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TECHNOLOGY, LABOR CHARACTERISTICS AND WAGE-PRODUCTIVITY GAPS***

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ABSTRACT: We use plant-level linked employer-employee data from Finland to estimate production functions where also employee characteristics (average age and education, and sex composition) are included. We also estimate similar models for wages to examine whether wages are based on productivity. Our aim is to explain productivity besides manufacturing, also in services. For the service sector plants, no data on capital input, working hours, or value added is available, and productivity has to be measured by sales per employee. We use a stepwise procedure to examine whether the results for manufacturing are affected when less satisfactory data is used. Then we proceed to estimate the final model for manufacturing and services combined. The effect of age on productivity is negative, but wages show strong positive age effects. Higher educational level leads to higher wage, but there is a clear productivity difference between non-technical and technical education. Some of the productivity effects of technical education are negative. Wage-productivity gaps (relative to the reference group, basic education) are positive for the highest level of technical education, but negative for the highest non-technical education. The share of female workers is negatively related to productivity. Also the wage effect is negative, but smaller in absolute value, leading to a positive female wage-productivity gap. However, the negative productivity effect disappears and the gap is negative if the model is estimated with fixed plant effects.

Key words: Productivity, wages, education, age, gender wage gap, linked employer-employee data

JEL codes: D240, J240, J310, J700

Ei-tekninen tiivistelmä:

Yhdistettyjä työntekijä-työnantaja –aineistoja käyttämällä tutkimuksessa estimoidaan tuotantoyhtälöitä, joissa selitettävänä tekijänä on toimipaikan työn tuottavuus ja selittävinä tekijöinä ovat toimipaikan sekä sen henkilökunnan ominaisuudet. Toimipaikkaominaisuuksista kontrolloidaan pääomakannan määrä, toimiala sekä toimipaikan ikä. Työntekijäominaisuuksista tarkasteltavana on henkilökunnan keskimääräinen ikä, koulutus ja sukupuolijakauma. Lisäksi estimoimme vastaavat palkkayhtälöt, joissa tuotantoyhtälön työn tuottavuus on korvattu toimipaikan keskipalkalla. Tuotanto- ja palkkayhtälön kertoimia vertailemalla voidaan päätellä, missä määrin henkilöominaisuuksien mukaiset palkkaerot heijastavat tuottavuuseroja.

Tutkimme tuottavuutta ja palkkoja sekä teollisuudessa että palveluissa. Palvelualan toimipaikoista ei kuitenkaan ole tietoa pääomasta, tehdyistä työtunneista eikä jalostusarvosta. Siitä syystä palvelujen osalta työn tuottavuus joudutaan mittaamaan liikevaihdon ja henkilömäärän suhteella. Vaiheittain etenemällä arvioimme, kuinka paljon tulokset muuttuvat teollisuudessa, kun tuottavuuden ja palkkojen välisiä suhteita tutkitaan vaillinaisemmalla aineistolla. Lopuksi estimoimme mallin, jossa on mukana sekä teollisuus että palvelut. Kaikissa malleissa toimialavaikutus on kontrolloitu tarkalla toimialatasolla.

Tulosten mukaan iäkkäiden henkilöiden työpaikat ovat vähemmän tuottavia kuin nuorempien. Sen sijaan palkkojen ja iän välillä on jo monesti aikaisemminkin havaittu voimakas positiivinen yhteys.

Korkean koulutuksen ja palkkatason välillä todetaan selvä positiivinen yhteys, mikä vastaa aikaisempia, henkilöaineistoihin perustuvia tutkimustuloksia. Tässä tutkimuksessa havaitaan hyvin huomattava tuottavuusero koulutusalan mukaan. Teknisluonnontieteellisellä koulutuksella havaitaan olevan joskus jopa negatiivinen tuottavuusvaikutus. Tämä luultavasti selittyy sillä, että teknisluonnontieteellistä koulutusta käytetään paljon tekniikoiden ja tuotantoprosessien kehittämisessä. Koska tämä työ sitoo tuotantopanoksia, välitön tuottavuusvaikutus voi olla jopa negatiivinen. Kehitystyön tuottavuustulokset voidaan odottaa kuitenkin ilmaantuvan viiveellä. Eräät aikaisemmat, suomalaisiin aineistoihin perustuvat analyysit antavat tukea tälle tulkinnalle. Niiden mukaan teknisluonnontieteellinen koulutus parantaa toimipaikan tuottavuutta vasta useiden vuosien päästä.

Tulosten mukaan naisten työpaikkojen tuottavuus on alempi kuin miesten. Ero on hieman suurempi kuin palkoissa. Tulos muuttuu olennaisesti, kun kiinteä toimipaikkavaikutus kontrolloidaan tilastollisilla välineillä. Tällöin tarkastellaan sitä, kuinka toimipaikan henkilöstöominaisuuksien muutokset yli ajan heijastuvat toimipaikan tuottavuuteen. Tällöin sukupuolten suhteen ei havaita tuottavuuseroa, mutta palkkaero miesten hyväksi esiintyy edelleen. Tulokset viittaavat siihen, että miesten ja naisten kohdentuminen erilaisiin toimipaikkoihin selittää tuottavuus- ja palkkaeroja.

On syytä huomata, että toimialatekijä on kontrolloitu. Aikaisemmassa tutkimuksessa on korostettu paljon sitä, että naiset ja miehet ovat keskittyneet eri toimialoille ja että tämä osaltaan selittää sukupuolten välisiä palkkaeroja. Tämän tutkimuksen tulokset puolestaan kertovat siitä, että sukupuolen mukainen segregaatio toimialojen sisällä muovaa tuottavuus- ja palkkaeroja olennaisella tavalla.

1. Introduction

Using linked employer-employee data to examine the influence of the work force structure on plant productivity and wage level provides a way of testing different theories of wage formation, general and specific human capital and incentive wage models[1]. Their implications on the shapes of wage and productivity profiles differ. Data sets on individual wages are commonly available, but the productivity of individuals is difficult to measure. Instead, plant-level production functions and wage equations that include worker characteristics as explanatory variables make productivity and wage profile comparisons possible.

When this kind of analysis is extended beyond manufacturing, which is typically analyzed, a key issue is that the data availability on plant characteristics is much more restricted for services. We concentrate in this paper on how the conclusions are affected when less satisfactory data are used. We proceed in a stepwise manner. First, we use Finnish manufacturing census plant data to estimate production functions in intensity form with labor productivity (value added per hours) as the dependent variable. Information on worker characteristics is derived from individual-level registers that can be matched to the plant data. They are included in the production function as explanatory variables. The capital input coefficient is allowed to vary by two-digit industries. Next, we examine whether the conclusions are affected if we do not use data on capital stock but instead estimate models for labor productivity and control technology differences by detailed industry dummies. Then we estimate a similar model where the labor input is measured by the number of employees, instead of hours.[2] Then we use information on manufacturing plants from the Business Register that has better coverage of plants, but limited data content. We estimate an otherwise similar model, but replace the output measure, value added, by sales. Finally, we estimate this last model using this register data on both manufacturing and services. In all cases, we also estimate models for wages with the same explanatory variables as in the productivity models. We calculate

1 See Hellerstein and Neumark (1995), Hellerstein, Neumark, and Troske (1999), Hæaegeland and Klette (1999), Crépon, Deniau, and Pérez-Duarte (2002), and Ilmakunnas, Maliranta, and Vainiomäki (2003). Only the productivity effects are examined by Griliches (1970) and more recent examples include Black and Lynch (2001), Haltiwanger, Lane, and Spletzer (1999), and Kramarz and Roux, (1999).

the wage-productivity gaps, i.e. differences in the impact of a worker characteristic on wage and productivity, to see how they are affected by the specification of technology and input and output variables in each step. These gaps measure the difference between wage and marginal productivity relative to the reference group.

We also examine whether the results are affected if we replace the estimated capital coefficient by observed average factor shares in two-digit industries and use total factor productivity as the variable to be explained. Most models are estimated using pooled plant data with plant vintage indicators included, but to study the sensitivity of the results to the estimation method, some of the models are estimated using plant fixed effects.

In Section 2 of the paper we discuss alternative ways of taking labor quality into account in production functions by including information on work force characteristics. Section 3 specifies the models to be estimated in our stepwise procedure. Section 4 presents estimation results, and Section 5 concludes the paper.

2. Quality adjusted labor input

In competitive markets, workers would receive a real wage that equals their marginal product. If productivity varies by worker characteristics like age, education, and gender, and labor markets are segmented so that these characteristics are priced differently, equality of real wage and marginal productivity can hold for each worker type. Alternative views of wage formation emphasize the role of firm-specific human capital and incentive effects of wages that can make wages deviate from productivity.

Empirical analysis of the relationship between wage and productivity is, however, difficult since the productivity of individuals is not observed, although their wages can be reasonably well measured. If the individuals are aggregated to the plant level, the connection between productivity and wage should still hold. The competitive hypothesis can be tested by estimating the impact of employee characteristics on production and

[2] More specifically, we use employment information from the Business Register, which is an alternative source of information. It uses full-time equivalent concept of labor, which, on the other hand, aims to take into account hours worked.

wages and by examining whether the relationships are similar. The characteristics that have been used in empirical studies include age, experience, education, and sex composition of the work force. These characteristics can be included in the production function in several alternative ways. The same issue is discussed in the work on empirical growth models, where the effect of human capital, or more specifically education, on productivity has been studied (e.g. Temple, 2001).

We illustrate the alternative specifications with education. One alternative is to include the worker characteristics in the same way as all the other inputs. We assume a Cobb-Douglas technology. Letting Y denotes value added, K capital, L labor input and EDU the average years of education, the production function is

$$Y = AK^{\alpha}L^{\beta}EDU^{\gamma} \qquad (1)$$

This specification has been used in aggregate growth studies and firm-level productivity studies (e.g. Griliches, 1970, Black and Lynch, 2001). It has the disadvantage of imposing higher returns to an additional year of education at low levels of schooling (although the elasticity of output with respect to education is constant). More recent growth models use a formulation, where education enters through a function $\gamma(EDU)$:

$$Y = AK^{\alpha}L^{\beta}e^{\gamma(EDU)} \qquad (2)$$

This is also implicitly or explicitly used in some firm-level studies of productivity. In the simplest case, the function that includes education is linear, $\gamma(EDU) = \gamma EDU$. In this case an additional year of education raises output always in the same proportion. Temple (2001) discusses some nonlinear alternatives for $\gamma(EDU)$ used in growth models, for example $\gamma(EDU) = \gamma_0 + \gamma_1 ln(EDU) + \gamma_2(1/EDU)$. The relationship can be estimated also nonparametrically (Kalaitzidakes, Mamuneas, and Stengos, 2001). Another issue is the measurement of the human capital variable. One alternative to years of education is to use the educational capital stock that is based on a rate of return to schooling that is consistent with results from individual-level data. This has been examined both with firm-level data (Griliches, 1970) and in the growth context (Pritchett, 2001, Temple, 2001).

Besides education, other worker characteristics can be included in the same way. In practice, most firm-level studies that include average worker characteristics include them in a way that is a hybrid of (1) and (2). In our earlier work (Ilmakunnas, Maliranta, and Vainiomäki, 2003) we used a formulation

$$Y = AK^{\alpha}L^{\beta}e^{\gamma(AGE,EDU,SEN)} \tag{3}$$

$$\gamma(AGE,EDU,SEN) = a_1*ln(AGE) + a_2(ln(AGE))^2 + b_1EDU + b_2EDU^2 + c_1ln(SEN) + c_2(ln(SEN))^2 \tag{4}$$

where *AGE* is the average age of the plant's work force, *EDU* is average years of education, and *SEN* is average years of firm-specific experience (seniority). This can be extended to include higher-order terms.

Another approach is that taken by Hellerstein and Neumark (1995, 1999), Hellerstein, Neumark, and Troske (1999), Hæaegeland and Klette (1999). It is also discussed in the growth context by Temple (2001) and in the context of union productivity effects by Brown and Medoff (1978). They start from the assumption that different types of employees are perfect substitutes, but may have different marginal productivities. Using education as an example, divide workers to two categories (e.g. low and high education) with shares s_1 and s_2. If we take group 1 as the base case, and scale its productivity equal to 1, the relative productivity of group 2 is measured by a parameter ϕ_2. The increase in productivity when we go from the base group to group 2 is therefore ϕ_2-1. The quality-adjusted labor input is

$$L^* = L[s_1 + \phi_2 s_2] = L[1 + (\phi_2-1)s_2] \tag{5}$$

where we have used the constraint that the sum of the shares equals one. The corresponding production function is

$$Y = AK^{\alpha}L^{*\beta} \tag{6}$$

In the general case of worker characteristics $k=1,\dots,K$ and workers divided to groups $j=1,\dots,J$, the share of workers in group j in terms of characteristic k is s_{jk}, and the relative increase in productivity when we go from the base group to group j in terms of characteristic j is denoted $\phi_{jk}-1$. The quality-adjusted labor input in this general case is

$$L^* = L[1 + (\phi_{21}-1)s_{21} + \dots + (\phi_{J1}-1)s_{J1}] \dots [1 + (\phi_{2K}-1)s_{2K} + \dots + (\phi_{JK}-1)s_{JK}] \qquad (7)$$

Crépon, Deniau, and Pérez-Duarte (2002) use a related approach, where the wage and productivity equations are combined and the markdown, i.e. the ratio of the coefficients of a share variable in the productivity and wage equations, is estimated directly.

In the present paper we use the shares of worker categories directly to explain the logarithm of productivity. This can be seen as an approximation to the approach initiated by Brown and Medoff (1978) and Hellerstein and Neumark (1995). We use total working hours H and the number of employees L as alternative input variables, but there is no information on hours worked by different employee groups. However, if the hours per worker do not differ much across the groups, we can use the employment shares in a similar relationship for quality adjusted hours:

$$H^* = H[1 + (\phi_{21}-1)s_{21} + \dots + (\phi_{J1}-1)s_{J1}] \dots [1 + (\phi_{2K}-1)s_{2K} + \dots + (\phi_{JK}-1)s_{JK}] \qquad (8)$$

where H is total hours worked in the plant. To simplify estimation, we can use the approximation

$$ln[1 + (\phi_{2k}-1)s_{2k} + \dots + (\phi_{Jk}-1)s_{Jk}] \approx (\phi_{2k}-1)s_{2k} + \dots + (\phi_{Jk}-1)s_{Jk} \qquad (9)$$

This gives a reasonable approximation unless the productivity profile is very steep (ϕ_{jk} increases fast with j for a given k) and at the same time the labor shares increase (share s_{jk} is increasing in j).

An alternative formulation that leads to the same end result is the following. Assume that quality adjusted hours H^* (or analogously quality adjusted L^*) are obtained by multiplying total hours by a term that depends on the structure of the work force:

$$H^* = exp(\Sigma_k[s_{1k} + \phi_{2k}s_{2k} + \ldots + \phi_{Jk}s_{Jk}])H$$
$$= exp(\Sigma_k[1 + (\phi_{2k}\text{-}1)s_{2k} + \ldots + (\phi_{Jk}\text{-}1)s_{Jk}])H \quad (10)$$

Here we need not assume that all groups of workers work the same hours. In fact, part of the productivity differential between plants with different work force structures may come from varying hours per worker across the groups.

All in all, we end up having the shares of workers in different categories directly as variables in a log-form production function. In the above example of two education groups, the γ function in (2) would be $\gamma(s_2) = 1 + (\phi_2\text{-}1)s_2$. This is implicitly the way in which variables that describe the work force structure have been used in some firm-level productivity studies (e.g. Haltiwanger, Lane, and Spletzer, 1999). A variant of this "share" approach is the labor quality index suggested by Griliches and Regev (1995), Q_L = 1 + ((engineers + 0.75*technicians) / total employees), which is used as a variable in a production function.

A common feature in all of the formulations is that although the work force structure has been used for quality adjusting the labor input, obviously they could as well adjust the constant term *A* in the production function. This follows from the Cobb-Douglas structure, but does not hold if e.g. a translog model is used, as in Hellerstein, Neumark, and Troske (1999), and Hæaegeland and Klette (1999). Note, however, that the interpretation of the parameters differs. If the worker group shares augment the labor input as in (6), one would estimate coefficients $\beta(\phi_{2k}\text{-}1)$, whereas if the shares augment the constant in the production function, the estimated coefficients would be directly $\phi_{2k}\text{-}1$. This has implications on the comparison of the impacts of worker characteristics on productivity and wage.

Theoretically, the impact of worker characteristics on productivity and wage can be assessed as follows. Assume that a firm chooses its labor quality, i.e. the combination of worker characteristics, optimally. The profits of the firm are $\pi = pY - wL - rK$, where p is price, and w and r are the input prices. The quality of the labor force q (this index is a function of various worker characteristics like EDU and AGE or worker group shares) affects output, but also influences costs, since the average wage for higher quality labor is higher: the production function is $Y = F(K,L,q)$ and the average wage is $w = w(q)$. The wage function reflects the fact that different labor qualities are priced differently in the market or by the firm if it does not take the wage as given. Profit maximization with respect to q implies the condition $p(\partial Y/\partial q) = L(\partial w/\partial q)$, which can be written as $pY(\partial \ln Y/\partial q) = wL(\partial \ln w/\partial q)$ or $(\partial \ln Y/\partial q)/\beta = (\partial \ln w/\partial q)$, where β is the labor income share (which equals cost share if profits are zero).

Assume first that labor quality affects both capital and labor neutrally and the production function is $Y = e^{\theta q}AK^{\alpha}L^{\beta}$. If the wage function has the form $w = w_0e^{\rho q}$, the above condition is $\theta/\beta = \rho$. If $\ln Y$ and $\ln w$ are regressed on q, the estimated effects of worker characteristics on production and wage are θ and ρ, respectively. Therefore, the estimated impact of labor quality on the logarithm of production has to be divided by the labor share before it is compared with the effect of labor quality on the logarithm of wage. On the other hand, if the labor input L is augmented by labor quality, the quality adjusted labor is $L^* = Le^{\theta q}$ and the production function is $Y = AK^{\alpha}L^{*\beta}$. The condition for optimal labor quality can be written as $(\partial \ln Y/\partial \ln L^*)(\partial \ln L^*/\partial q)/\beta = \theta = \rho$. This follows since when profits are maximized with respect to L, $\partial \ln Y/\partial \ln L^*$ equals the labor share. In this case the estimated impact of worker characteristics on the logarithms of production and wage are $\beta\theta$ and ρ, respectively, whereas θ and ρ should be compared. We should again divide the estimated effect of labor quality on $\ln Y$ by the labor share. The interpretation of the estimation results therefore depends on whether labor augmenting or neutral labor quality effects are assumed, but in both cases scaling the estimate by the labor share is necessary (see also Bloom, Canning, and Sevilla, 2002). These results hold for a firm that chooses labor quality optimally in a static world. Evidence on deviation from this rule can be interpreted to support other, dynamic elements in wage setting, like incentive effects and accumulation of firm-specific human capital. Alternatively, it is a sign of inefficiency in the labor market or the firm's failure to adjust labor quality.

3. Productivity models

From a Cobb-Douglas production function with assumption (9) or (10) we obtain the following productivity equation, **Model A**:

$$ln(Y/H) = \theta + \alpha ln(K/H) + \delta lnH + \Sigma_k[\phi^*_{2k}s_{2k}+\ldots+\phi^*_{Jk}s_{Jk}] + \varepsilon \qquad (11)$$

where $\phi^*_{jk} = \beta(\phi_{jk}-1)$, ε is a random error term, and the term $\delta lnH = (\alpha+\beta-1)lnH$ takes into acount deviation from constant returns (cf. Griliches and Ringstad, 1971).

We allow for technological differences between sectors by letting the coefficients of $ln(K/H)$ and lnH to vary by 2-digit industry (23 industries). To allow for technical change that can vary over time and across industries, and to deflate the output measure the term θ includes the interactions of year dummies and 2-digit industry dummies. In addition, we have also included plant generation dummies. These vintage variables can be interpreted as a quality adjustment of the capital input.

Since in the Cobb-Douglas function marginal product of the labor input is proportional to average product, i.e. $\partial Y/\partial H = \beta Y/H$, log of marginal product is simply log of average productivity plus a constant, $ln(\partial Y/\partial H) = \beta + ln(Y/H)$. Therefore the coefficients of (11) give directly the influences of the variables on the marginal product. A wage model is also estimated, where $ln(W_H)$, log of average hourly wage, is explained by all the variables that appear in the right-hand side of (11). The industry and time indicators and their interactions take care of the deflation of the wage. If wage setting is based on marginal productivity, the slopes of the productivity and wage equations with respect to worker characteristics should be similar. Note that this is a necessary, but not sufficient condition for the equality of wage and marginal productivity. Wage can be above or below marginal productivity, even when the slopes are the same.

The wage variable is the average hourly wage, which can be regarded as an hour share weighted average of the wages of the employee groups. Therefore it might be more appropriate to use as weights s_{jk} the shares of total working hours of the different groups.

However, only data on plant aggregate hours are available. If all groups have approximately the same average hours per worker, this does not cause problems. In any case, the same weights are used both in the productivity and wage equation.

Experience with the estimation of production functions shows that the estimated capital coefficients (i.e., the income share of capital) often tend to be unreasonably low (Griliches and Regev, 1995, Griliches and Mairesse, 1998). Therefore we estimate a model that is otherwise the same as Model A, but the industry-specific parameters α are chosen a priori to be equal to the average observed capital shares in two-digit industries. With this information, the total factor productivity is calculated as $ln(TFP) = ln(Y) - \alpha ln(K) - (1-\alpha)ln(H)$. This is used as the dependent variable in **Model B**:

$$ln(TFP) = \theta + \delta lnH + \Sigma_k[\phi^*_{2k}s_{2k}+\ldots+\phi^*_{Jk}s_{Jk}] + \varepsilon \qquad (12)$$

We again take deviation from constant returns to scale into account by including the term *lnH*. All indicator variables are the same as in Model A. The wage model that corresponds to Model B is the same as in case of Model A.

We would prefer to use Model A (11) to test the impact of worker characteristics on productivity. However, when we move beyond manufacturing, data problems arise. Often reliable data on capital input is not available. This is especially the case for other industries than manufacturing. One way of testing how much this matters is to drop the capital input variable and allow for technological differences through industry dummies at a more detailed level. In this case the productivity equation is **Model C**:

$$ln(Y/H) = \theta + \delta lnH + \Sigma_k[\phi^*_{2k}s_{2k}+\ldots+\phi^*_{Jk}s_{Jk}] + \varepsilon \qquad (13)$$

The coefficients of the year dummies (included in θ) and *lnH* vary by 3-digit industries (101 industries). Note that although *lnH* takes into account the impact of the scale of labor input on productivity, its coefficient δ can no longer be directly interpreted as $\alpha+\beta-1$, since capital input is not included. Again, a similar wage model is estimated. Plant vintage indicators are included in both productivity and wage equation.

The above models use working hours as the labor input variable, but data on hours are not available for the service sector. The next step is to estimate a model that is otherwise similar to (13), but as labor input we use the number of employees L. Comparison to (13) then gives an impression on how much the input measure matters. The model is **Model D**:

$$ln(Y/L) = \theta + \delta lnL + \Sigma_k[\phi^*_{2k}s_{2k} + ... + \phi^*_{Jk}s_{Jk}] + \varepsilon \quad (14)$$

where θ and δ vary by 3-digit industry. The model also includes vintage dummies. The corresponding wage model has log of average wage per employee, lnW_L, as the dependent variable and the same explanatory variables as in Model D. All of the above models A to D can be estimated for manufacturing plants using data from the Finnish Industrial Statistics and Employment Statistics, as will be explained in the next Section.

The final step is to estimate a model that is otherwise similar to (14), but as an output measure we use total sales S. This is motivated by the fact that for the service sectors, no plant-level value added data are available. Comparison to (14) then gives an impression on how much the output measure matters. At this stage, we use Business Register and Employment Statistics data. The model is **Model E**:

$$ln(S/L) = \theta + \delta lnL + \Sigma_k[\phi^*_{2k}s_{2k} + ... + \phi^*_{Jk}s_{Jk}] + \varepsilon \quad (15)$$

where the interactions of 3-digit industry dummies with the year dummies and lnL are included (101 industries in manufacturing, 196 when services are also included). Besides technological differences, the interactions of the time dummies and industry dummies account for industry-specific price changes, since the sales data are not deflated. Since plant age is more reliably available for manufacturing plants in the Industrial Statistics than for the Business register plants, we do not include it in Model E. Wage models that are analogous to (15) are also estimated with lnW_L, log of average wage per employee, as the wage variable.

Model E and the corresponding wage model are first estimated for manufacturing using plants in the Business Register that can also be found in the Industrial Statistics to see whether similar conclusions are obtained as with Model D. Then Model E and the wage equation are estimated for the manufacturing plants that appear in the Business Register (this is called Model E2), and finally whole the whole business sector.

4. Results

We use data that are from various registers of Statistics Finland from the years 1988-98. The data on employee characteristics and the average annual earnings is from Employee Statistics that in principle cover the whole working age population. The employees can be matched to plants based on information on their primary employer in the last week of the year. We have calculated the following plant employee characteristics: education and field of study (shares of employees in the following groups: comprehensive school (EDU), upper secondary or vocational technical (TEDU2) or non-technical (NTEDU2) education, polytechnic or lower university degree in a technical (TEDU3) or non-technical (NTEDU3) field, higher university degree in a technical (TEDU4) or non-technical (NTEDU4) field), age (shares of employees in groups: 15-24 (AGE1), 25-34 (AGE2), 35-44 (AGE3), 45-64 (AGE4)), and sex (shares of women and men). The reference group is men in age group 15-24 with comprehensive school education.

For manufacturing, we use information on value added, hours worked, average hourly wage, average wage per employee, capital stock, and plant age from the Industrial Statistics (IS)[3]. The hours information deals with plant totals and cannot be linked to individuals. The plants are classified to five age groups from the oldest (GEN1) to the youngest (GEN5) based on the year when they appear in the Industrial Statistics. The Industrial Statistics covers until 1994 all plants with at least 5 employees, but after that the lower limit for plant size has been higher. For both manufacturing and services, we use data on total sales and the number of employees from the Business Register (BR). It covers in principle all plants, but has a limited data content. The value added or sales figures have not been deflated, but instead industry-specific price changes have been taken into account by including industry dummies, time dummies, and their interactions into the models.

[3] The impact of more detailed plant characteristics on productivity is studied in Maliranta, 1998.

More detailed information on the process of matching employees and plants is presented in Ilmakunnas, Maliranta, and Vainiomäki (2001). In the manufacturing sector, the plant panel includes 39 000 - 46 000 plant-year observations after deleting observations with missing worker characteristics or capital input data. Using manufacturing plants that appear in the Business register we have 86 000 observations in the panel. When services are also included, we have 317 000 plant-year observations. We have excluded those service industries where either plant definition or sales measurement is difficult. Hence transportation, banking, public sector activities, health, education, and social and private services are excluded. The remaining service sector plants are in trade, hotels and restaurants, communications, real estate, and business services.

We present results from estimation with pooled data (total estimates). Some of the characteristics have fairly little variation over time, whereas cross-plant differences are large. In particular, the plant vintage variable is time invariant. We believe that much of the unobserved plant effects can be taken into account through these variables. Within estimation would therefore wipe out much of the variation in the data. However, some models were estimated with plant fixed effects. In these cases the variables that are interactions of industry dummies with year dummies, capital, or the scale term, as well as the plant generation dummies were left out. However, year dummies were included separately. All of the models were estimated using weighting by plant employment. This can be justifies by our desire to obtain results that reflect the whole worker population in manufacturing or business sector. In unweighted estimation the large number of small plants would dominate the results.

Table 1 shows the estimation results for manufacturing. When the capital stock is included (Model A) the non-technical educational level has a positive effect on productivity, compared to the reference group 1. However, technical education levels 2 and 4 have a negative effect. These findings are consistent with those by Maliranta (2000). One interpretation of this somewhat surprising result is that plants that have a high share of employees with technical skills are involved in developing new products and processes, whereas personnel with non-technical skills is more involved with applying and commercializing the technology. The latter may therefore appear to have higher productivity. Empirical support for these considerations was obtained in Maliranta (2003). It was found that an increase in technical skills was initially negatively reflected in productivity growth, but positively in a half decade.

As to age, there is a negative productivity effect of age groups 3 and 4. The plants of female workers have a significantly lower level of productivity. The coefficients of the plant generation dummy variables show that productivity is inversely related to plant age.

Looking at the results on wage model A, we notice that education has a strong influence on wage in the highest education groups, irrespective of the field of education. Also age has a clear positive impact on wage. It seems that there is a strong seniority influence on wage setting, which is not based on productivity. Wages are clearly lower in plants with female workers, since the share of women has an approximately 26 percent negative impact on hourly pay. New plants have higher wages, but wages do not increase as fast as productivity when we go from the oldest plants to the youngest.

Figure 1 shows the distribution of the industry-specific coefficients of $ln(K/H)$ in the productivity equation (23 industries). The estimated values are fairly small and there are some negative coefficients. Since the coefficients are small, most of the implied values of β are close to one. Therefore, if the coefficients of the worker characteristics variables are interpreted as terms $\phi^*_{jk} = \beta(\phi_{jk}-1)$, the estimates are close to the percentage productivity difference to the reference group. The distribution (Epanechnikov kernel density) of the industry-specific coefficients of the scale term lnH is shown in Figure 2. In Model A, most of the coefficients (23 industries) are centered on zero, indicating that on average, there are constant returns to scale. Although there are deviations from constant returns to scale, they are in most cases moderate.

Given that the coefficients of ln(K/H) should be close to the actual factor input shares (also shown in Figure 1), these values seem too low. It is useful to estimate the impact of the employee characteristics also by restricting the capital parameter a priori and by using total factor productivity as the dependent variable.

	Model A		Model B	Model C		Model D	
	ln(Y/H)	$ln(W_H)$	*ln(TFP)*	*ln(Y/H)*	$ln(W_H)$	*ln(Y/L)*	$ln(W_L)$
Constant	2.903	3.382	0.598	4.571	3.909	5.184	4.407
	1.60	7.37	0.35	3.71	12.39	4.60	14.58
TEDU4	-0.354	0.779	-0.608	-1.347	0.743	-1.281	0.795
	-4.48	38.91	-7.24	-19.47	41.98	-18.33	42.40
TEDU3	0.286	0.255	0.200	0.245	0.248	0.320	0.320
	6.25	21.98	4.05	5.67	22.45	7.35	27.30
TEDU2	-0.084	0.048	-0.061	-0.117	0.010	-0.105	0.020
	-2.66	5.99	-1.81	-3.86	1.28	-3.43	2.37
NTEDU4	1.134	0.833	1.660	0.657	0.978	0.880	1.184
	7.45	21.58	10.13	4.63	26.97	6.15	30.84
NTEDU3	0.048	0.410	0.337	-0.418	0.362	-0.419	0.357
	0.54	17.98	3.47	-4.90	16.58	-4.87	15.46
NTEDU2	0.126	0.054	0.396	-0.031	-0.015	-0.033	-0.020
	1.98	3.36	5.79	-0.51	-0.97	-0.56	-1.25
EDU1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
AGE4	-0.155	0.385	-0.090	-0.186	0.323	-0.282	0.225
	-2.86	28.00	-1.54	-3.68	24.98	-5.53	16.38
AGE3	-0.121	0.358	-0.076	-0.074	0.308	-0.208	0.176
	-2.24	26.20	-1.30	-1.47	23.80	-4.06	12.83
AGE2	0.056	0.199	0.117	0.100	0.157	0.017	0.076
	0.89	12.33	1.69	1.70	10.48	0.29	4.78
AGE1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Women	-0.494	-0.258	-0.298	-0.563	-0.246	-0.596	-0.279
	-21.99	-45.26	-12.54	-23.94	-40.83	-25.10	-43.75
Men	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
GEN1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
GEN2	0.061	0.005	0.091	0.028	0.006	0.029	0.007
	6.15	2.09	8.45	3.03	2.55	3.11	2.89
GEN3	0.105	0.014	0.157	0.083	0.007	0.087	0.012
	8.84	4.53	12.19	7.39	2.58	7.62	3.81
GEN4	0.065	0.038	0.252	-0.066	0.023	-0.066	0.022
	5.06	11.83	18.73	-5.81	7.80	-5.70	7.15
GEN5	0.135	0.051	0.540	-0.030	0.009	-0.034	0.006
	8.25	12.31	32.55	-2.20	2.51	-2.48	1.65
*ln(K/H)**ID	2-digit	2-digit	2-digit	No	No	No	No
*ln(H)**ID	2-digit	2-digit	2-digit	3-digit	3-digit		
*ln(L)**ID						3-digit	3-digit
YearD*ID	2-digit	2-digit	2-digit	3-digit	3-digit	3-digit	3-digit
N	39200	39200	39200	46175	46175	46175	46175
R^2	0.399	0.773	0.566	0.405	0.777	0.406	0.751

Note: t-values in parentheses. Ref. indicates reference group. YearD denotes set of year dummies and ID set of industry dummies. Coefficients of industry-specific terms not reported. Data source: Industrial Statistics, Employment Statistics.

Table 1: Productivity and wage models for manufacturing

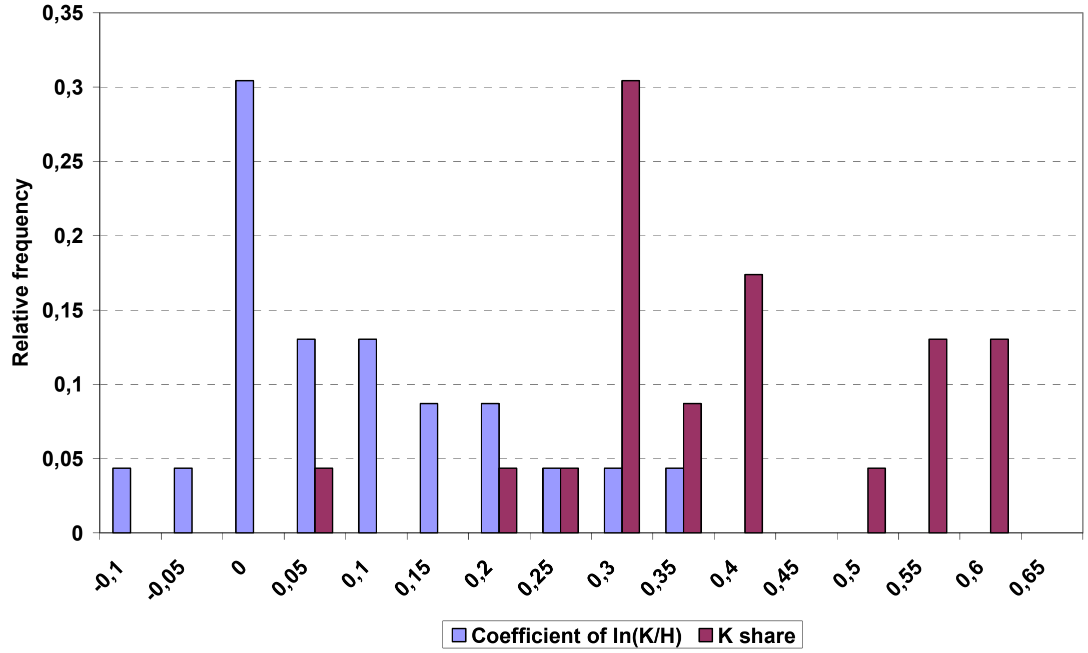

Figure 1: **Distributions of industry-specific capital coefficients (Model A) and observed shares**

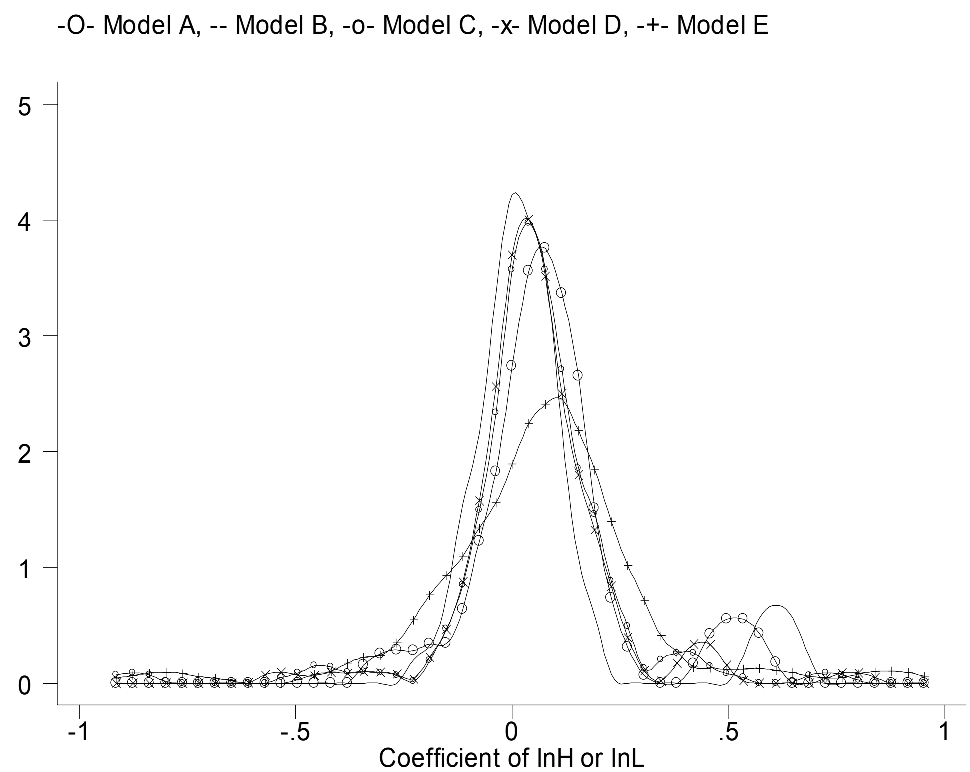

Figure 2: **Distribution of industry-specific coefficients of lnH or lnL in manufacturing**

The estimates of Model B show an even stronger positive productivity impact from non-technical education. There is now a less negative age effect from the share of the oldest groups, AGE 3 and AGE4, and the negative impact of the female share is now much weaker than in model A. It seems that women work more in plants with low capital intensity. If the capital coefficient is underestimated, the productivity contribution of women is also biased downwards. Similarly, it may be that plants with high capital intensity have an older work force, which leads to overestimation of the age effect when the capital coefficients are biased downwards.

As to the distribution of the scale terms in Model B, where the capital coefficients are set a priori at a higher level than those estimated in Model A, we can see that they are centered on small negative values. Therefore, the scale term adjusts the returns to scale back to a lower level.

Model C is estimated without the capital input and with a more detailed industry classification in the interaction terms. The main difference to Model A is the more mixed productivity profile by education. The coefficient of the highest technical education group TEDU4 drops further, and the coefficients of medium-level non-technical education, NTEDU2 and NTEDU3, also become negative. The age and gender effects are in line with those in Model A. Plant vintage effects drop and become negative in the youngest groups. Figure 2 shows that the distribution of the industry-specific coefficients of the scale term *lnH* (101 industries) is again centered on zero, although the distribution is less peaked than in Model A.

In Model D hours are replaced by the number of employees. The estimates are reasonably close to those from Model C. Also the distribution of the industry-specific coefficients seems to be very similar in these two models.

In Table 2 we use sales per employee as the productivity variable in the estimation of Model E. The results for manufacturing (using a panel of plants that appear both in BR and IS) show that compared to model D, the impact of the technical education changes somewhat, although the signs of the education groups stay the same. As to non-technical education, the coefficient of the highest education group increases considerably and that of group 3 becomes again positive. The pattern of the age effects is otherwise the same as before, but age starts to decrease productivity already from age group AGE2. The negative impacts are larger in absolute value than in Model D. The impact of the female share stays close to that in Model D. When a larger set of plants is used in estimation of Model E2 for manufacturing (all manufacturing plants that appear in BR), the results do not change much. The main exception is that the medium level of non-technical education has a negative impact on productivity. In both estimations the wage models are fairly close to the wage model D in Table 1.

When *ln(S/L)* is the dependent variable, the distribution of the coefficients of *lnL* is somewhat flatter than the distributions of the scale terms in the other models (Figure 2). However, even in this case the mode is close to that of the other distributions.

Table 2 shows also the results for Model E for the business sector where manufacturing and services are pooled. These should be compared to the results for manufacturing obtained with the larger plant panel (Model E2). In the business sector even the highest level of technical education has a positive productivity impact, but the impact of group TEDU3 is smaller than in manufacturing. Non-technical education has a positive productivity effect which increases with the level of education. The highest level, however, has a smaller impact than in manufacturing. The differences between the sectors may be related to a different role played by technical and non-technical education in services and manufacturing. The pattern of negative age effects is similar to that in manufacturing, but the effects of the oldest two age groups are lower in absolute value than in manufacturing. The impact of the female share is now clearly lower in absolute value, approximately -0.3 in the business sector, compared to -0.5 in manufacturing.

As to wages, the effects of worker characteristics are fairly similar in manufacturing and the business sector. This may be related to the fairly centralized wage negotiation system, which results in a somewhat similar return to worker characteristics in all sectors.

The impact of education has a negative or insignificant effect on productivity both with technical and non-technical education in fixed effects estimation (Table 3). However, in the business sector the highest educational levels still have positive coefficients. Also age has a negative impact both in manufacturing and the business sector which is

	Manufacturing				Business sector	
	Model E, plants in BR and IS		**Model E2, plants in BR**		**Model E**	
	ln(S/L)	*ln(W_L)*	*ln(S/L)*	*ln(W_L)*	*ln(S/L)*	*ln(W_L)*
Constant	3.449	8.308	4.814	8.920	4.260	8.826
	1.75	23.09	22.82	226.17	59.13	624.66
TEDU4	-1.091	0.869	-1.215	0.952	0.261	0.863
	-14.52	63.29	-21.20	88.89	11.91	200.99
TEDU3	0.900	0.353	0.678	0.308	0.286	0.367
	19.93	42.80	22.57	54.86	22.25	145.61
TEDU2	-0.267	-0.005	-0.224	0.009	-0.172	0.000
	-8.51	-0.88	-10.78	2.36	-14.74	0.15
NTEDU4	2.562	0.982	1.395	0.837	0.681	0.922
	17.09	35.85	14.22	45.61	20.31	140.17
NTEDU3	0.588	0.450	-0.021	0.352	0.252	0.365
	6.65	27.87	-0.39	35.19	15.73	116.34
NTEDU2	-0.102	0.002	-0.081	0.026	0.162	0.103
	-1.67	0.16	-2.19	3.76	11.73	38.03
EDU1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
AGE4	-0.667	0.309	-0.558	0.308	-0.222	0.337
	-12.91	32.77	-17.52	51.78	-15.05	116.25
AGE3	-0.309	0.256	-0.269	0.253	-0.114	0.285
	-5.97	27.09	-8.35	42.05	-7.57	96.79
AGE2	-0.185	0.183	-0.114	0.172	-0.113	0.149
	-3.09	16.68	-3.16	25.62	-6.97	46.71
AGE1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Women	-0.515	-0.302	-0.524	-0.289	-0.298	-0.253
	-20.99	-67.39	-30.52	-90.06	-36.52	-157.79
Men	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
GEN1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
GEN2	0.023	0.010	0.045	0.009	0.061	0.011
	2.39	5.48	6.11	6.81	10.06	9.56
GEN3	0.112	0.019	0.150	0.023	0.165	0.025
	9.63	8.81	16.46	13.54	22.08	17.37
GEN4	0.095	0.022	0.138	0.025	0.135	0.024
	8.08	10.34	15.14	14.65	18.32	16.71
GEN5	0.001	0.018	0.007	0.022	0.034	0.025
	0.10	6.84	0.65	10.73	3.98	14.72
*ln(L)**ID	3-digit	3-digit	3-digit	3-digit	3-digit	3-digit
YearD*ID	3-digit	3-digit	3-digit	3-digit	3-digit	3-digit
N	44026	44026	86609	86609	317836	317836
R^2	0.573	0.847	0.519	0.815	0.516	0.781

Note: t-values in parentheses. Ref. indicates reference group. YearD denotes set of year dummies and ID set of industry dummies. Coefficients of industry-specific terms not reported. Data source: Business Register, Employment Statistics.

Table 2: Productivity and wage models for manufacturing and the whole business sector

	Manufacturing					Business sector	
	ln(Y/H)	*ln(W$_H$)*	*ln(TFP)*	*ln(S/L)*	*ln(W$_L$)*	*ln(S/L)*	*ln(W$_L$)*
TEDU4	-0.514	0.260	-0.144	0.070	0.678	0.168	0.529
	-3.58	7.97	-0.84	0.84	40.72	5.05	79.89
TEDU3	-0.297	0.101	-0.306	-0.100	0.307	-0.017	0.229
	-4.21	6.33	-3.68	-2.63	40.51	-0.97	66.91
TEDU2	-0.063	0.010	0.120	-0.208	0.065	-0.061	0.050
	-1.00	0.70	1.58	-6.57	10.31	-3.87	16.16
NTEDU4	-0.061	0.190	-0.898	-0.261	0.471	0.443	0.489
	-0.26	3.53	-3.01	-2.10	18.86	10.23	56.81
NTEDU3	-0.197	0.093	-0.421	-0.032	0.302	0.035	0.175
	-1.64	3.43	-2.84	-0.54	25.57	1.84	45.91
NTEDU2	-0.209	0.025	-0.176	-0.114	0.081	-0.053	0.077
	-2.29	1.21	-1.60	-2.62	9.28	-3.28	24.23
EDU1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
AGE4	-0.548	0.052	-0.516	-0.540	0.106	-0.362	0.151
	-8.47	3.56	-6.70	-16.48	16.17	-23.45	49.23
AGE3	-0.466	0.095	-0.585	-0.354	0.078	-0.265	0.108
	-7.98	7.15	-8.45	-12.05	13.29	-18.99	38.75
AGE2	-0.281	0.113	-0.402	-0.182	0.084	-0.133	0.063
	-4.58	8.12	-5.50	-6.15	14.20	-9.95	23.59
AGE1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Women	-0.011	-0.069	-0.058	-0.094	-0.125	0.041	-0.137
	-0.19	-5.49	-0.89	-3.13	-20.72	3.07	-51.32
Men	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
YearD	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46175	46175	39200	86609	86609	317836	317836
R^2	0.681	0.906	0.780	0.852	0.935	0.865	0.937

Note: t-values in parentheses. Ref. indicates reference group. YearD denotes set of year dummies. Data source: Industrial Statistics, Business Register, Employment Statistics.

Table 3: Models with fixed plant effects

stronger than with pooled data. The wage effects of education and age are clearly positive, but smaller than without fixed effects. Interestingly, in fixed effects estimation the female productivity effect is insignificant in manufacturing and significantly positive in the business sector, whereas a significantly negative wage effect remains in both cases.

The relative wage-productivity gaps are shown in Figures 3 to 6. The columns are calculated as the coefficient of a worker group in the wage equation minus the ratio of the coefficient of the worker group in the productivity equation and the labor share. The columns measure the deviation of the gap from the reference group. As the labor share we use $\overline{\beta} = \overline{\delta} + 1 - \overline{\alpha}$ where $\overline{\delta}$ is the average of the estimated coefficients of *lnH* and $\overline{\alpha}$ is the average of the industry-specific coefficients of *ln(K/H)* in Model A and the average of observed labor shares in Model B. This gives $\overline{\beta} = 0.27 + 1 - 0.10 = 1.17$ for Model A and $\overline{\beta} = -0.07 + 1 - 0.38 = 0.55$ for Model B. The high value in Model A reflects the unreasonably low coefficients of the capital input variable and positive values for the coefficient of the scale term. For the other models that do not include the capital input, we use $\overline{\beta} = \overline{\delta} + 1$ as the factor by which the impact of worker characteristics on productivity is scaled. This is 1.02 in Model C, 1.01 in Model D, 1.02 in Model E, and 1.03 in Model E for the business sector.

Figures 3 and 4 clearly show that technical and non-technical education give very different patterns for the wage-productivity gaps. The gaps increase with the level of technical education, with the exception of level TEDU3, which has a negative gap. The positive gaps result from a combination of positive coefficients in the wage equation and negative coefficients in the wage equations. In the group TEDU3 the productivity coefficient is positive, which results in a negative gap. For those with non-technical skills the productivity effects are more often positive, which tends to give negative wage-productivity gaps. With a low level of non-technical education the gaps are small, increase in most cases in group NTEDU3, and fall with the highest education level. Model B for manufacturing is the exception, since it always gives a negative gap. Some of the gaps for group NTEDU4 are even strongly negative.

The wage-productivity gaps by age group are shown in Figure 5. The gap has a strong, increasing trend with age in all of the models. This is the result of strong seniority effects in wage and mostly negative effects in productivity. There is actually fairly little variation across the models, except in the highest age group.

The female wage-productivity gap is shown in Figure 6. Although the wage effect is negative, the negative productivity effect is larger in absolute value, so that the wage-productivity gap is positive. However, fixed effect estimation produces clearly negative female wage-productivity gaps.

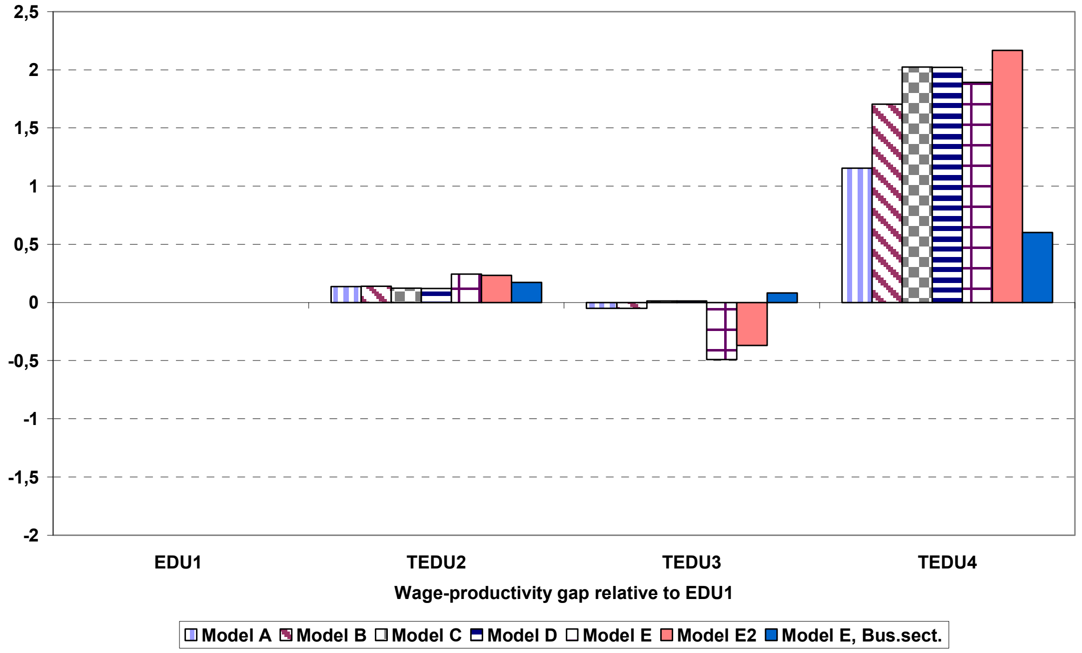

Figure 3: **Relative wage-productivity gap by the level of technical education**

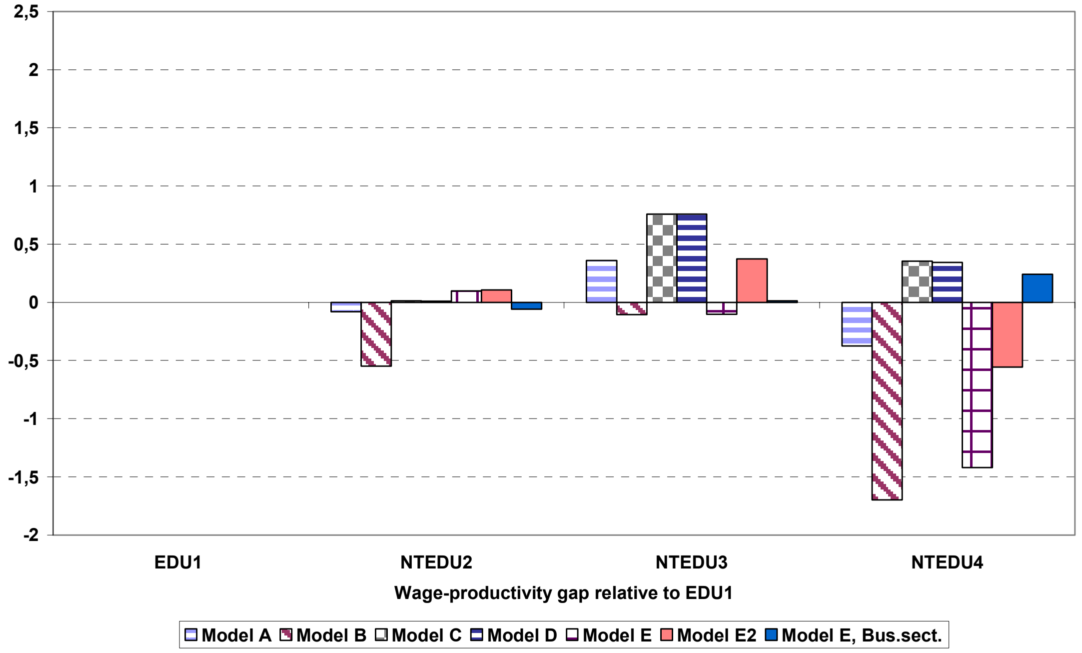

Figure 4: **Relative wage-productivity gap by the level of non-technical education**

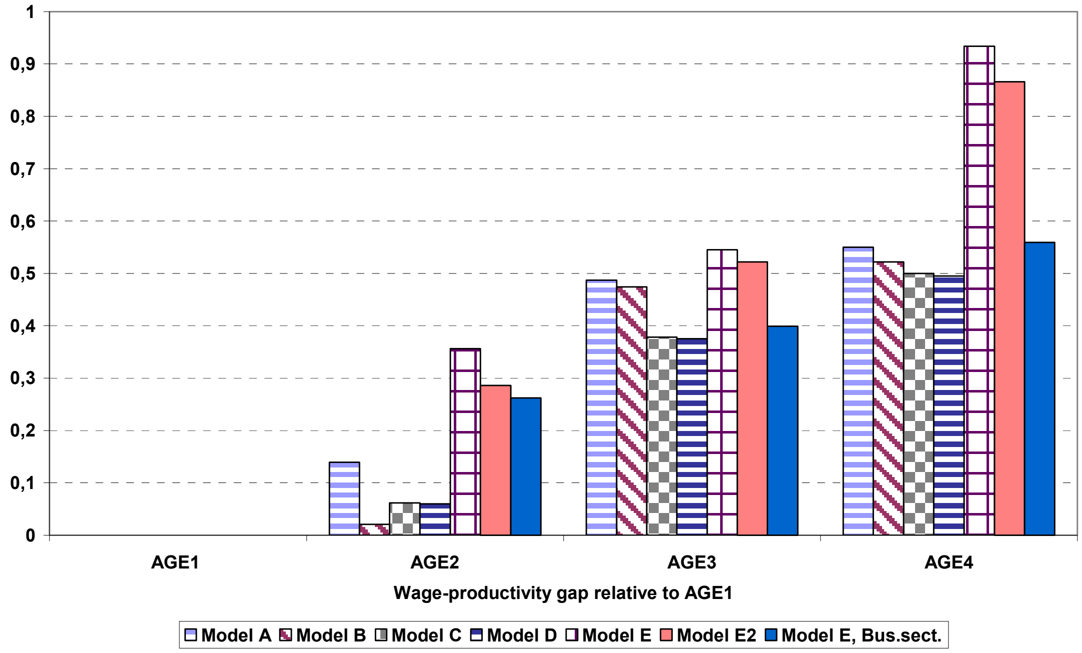

Figure 5: Relative wage-productivity gap by age group

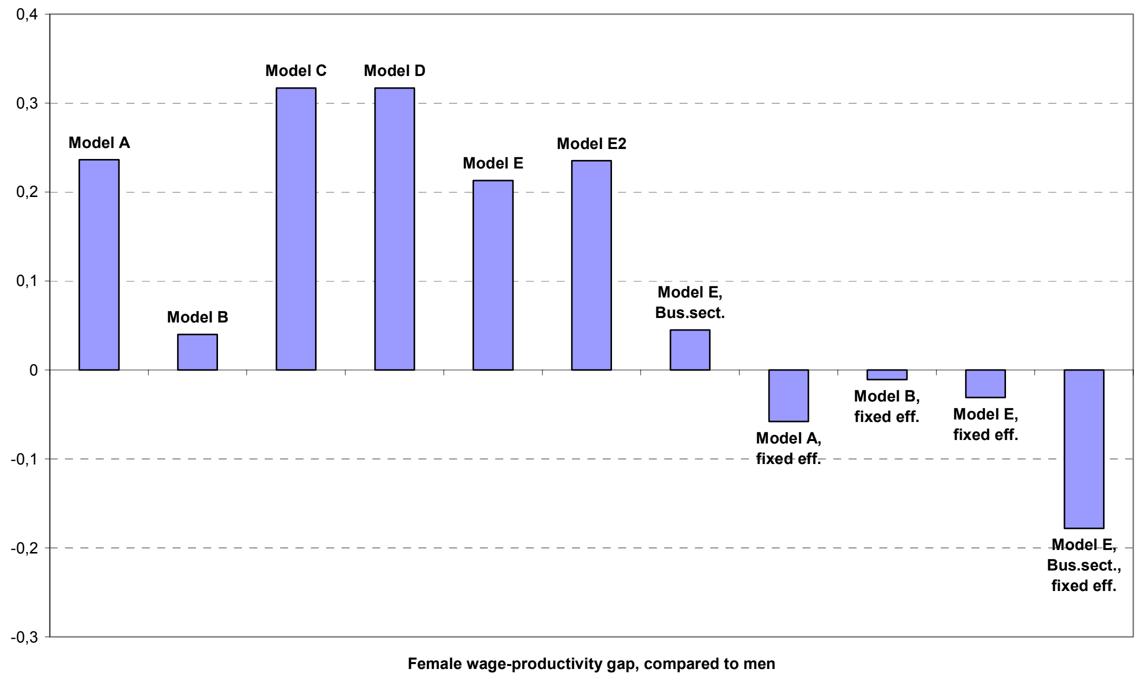

Figure 6: Female wage-productivity gap

The wage-productivity gaps according to the level of education are smaller in the business sector than in manufacturing. For the whole business sector the gap stays positive even with the highest non-technical education. The relative wage-productivity gap has a positive trend by age in the business sector, but the age effect is not quite as strong as in manufacturing. Finally, the female wage-productivity gap is smaller in the business sector than in manufacturing (using model E2 for manufacturing). In fixed effects estimation the female gap becomes in this case clearly negative.

5. Conclusions

We have examined the influence of worker characteristics on productivity and wages using plant-level data. Higher education has in general a positive influence on productivity, but the effect is stronger for non-technical education than for technical education. The wage and productivity effects of education are not monotonous when education increases, which may partly be due to the educational classifications used. Productivity is ”undercompensated” especially for those with the highest level of non-technical education.

Although the productivity effect of age varies somewhat from model to model, the pattern of the relative wage-productivity gap by age is among the most robust results. This is most likely due to strong seniority effects in wage setting. Our results can be interpreted to support incentive based wage setting (Lazear, 1998). Another interpretation is strong insider influences in collective wage bargaining.

The share of female workers is negatively related to productivity, but this productivity gap is not fully reflected in pay. However, this effect disappears when fixed effects estimation is used. This supports the results of Haltiwanger, Lane, and Spletzer (1999, 2000). They conclude that plants tend to get a certain work force composition when they are established, but over time this changes fairly little. Therefore, fixed effects estimation tends to wipe out some of the effects. A priori chosen (higher) capital input coefficients in the model for TFP lead to higher female productivity, which may result from a higher share of females in plants with low capital intensity.

We can compare our results to those obtained in other studies. Most of the relevant research has used different control variables. However, we can still draw some comparisons. Hellerstein and Neumark (1995) using Israeli data let the age-earnings and age-productivity profiles vary by occupation. For the unskilled and less skilled that cover most of the work force they find that the earnings and productivity profiles are fairly similar. Hellerstein, Neumark, and Troske (1999) using US data find that productivity and wage increase with age, except for the oldest age group in some specifications, and their patterns are fairly similar. They include education as the share of workers with some college education. It has a clear positive impact on productivity impact and a somewhat smaller impact on wage. Both of these studies conclude that wages are roughly based on productivity and that the results are consistent with general human capital. Crépon et al. (2002) use French data and conclude that the relationship of productivity and age is inverse U-shaped, but wage is increasing in age. In manufacturing wage increases with skill level, but productivity increases even more. In non-manufacturing wage increases more than productivity when the skill level raises. Hægeland and Klette (1999) use Norwegian data and find that productivity and wage increase with education and the highly educated are roughly paid by productivity. Medium-level potential experience (age minus education years) gave higher productivity than short experience, but with long experience productivity declined although still stayed higher than with short experience. Medium-level experience was underpaid, but the wage premium for long experience corresponded to the productivity premium. They concluded that the wage-experience profile only partly reflected the productivity profile.

Our results differ from those obtained with Israeli and US data, since we find evidence against productivity-based wage setting when age is concerned. Obviously both institutional differences between countries and differences in the approach and worker characteristics used can explain the results. The Norwegian results on education are somewhat similar to ours for the medium levels of education, and the results on general experience are roughly comparable to our results concerning age. Finally, the French results on the age effect on productivity and wage seem to agree with ours.

As to the share of females, Hellerstein, Neumark and Troske (1999) find that the relative productivity is 84 percent of that of men, but the wage only 55 percent. Hellerstein and Neumark (1999) find that the share of females has a coefficient slightly above 0.8 in the productivity equation and slightly below 0.8 in the wage equation. Hægeland and Klette (1999) estimate the female productivity and wage effects to be both slightly above 0.8. Crépon et al. (2002) report that the share of females has almost the same coefficient in the productivity and wage equations that is slightly under 0.9 for manufacturing and over 0.9 for non-manufacturing. When the markdown (which corresponds to the ratio of the coefficients in the productivity and wage equations) is estimated directly, it is not significantly different from 1, although the result is sensitive to the estimation method. Interestingly, the productivity effect seems to be almost the same in all these studies, but the wage effects differ. It is likely that there is a similar selectivity of female workers to certain kinds of plants in all these countries, but the wage setting institutions are not similar. In our case, however, the negative productivity effect is larger. Fixed effects estimation gives results that are closer to these other studies.

The purpose of the paper was also to examine how one can overcome data problems. If attention is restricted to manufacturing, fairly good data on plant characteristics are available. However, in the service sector the data are more limited. We found out that using step-by-step more limited data still gave a fairly consistent picture on the influence of especially average worker age in manufacturing. Also the effect of the level of technical education is fairly similar in all of the models, but there is much more variation in the impact of non-technical education. Using different kinds of educational classifications would be worthwhile to see the sensitivity of these conclusions. All in all, our results show that the simplest model can be used also for the whole business sector, especially when the emphasis is on age and gender effects.

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