10 (4.64)	0.10 (3.10)
$\epsilon_{x_s^* z_o}$	0.08 (6.34)	0.10 (3.45)
$\epsilon_{x_u^* z_o}$	0.09 (4.66)	0.19 (3.98)
based on static factor demands		
$\epsilon_{x_h^* z_o}$	0.11 (3.12)	0.11 (2.20)
$\epsilon_{x_s^* z_o}$	0.02 (0.73)	0.02 (1.44)
$\epsilon_{x_u^* z_o}$	0.09 (3.39)	0.11 (2.91)

Table 8 presents the elasticities of OCM capital with respect to the different skill levels based on different deflators for OCM investment for the manufacturing sector. Column one and two contain the OCM capital elasticities based on the French and German deflator of OCM investment. The most striking feature of Table 8 is that the impact of OCM capital on employment are somewhat sensitive with respect to the choice of the deflator of OCM investment. Particularly, the OCM effect is sensitive to the choice of the German deflator which is used to construct the OCM capital stock. As noted previously, the German price index for the OCM equipment may understate the true price decline.

Based on the French deflator the (long-run) elasticity of highly skilled workers with respect to OCM capital is 0.10 for the dynamic factor demand model and 0.11 for the static factor demand model. This indicates that between 62 and 68 percent of the observed increasing employment of university graduates can be explained by the increase in the OCM capital stock given the average growth rate of OCM capital stock across manufacturing industries about 22.4 percent per year. Based on the U.S. deflator, the elasticity of highly skilled workers with respect to the OCM capital stock is 0.10 for the dynamic factor demand model and 0.13 for the static factor demand model (see Table 5 and Table 7). Given the growth rate of the OCM capital stock based on the U.S. price index for OCAM plus photocopiers and related equipment (converted in local currency) of about 20.4 percent per year, between 62 and 74 percent of the expanding employment of highly skilled workers can be explained by the increase in the OCM capital stock. A comparison between both deflators shows that the OCM effect as well as the OCM elasticities based on the French deflator are quite similar to the OCM effect and elasticities based on the U.S. deflator (converted into a common currency).

The effects of the OCM capital stock on the employment change of university graduates are considerably lower when the German deflator is used to construct OCM capital stocks. Based on the German deflator for OCM investment, the elasticities of OCM capital with respect to highly skilled workers are 0.10 and 0.11 for the different specifications and are similar to the corresponding elasticities based on the French deflator. Given an increase in the OCM capital stock based on the German deflator of about 10 percent per year, between 34 and 37 percent of the observed expanding employment for university graduates can be attributed to the increase in the OCM capital stock. The results clearly indicate that impact of OCM capital is underestimated when the German price index for the OCM equipment is used to construct OCM capital stocks.

Sources of employment change by skill level

Given the elasticities of factor demand, one can calculate how much of the observed change in employment can be attributed to the effects of prices, output, two types of capital and time. After a total differentiation of the labor demand equations and the following transformation into growth rates, the percentage change of employment of the different educational qualification levels can be written as:

$$\frac{\Delta x_{gnt}}{x_{gnt}} \simeq \sum_{j=h,s,u,m} \varepsilon_{x_g p_j} \frac{\Delta p_{jnt}}{p_{jnt}} + \sum_{i=k,o,y} \varepsilon_{x_g z_i} \frac{\Delta z_{int}}{z_{int}} + \varepsilon_{x_g t},$$

where $\Delta x_{gnt}/x_{gnt}$ denotes the actual employment growth rate of the three types of labor ($x_g = h, s, u$ for $g = 1, 2, 3$, respectively) which should be close to the predicted employment growth rate. The first term on the right-hand side captures the price effects calculated as the product of price changes and the estimated price elasticities; the second term on the right-hand side measures the impact of the two types of capital and the impact of output. The results of the decomposition analysis appear in Table 11. Both the observed and the predicted employment change are given in column one and two of Table 11. Column 3 to 7 contains the different sources of employment change in percent of the actual employment change. Column 8 contains the total predicted change as a percentage of actual change. In general, the predicted changes are relatively close to the observed ones. For instance, the average growth rate of the employment of highly skilled workers across manufacturing industries is about 3.6 percent which is close to the prediction of 3.8 percent for the static model and 4.1 for the dynamic model. Note that for this application the static factor demand model gives better predictions than the dynamic factor demand model. Therefore, the interpretation of results focuses on the sources of employment change obtained from the static model.

Table 11: Sources of employment change of university graduates and unskilled workers

types of worker	employment change per year ob-served	employment change per year pre-dicted	Sources in percent of **actual** change: price effect	out-put effect	general capital effect	OCM capital effect	time effect	to-tal
			manufacturing, static BC, split sample					
highly skilled	3.6	3.8	0^a	0^a	11	72	22	104
unskilled	−3.9	−3.6	19	−15	−1	−73	161	91
			manufacturing, PECM-BC					
highly skilled	3.6	4.1	−15	0	9	61	59	114
unskilled	−3.9	−2.5	19	−8	−2	−80	136	64
			non-manufacturing, static BC					
highly skilled	5.0	4.4	22	0^a	54	34	−21	89
unskilled	−2.7	−2.3	110	−68	27	−131	146	84

Notes: [a]Insignificant elasticities are included.

For manufacturing industries, the main cause of the increase in the demand of highly skilled workers is the growing OCM capital stock. Here, 72 percent of the employment change of university graduates can be explained by computerization during the period 1978-1994. Using U.S. manufacturing data for the period 1959-1989, Morrison-Paul and Siegel (2001) find that the accumulation of high-tech capital has accounted for 9 percent of the expanding employment for college graduates for the period 1959-1989. The effect of general capital, however, is quite small. In manufacturing, the increase in general capital only explains 9 percent of the increasing employment of highly skilled workers.

In non-manufacturing industries, 34 percent of the observed employment change of highly skilled workers can be attributed to the increase in the OCM capital stock. For non-manufacturing, the effect of general capital on the demand for heterogeneous labor is more important than for manufacturing. Here, about 54 percent of the increase in employment of university graduates can be explained by the increase in general capital. Furthermore, 27 percent of the decreasing employment of unskilled workers can be explained by the increase in general capital.

Price and output effects play a minor role in explaining the employment change of highly skilled workers and medium-skilled workers. Wage effects and substitution effects between different types of labor and between labor and material inputs, however, are more important in explaining the decreasing employment of unskilled workers. In the non-manufacturing sector, the wage and substitution effects between labor and material inputs are considerably more important than the effects of general capital in explaining the decreasing employment of unskilled workers.

5. Conclusions

The purpose of this paper has been to investigate the relationship between the increased growth of the OCM capital stock and the labor demand for different educational qualification groups. Static and dynamic factor demand models assuming a generalized Box-Cox, a generalized Leontief, a normalized quadratic and a translog functional form of the cost function are employed. This paper develops new estimates of the office machinery and computer (OCM) capital stock. U.S. price indices (adjusted for exchange rate changes) are used as deflators for OCM investment. Estimates using French and U.S. deflators for OCM investment imply that the growth in the German OCM capital stock based on the official OCM investment deflators is significantly underestimated by about 10 percentage points per year. We also examine the sensitivity of the key elasticities with respect to the deflator for OCM investment. Questions concerning sensitivity of the results with respect to the the choice of the functional form were also addressed.

The empirical results indicate that the accumulation of the OCM capital stock is the major factor contributing to the shift in labor demand towards highly skilled workers. Accumulation of OCM capital accounts for between 60 and 71 percent of the expanding employment of university graduates in manufacturing industries between the period 1978-1994. In non-manufacturing industries, both OCM capital and general capital accounted for nearly all of the change in the employment of university graduates. Contrary to expectation, we also find a positive impact of the OCM capital stock on the demand for unskilled workers. Furthermore, accumulation of general capital tends to reduce unskilled workers. Wage effects and substitution effects between labor and material inputs play a minor role in explaining employment changes of highly skilled and medium-skilled workers, but these effects are more important in explaining the demand for unskilled workers. Finally, the results of the effects of the OCM capital stock are somewhat sensitive to the choice of the deflator of OCM investment which is used to construct the OCM capital stock. Estimates based on the German deflator significantly underestimate the effect of OCM capital on the employment of highly skilled workers.

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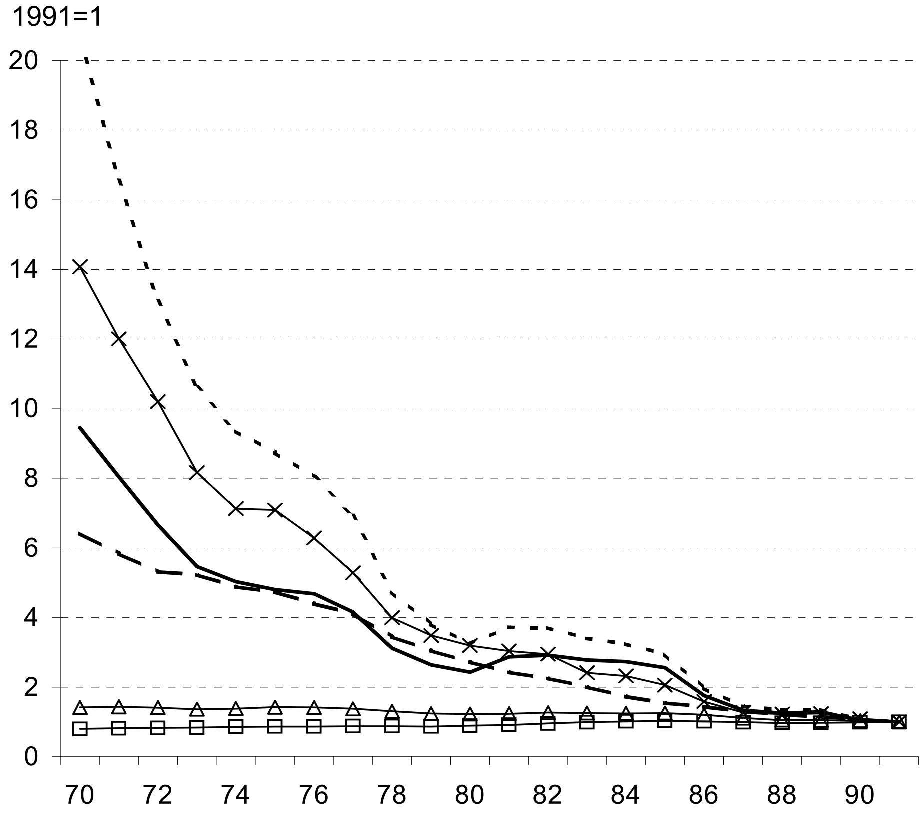
Figure 1: Deflators for OCM investment and output, 1970-1991



U.S deflator for OCAM investment (converted into DM using current DM/US$ exch. rate),

French deflator for OCM investment (converted into DM using current DM/FF exch. rate)

U.S deflator for OCAM investment plus photocopy and related equipment (converted into DM using current DM/US$ exch. rate)

U.S deflator for OCAM investment plus photocopy and related equipment (converted into DM using PPP between DM and US$)

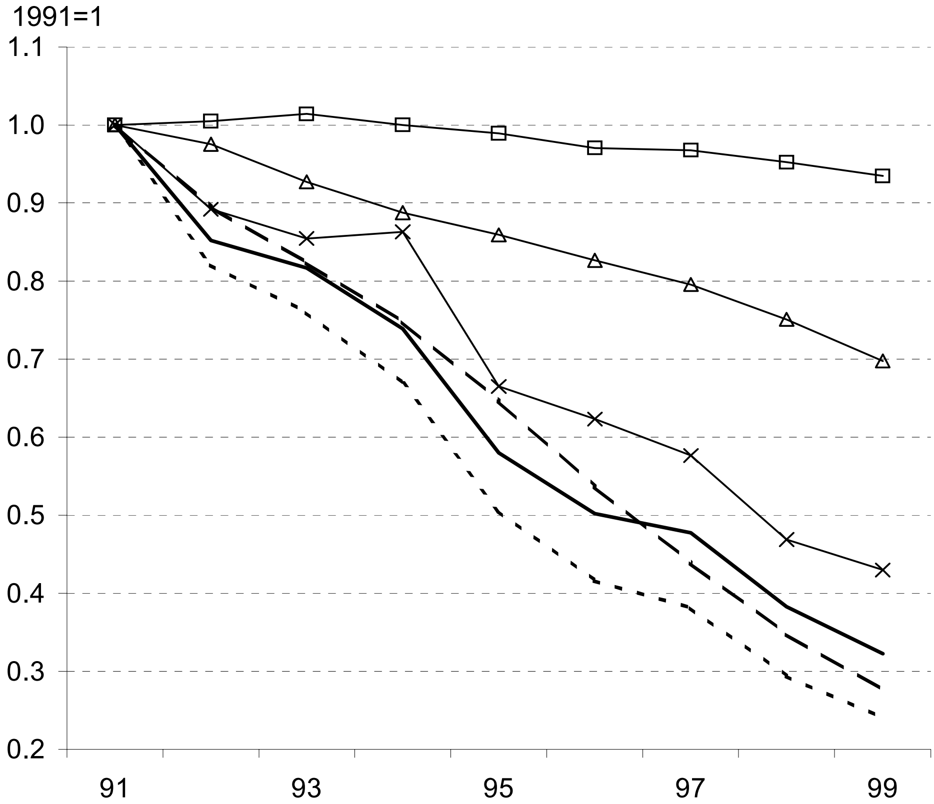
German producer prices of the OCM industry (DM)

German deflator for OCM investment (DM)

Notes: OCM denotes: office machinery and computers, OCAM denotes office computing (incl. peripheral equipment) and accounting equipment. PPP are Purchasing Power Parities for GDP.

Sources: U.S Bureau of Economic Analysis, NIPA Table 5.9, 5.8 and 7.8, INSEE, Statistical Office Germany, own calculations.

Figure 2: Deflators for OCM investment and output, 1970-1991



- - - U.S deflator for OCAM investment (converted into DM using current DM/US$ exch. rate),

—×— French deflator for OCM investment (converted into DM using current DM/FF exch. rate)

—— U.S deflator for OCAM investment plus photocopy and related equipment (converted into DM using current DM/US$ exch. rate)

— — U.S deflator for OCAM investment plus photocopy and related equipment (converted into DM using PPP between DM and US$)

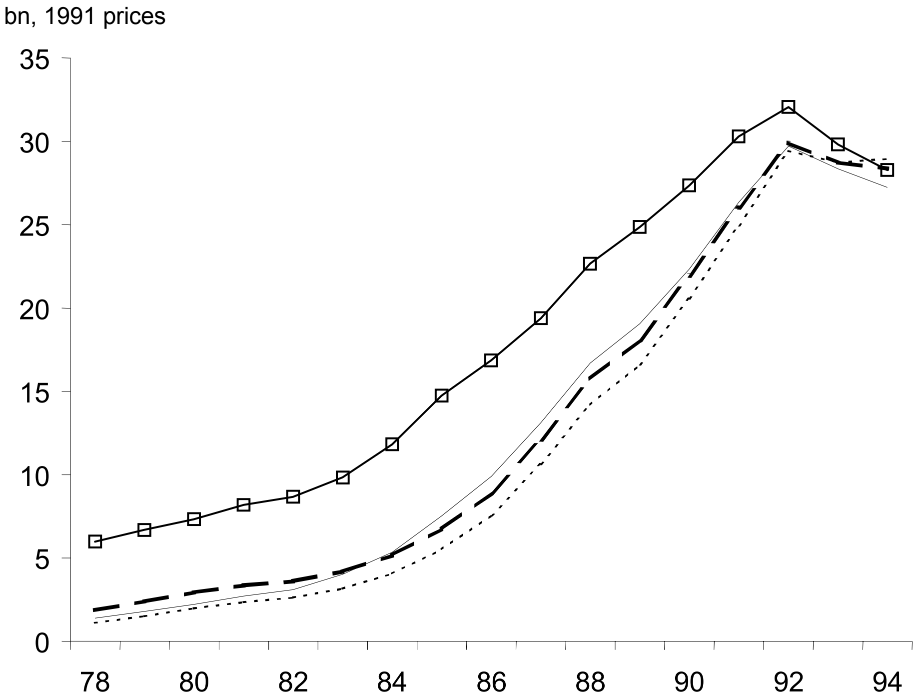
—△— German producer prices of the OCM industry (DM)

—□— German deflator for OCM investment (DM)

Notes: OCM denotes: office machinery and computers, OCAM denotes office computing (incl. peripheral equipment) and accounting equipment. PPP are Purchasing Power Parities for GDP.

Sources: U.S Bureau of Economic Analysis, NIPA Table 5.9, 5.8 and 7.8, INSEE, Statistical Office Germany, own calculations.

Figure 3: Evolution of the OCM capital stock in manufacturing



OCM capital stock 1: investment is deflated by the U.S deflator for OCAM investment, converted into DM using current DM/US$ exchange rate

OCM capital stock 2: investment is deflated by the French deflator for OCM investment (converted into DM using current DM/FF exch. rate)

OCM capital stock 3: investment is deflated by the U.S deflator for OCAM investment plus photocopiers and related equipment (converted into DM using current DM/US$ exchange rate)

OCM capital stock 4: investment is deflated by the German producer prices of the OCM industry

Notes: OCM capital stocks are estimated using PIM. Real investments were computed by dividing nominal investments by the price indices described above. The depreciation rate is 0.2729 between 1970 -1977 and 0.3119 between 1978 - 1994.