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Technological changes and skill composition

Evidence from matched employer-employee data

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Preface

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Abstract

In this paper we carry out a structural analysis of the changes in relative wages and the effect of skill-biased technical changes on the development of relative labour demand. The empirical model is based on a production function in which capital and two types of labour – high skilled and low skilled – are specified as inputs. The classification of high- and low-skilled workers is based on information extracted from estimated wage equations. We estimate separate wage equations for two narrowly defined Norwegian industries, Electrical and optical equipment and Machinery, using unbalanced employer-employee panel data for the period 1995- 2004. Both a skill premium, given by observed and unobserved individual characteristics, and variables unrelated to skill contribute to the observed wages. Each individual-observation is then divided into skill categories according to the predicted skill premium. The results show that in both industries, the share of highskilled man-hours has increased by 20 per cent from 1996 to 2004 while the relative wage between high skilled and low skilled is rather constant. In Electrical and optical equipment, a high-tech industry, all of the increase in the relative demand for high-skilled is accounted for by skill-biased technical change, compared to about 50 per cent in Machinery (a traditional manufacturing industry). In addition we find a strong link between innovations and investments in the long run, although the speed of adjustment of capital towards the equilibrium path appears quite slow.

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1 Introduction

In developed economies, the demand for labour has shifted towards high-skilled workers.[1] The change in the demand for skills has been seen as the effect of skill-biased technological change and globalisation. In the most recent literature (see for instance Autor et al., 2007) it has been pointed out that new technology, and in particular computerization, "has non-monotone impacts on the demand for skill throughout the earnings distribution... [It has]... raised demand for skill among higher-educated workers, depressed skill demands for 'middle-educated' workers, and left the lower echelons of the wage distribution comparatively unscathed". To understand the nature of the increased demand for skills, one needs a skill-measure that takes into account several attributes, for instance educational length and type, and experience.

Economic theory and empirical evidence suggest that there is a key link between the skill level of the workforce and economic performance, both at the firm and the economy-wide level. This idea was first formalised by Nelson and Phelps (1966). In their model, educated workers have a comparative advantage in innovation, imitation and implementation of new technologies. Thus the effect of increased skills occupies a key role in explaining both economic growth and the change in the wage distribution observed in many countries. Furthermore, seen from a policy point of view, a proper skill measure may be very useful for understanding future skill-demand trends and may therefore be important for educational policy.

Traditionally, labour inputs are measured either as number of employees or number of man-hours. The most common way of classifying high- and low-skilled workers is based on years of schooling. Another idea is to assume that the relative efficiency of any two workers equals their wage ratio (see Griliches, 1960) so that one can calculate quality adjusted man-hours. Both methods have their obvious shortcomings. Years of schooling may be a very rough proxy for skill. Other variables, observed and unobserved, should also be taken into account (see the discussion in Borghans et al., 2001).

[1] For an overview, see Machin (2003).

Observed wage differences do not only reflect skill differences, but also variables unrelated to skill, such as, regional and temporal variations in labour market conditions, rent sharing, workers' bargaining power, and transient fluctuations. A related issue is how one measures firms' productivity and success. Until rather recently, empirical analyses of firms' productivity and success have been concentrated on firm characteristics, and less on the characteristics of the workforce in each firm due to lack of linked employer-employee data. Only with such data one would be able to understand the role of the skill composition for firms' productivity. This in turn is important for understanding why some firms are more successful than others.

In this paper we use a wage equation framework to predict what wage an individual would get if he/she changed job or what he/she would earn in any spot labour market given his/her characteristics. We assume that both a skill premium, given by observed and unobserved individual characteristics, and variables unrelated to skill such as labour market area, fixed time effects and transient errors contribute to the observed wages. Each observation on man-hours is then divided into skill categories according to whether the skill premium lies in a particular interval. The predicted wages are used to identify low- and high-skilled labour.

The main goal of this paper is to conduct a structural analysis of the changes in relative wages and the effect of skill-biased technical changes on the development of relative labour demand. The empirical model is based on a production function specified with two types of labour – high skilled and low skilled – and capital as inputs. The two types of labour are assumed to be imperfect substitutes. We also take into account heterogeneity in labour within groups, by constructing quality adjusted man-hours within each of the two groups of labour. This is an extension to most other literature in the field, see for instance Hægeland and Klette (1999), who assume that workers from the various skill categories are perfect substitutes after quality adjustment. The firms face two types of technological changes; one skill neutral and one skill biased. With the model in hand, an index for skill-biased technical change is quantified at the industry level.

Using Norwegian data, it might be useful to describe particular features of the skill composition and wages. In Figure 1 we show an index for the share of high-skilled man-hours and the relative wages (at the industry level) between high and low skilled.[2] We see that the relative wages are more or less constant over time, while a skill-upgrading takes place simultaneously. Thinking of the revealed pattern in a supply-demand framework (with relative employment (high-skilled/low-skilled), and relative wages (high skilled/low skilled), horizontal and vertical axis, respectively) the rather constant relative wages together with increased employment of high-skilled is consistent with a shift in both the relative demand and supply curves outwards.

<Figure 1 about here>

Existing literature applying Norwegian data has revealed a change in the wage distribution. While the returns to education and experience did not increase during the last part of the previous century – instead we witnessed a wage compression (see for instance Kahn, 1998 and Hægeland et al., 1999) –, the newest data indicate that wage inequality is now rising in Norway. This seems to be due to increased return to the individual-specific unobserved skill component, not higher premiums on formal education and experience. As the demand for high-skilled workers increased during the 80ties and 90ties (Kahn, 1998) – which ceteris paribus led to increased skill premiums – the relative supply of high skilled workers also rose. Of course, the net effect on the skill composition of the workers and their relative wages depend on both the demand- and supply-side changes, of which the former is the focus of the current paper.

The paper proceeds as follows. In Section 2 we present our model, while we in Section 3 describe the construction of the variables. In Section 4 we discuss our classification of workers as high and low skilled. Thereafter, in Section 5, we describe our labour quality indices used within the group of high-skilled workers and within the group of low-skilled workers. In Section 6 we discuss the empirical results. Section 7 concludes the paper.

[2] Details about our skill-measure are given later in the paper.

2 The model

Consider the value added production function

$$Q_{it} = A_{it} K_{i,t-1}^{\gamma} \left[(\beta_{it} \overline{H}_{it})^{\rho} + \overline{L}_{it}^{\rho} \right]^{\varepsilon/\rho}, \ \rho < 1, \tag{1}$$

where $Q_{it}, \overline{H}_{it}$ and $\overline{L}_{it}$ are output (value added), and high- and low-skilled labour inputs, respectively, while $K_{i,t-1}$ and A_{it} denote capital and neutral technical change. Subscript i denotes firm, and t denotes year. We assume that capital services in year t are determined by the capital stock at the end of $t-1$, i.e., capital is assumed to be a quasi-fixed input (in the short run). The variable β_{it} is essential for the relative productivity of high- and low-skilled labour input. In particular,

$$\frac{\frac{\partial Q_{it}}{\partial H_{it}}}{\frac{\partial Q_{it}}{\partial L_{it}}} = \beta_{it} \left(\frac{\overline{H}_{it}}{\overline{L}_{it}} \right)^{\rho-1}.$$

In most analyses of labour-labour substitution, man-hours from different skill groups are assumed either to be perfect substitutes ($\rho = 1$), or the elasticity of substitution is assumed to be one, i.e., corresponding to a Cobb-Douglas production function ($\rho = 0$). We allow the elasticity of substitution between high- and low-skilled workers to be arbitrary. We also allow workers within the two skill groups to be heterogeneous, but, to simplify, we assume that they are perfect substitutes after a suitable correction for efficiency differences. As we show in Section 5, this means that we can write

$$\begin{aligned} \overline{H}_{it} &= H_{it} \chi_{it}^{h} \\ \overline{L}_{it} &= L_{it} \chi_{it}^{l}, \end{aligned} \tag{2}$$

where, for high- and low-skilled workers, respectively, H_{it} and L_{it} are total man-hours, and χ_{it}^{h} and χ_{it}^{l} are labour quality indices, to be defined formally in Section 5. As a special case, man-hours within the two skill groups may be homogeneous, in which case $\chi_{it}^{h} = \chi_{it}^{l} = 1$.

Short-run cost minimization, given firm-specific factor prices for high- and low-skilled labour, w_{it}^{l} and w_{it}^{h}, treating $K_{i,t-1}$ as a quasi–fixed input, yields the conditional cost function

$$C(K_{i,t-1}, Q_{it}) = c_{it} \left(\frac{Q_{it}}{A_{it} K_{i,t-1}^{\gamma}} \right)^{\frac{1}{\varepsilon}}, \tag{3}$$

where

$$c_{it} = \left[(w_{it}^h/\chi_{it}^h\beta_{it})^r + (w_{it}^l/\chi_{it}^l)^r\right]^{\frac{1}{r}} \tag{4}$$

and $r = \rho/(\rho - 1)$. The conditional (short-run) factor demand functions are easily derived from (3) by applying Shephard's lemma (see Appendix A.1). Allowing for transient (white noise) error terms $e_{it,k}$, $k = H, L$, in the equations for $\ln H_{it}$ and $\ln L_{it}$ then gives

$$\ln H_{it} - \ln L_{it} = -r\ln(\beta_{it}\chi_{it}^h/\chi_{it}^l) + (r-1)\ln\left(\frac{w_{it}^h}{w_{it}^l}\right) + \widetilde{e}_{it}, \tag{5}$$

where $r - 1$ is the elasticity of substitution between high- and low-skilled workers and $\widetilde{e}_{it} = e_{it,H} - e_{it,L}$.

Skill biased technical change is associated with an increase in the ratio H/L for given relative price w_{it}^h/w_{it}^l. Thus, in our model changes in the relative number of man-hours by high- and low-skilled workers can be decomposed into three parts: skill-biased technical change, $-r\ln(\beta_{it})$, change in relative wages, w_{it}^h/w_{it}^l, and temporary fluctuations in the data, $\widetilde{e}_{it}$. Equation (5) suggests a simple way to estimate r. Assuming a multiplicative structure for β_{it} such that

$$\beta_{it} = \beta_i\beta_t,\ \beta_i > 0, \beta_t > 0,$$

i.e., β_{it} is the product of a firm-specific effect, β_i, and an industry-wide time-effect β_t, and reformulating (5) in terms of relative wage costs, we obtain

$$\ln w_{it}^h H_{it} - \ln w_{it}^l L_{it} = -r\ln\beta_i - r\ln\beta_t + r\ln\left(\frac{w_{it}^h/\chi_{it}^h}{w_{it}^l/\chi_{it}^l}\right) + \widetilde{e}_{it}. \tag{6}$$

The unknown parameters in (6) can be estimated from panel data. The parameters of main interests are $-r\ln\beta_t$ and r. However, the β_i parameters will also be of interest, because they enter the price index c_{it}, which we will use later. We will consider the β_t parameters as fixed (to be estimated) and the β_i's as random parameters (to be predicted).

Demand and supply To obtain the complete system of output supply and factor demand resulting from optimizing behaviour, we first make the additional assumption of monopolistic competiton: Each firm faces the demand function

$$Q_{it} = \Phi_t P_{it}^{-e},\ e > 1. \tag{7}$$

A justification for, and interpretation of, the demand function (7) is found in Dixit and Stiglitz (1977).[3] We do not observe output, but instead sales, $S_{it} = P_{it}Q_{it}$. Short-run profit maximization, given $K_{i,t-1}$, leads to the following system of equations:

$$\begin{aligned}\begin{bmatrix} \ln S_{it} \\ \ln w_{it}^h H_{it} \\ \ln w_{it}^l L_{it} \end{bmatrix} &= \begin{bmatrix} \frac{e-1}{\varepsilon+e-e\varepsilon} \\ \frac{e-1}{\varepsilon+e-e\varepsilon} \\ \frac{e-1}{\varepsilon+e-e\varepsilon} \end{bmatrix} \ln A_{it} + \begin{bmatrix} -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} \\ -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} \\ -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} \end{bmatrix} \ln c_{it} - \begin{bmatrix} 0 \\ r \\ 0 \end{bmatrix} \ln(\beta_i \beta_t) \\ &\quad + r \begin{bmatrix} 0 \\ \ln(w_{it}^h/\chi_{it}^h) \\ \ln(w_{it}^l/\chi_{it}^l) \end{bmatrix} + \begin{bmatrix} \frac{1}{\varepsilon+e-e\varepsilon} \\ \frac{1}{\varepsilon+e-e\varepsilon} \\ \frac{1}{\varepsilon+e-e\varepsilon} \end{bmatrix} \ln \Phi_t + \mathbf{1}\, \frac{\gamma(e-1)}{\varepsilon+e-e\varepsilon} \ln K_{i,t-1} + \begin{bmatrix} e_{it,S} \\ e_{it,H} \\ e_{it,L} \end{bmatrix}\end{aligned} \tag{8}$$

where $\mathbf{1} = [1,1,1]'$, and $[e_{it,S}, e_{it,H}, e_{it,L}]'$ is a white noise vector.

Next consider capital dynamics. Given that the adjustment cost function is weakly convex (with a possible kink at zero due to partial irreversibilities), then the actual capital stock at the end of year t, K_{it}, and the frictionless capital stock, K_{it}^*, will have the same long run growth rate (see equation 3.1 in Bloom et al., 2007). That is,

$$\ln K_{it} = \ln K_{it}^* + \text{error},$$

where the error term is stationary and K_{it}^* is the capital stock the firm would choose with costless adjustment and reversibility, i.e., if the marginal revenue of capital is equal to the Jorgensonian user cost. We show in Appendix A.2 that K_{it}^* is given by

$$\ln K_{it}^* = \text{constant } + \kappa_c \ln c_{it} + \kappa_A \ln A_{it} + \kappa_q \ln q_{Kt}, \tag{9}$$

where

$$\begin{aligned}\kappa_A &= \frac{e-1}{\gamma - \gamma e + \varepsilon + e - \varepsilon e} \\ \kappa_c &= -\varepsilon \kappa_A,\end{aligned} \tag{10}$$

[3]In their derivation, $e = 1/(1-\widetilde{\rho})$, where $\widetilde{\rho} \in (0,1)$ is the elasticity of substitution between the demand for the different varieties of the product, whereas the term Φ_t captures the aggregate demand for the industry's product.

κ_q is a fixed coefficient and q_{Kt} is the user price of capital, assumed to be common to all firms present in year t. Furthermore, for simplicity we assume that the short-run dynamics of capital formation can be described by a 1. order linear "gap technology":

$$\Delta \ln K_{it} = (\pi - 1)(\ln K_{i,t-1} - \ln K^*_{it}) + e_{it,K}, \tag{11}$$

where $|\pi| < 1$ is an autoregressive coefficient and $e_{it,K}$ is an error term. The resulting system of equations can then be written as

$$y_{it} = \Gamma \ln A_{it} + \Theta x_{it} + d_t + e_{it}, \tag{12}$$

where

$$y_t = \left[\begin{array}{cccc} \ln S_{it}, & \ln w^h_{it} H_{it}, & \ln w^l_{it} L_{it}, & \ln K_{it} \end{array}\right]',$$

$$x_{it} = \left[\ln c_{it}, \ln(\beta_i), \ln(w^h_{it}/\chi^h_{it}), \ln(w^l_{it}/\chi^l_{it}), \ln K_{i,t-1}\right]',$$

d_t is an industry-specific time effect (at the two digit NACE level), and $e_{it} = \left[\begin{array}{cccc} e_{it,S}, & e_{it,H}, & e_{it,L}, & e_{it,K} \end{array}\right]'$, where

$$e_{it} \sim N(0, \Sigma),$$

where Σ is an unrestricted covariance matrix.The coefficient matrices Γ and Θ have the following structure:

$$\Gamma = \left[\begin{array}{c} \frac{e-1}{\varepsilon+e-e\varepsilon} \\ \frac{e-1}{\varepsilon+e-e\varepsilon} \\ \frac{e-1}{\varepsilon+e-e\varepsilon} \\ (1-\pi)\kappa_A \end{array}\right], \Theta = \left[\begin{array}{ccccc} -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} & 0 & 0 & 0 & \frac{\gamma(e-1)}{\varepsilon+e-e\varepsilon} \\ -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} & -r & r & 0 & \frac{\gamma(e-1)}{\varepsilon+e-e\varepsilon} \\ -\frac{\varepsilon(e-1)}{\varepsilon+e-e\varepsilon} & 0 & 0 & r & \frac{\gamma(e-1)}{\varepsilon+e-e\varepsilon} \\ (1-\pi)\kappa_c & 0 & 0 & 0 & \pi \end{array}\right]. \tag{13}$$

Note that a shift in A_{it} has the same (proportional) effect on sales and the outlays of the two labour inputs. However, since A_{it} is a latent variable, the components of Γ can only be identified up to a proportionality constant. On the other hand, since r, β_t and β_i are estimated in the first stage, we can estimate c_{it} from (4). Hence we may consider x_{it} as an observed vector. Thus we can identify $\varepsilon(e-1)/(\varepsilon + e - e\varepsilon)$ and γ/ε from Θ.

We assume, provided the firm enters the sample at $t = 1$, that

$$\begin{aligned} \ln A_{it} &= \left\{\begin{array}{ll} \ln A_{i1} & t = 1 \\ \phi \ln A_{i,t-1} + \eta_{it} & t = 2, ..., T, \end{array}\right. \\ \ln A_{i1} &\sim \mathcal{IN}(0, \tau_1),\ \eta_{it} \sim \mathcal{IN}(0, 1), \end{aligned} \tag{14}$$

where ϕ is an autoregressive parameter and η_{it} is an innovation term. In order to obtain identification, both the initial value, $\ln A_{i1}$, and the subsequent innovations, η_{it}, must have zero mean, since any non-zero mean will be indistinguishable from the industry-wide intercept d_t in (12). Moreover, to identify Γ we standardize $\ln A_{it}$ by requiring that the innovations, η_{it}, have unit variance. The variance τ_1 of $\ln A_{i1}$ then characterizes the cross-sectional heterogeneity across firms in their first observation year relative to the innovation variance.

3 Data and variables description

For this analysis we have constructed panels of annual firm-level data for Norwegian firms in selected industries, covering the period 1995–2004.[4] The selected industries are the Manufacture of machinery and equipment (NACE 29) and the Manufacture of electrical and optical equipment (NACE 30–33). The first industry is a traditional manufacturing industry, whereas the second is a high-tech industry. For short, we refer to them as *Machinery* and *Electrical equipment*, respectively. The two manufacturing industries accounted for about 17 per cent of man-hours worked in the manufacturing sector in the sample period. Focusing on narrowly defined industries has the advantage of reducing the heterogeneity in the sample that is due to systematic differences in technology, factor prices and demand conditions between the different types of industrial activities. We account for industry-wide effects in our empirical model by using time-specific intercepts.

The main part of the empirical analysis is carried out at the firm level, at which accounting information is available. A firm is defined as “the smallest legal unit comprising all economic activities engaged in by one and the same owner” and corresponds in general to the concept of a company (see Statistics Norway, 2000). The population of joint stock companies is a subset of all manufacturing firms and comprises about 90 per cent of total man-hours in manufacturing in 2003. A firm may consist of one or more establishments (plants). The establishment is the geographically local unit doing

[4]The same constructed data base has also been utilized by Nilsen et al. (2008) for analyzing the effect of lumpy investment on selected variables and by Nilsen et al. (2009) for growth accounting at the industry level with a special focus on heterogeneous labour.

economic activity within an industry class. About 80–90 per cent of the firms in our database are single-establishment firms.

The data from the accounts statistics are supplemented with data from three other registers: The structural statistics, The Register of Employers and Employees (REE), and The National Education Database (NED). Table 1 presents an overview of the main variables and data sources used in our study. The data sources are described in more detail in Appendix B.1.

<Table 1 about here>

Our model contains the following variables: sales (defined as operating revenue), capital, man-hours worked by high-skilled workers, man-hours worked by low-skilled workers and corresponding hourly wage rates constructed by dividing annual salary by contracted hours of work.[5] In general, all costs and revenues are measured in nominal prices, and incorporate direct taxes and subsidies, except VAT. We have deflated the nominal variables with industry-wide deflators.

The method for calculating the capital stocks in current prices is based on combining book values from the financial accounts with gross investment data.[6] Our econometric model contains a single aggregate capital variable, constructed as a Törnqvist volume index with time-varying weights that are common to all firms in the same industry.[7] An important property of the Törnqvist index is that it can be formulated equivalently in terms of the rental costs of capital (see OECD, 2001). Thus it is possible to aggregate owned capital (which are taken into the firm's balance sheet) and leased capital by summing over the corresponding rental costs.[8]

For each industry, we distinguish between two skill groups, high skilled and low skilled. We classify the workers as low and high skilled according to their predicted

[5] Note that in the manufacturing industry most workers are employed on a full-time basis and hours worked mostly follow contractual hours contained in the agreement between firms and unions.

[6] See Raknerud et al. (2007) for technical details and an evaluation of the data quality.

[7] Capital is divided into two groups of assets in the database: (i) Buildings (which have long service lives) and (ii) Equipments (with short or medium service lives).

[8] The rental cost of capital of type j is calculated as $R_{it}^{j} = q_{K,t} K_{it}^{j}$,where $q_{K,t} = (\iota + \delta_j) w_t^k$, where j denotes either Equipments or Buildings. The median depreciation rate δ_j is about 0.2 for Equipments and 0.05 for Buildings. These are obtained from the accounts statistics, see Raknerud et al. (2007). The real rate of return, ι, which we calculated from the average real return on 10-year government bonds in the period 1996–2002, is 4.2 per cent.

wages. A high predicted wage mirrors that the worker is relative productive and hence can be considered to be high skilled. To predict wages we construct and estimate wage equations, described in detail in the next section. After identification of workers as high and low skilled, we construct the variables H and L as the sum of contracted man-hours worked by high- and low-skilled employees in the given firm, and hourly wages, w^h and w^l, as the average predicted hourly wage rates, where the weights are based on the man-hours for high- and low-skilled workers.

Our observation period is the 10-year period 1995–2004. Initially *all* firms in an industry that were operating during this period were included in the sample. Some "cleansing" of the data has been performed. A firm was excluded from the sample if: (i) the value of a variable is missing for two or more subsequent years; or (ii) the firm is observed in a single year only. Moreover, we miss one observation year, i.e., 1995, because of the lag in the equation for capital. As a result, the final samples consist of 841 firms in Machinery and 560 firms in Electrical equipment. On average the annual workers in the two industries are, respectively, 26,884 and 23,908.

4 Classification of workers as high and low skilled

The workers are classified as low and high skilled according to whether their predicted wages are above or below some threshold. The wage relation of worker p in period t is defined as follows:

$$\begin{aligned}\log(W_{pt}) &= \alpha + \beta_1 edu_{pt} + \beta_2 edutype0_{pt} + \beta_3 edutype4_{pt} + \beta_4 edutype5_{pt} + \\ &\quad + \beta_5 ex_{pt} + \beta_6 ex_{pt}^2 + \beta_7 ex_{pt}^3 + \beta_8 ex_{pt}^4 + \beta_9 male_p \qquad (15)\\ &\quad + \sum_{k=1}^{5} \gamma_k regk_{pt} + \eta_t + \nu_p + \varepsilon_{pt}.\end{aligned}$$

Here edu is the education length calculated in number of years corresponding to the highest education level of the person. The education levels are described in Appendix B.1, Table 14. An inspection of the data shows that mainly workers with the following three types of education are represented in the chosen industries: education in "General programs" (code 0), "Business and Administration" (code 4) and education in "Natural Sciences, Vocational and Technical subjects" (code 5).[9] Then *edutypej* is the dummy for education type j (j = 0, 4, 5) and ex is potential experience. We represent experience as a fourth order polynomial in order to capture in a flexible way the marginal effect of experience. We take into account the gender of the worker ($male_p$) and fixed time effects (η_t) as well. Time-invariant unobserved individual hetereogeneity is represented by random effects, ν_p.

The wage rates analysis is based on a classification of 7 typologies of regions elaborated for all Nordic countries and used by Nordregio in Stockholm (see Edvardsson et al., 2004 and Persson et al., 2004).[10] Since only one economic region in Norway corresponds to typology 3, we merge it with typology 4 and rename the group as 'Regional centres' resulting in six groups of economic regions, cf. Table 2.

<Table 2 about here>

For an observation to be included in the sample for the wage equation estimation we require that the employee in a specific time period works full-time. This is done since part-time work for some persons goes along with unrealistic low or high hourly wage rates. We omit observations which are viewed as either unusual high or unusual low wage rates, defined by threshold values obtained using quantile regressions for the two sectors. For more details on this procedure see Appendix B.2.

Summary statistics, for the final sample, of the variables used in the wage equations that are not dummy variables are displayed in Table 3. Table 4 provides information about the share of observations in different years and regions, the gender composition, and the type of education composition for the final sample.

<Tables 3 and 4 about here>

[9] According to the Norwegian standard classification of education (NUS2000), there are nine types of education in addition to the major group labelled "unspecified type of education" (cf. Appendix B.1, Table 15).

[10] This classification is done according to some regional characteristics such as size and status of the region. The definition of 7 typologies and distribution of 86 Norwegian economic regions on these typologies can be found in Stambøl (2006).

The wage equation 15 is estimated separately for Machinery and Electrical Equipment using GLS on unbalanced panel data for the years 1995–2004. The GLS estimates look rather reasonable, see Table 5. One additional year of education increases the expected hourly wage with about 6 and 7 per cent in Machinery and Electrical Equipment, respectively. The turning points of the experience profiles are 32 years in both industries. As shown by the estimated effect of the gender variable females have cet. par. lower wage rates than males in both industries. The ratio of the variance of the firm specific random term to the variance of the gross error term is 0.77 and 0.79 in Machinery and Electrical Equipment, respectively. The year specific effects increase over time. This is related both to the fact that we use nominal wage as the response variable, as well as to a general increase in real wage over time, stemming from a lasting increase in productivity.

<Table 5 about here>

Having the wage estimation results at hand, we predict the individual wages. For the individuals involved when estimating the wage equations, i.e., the full-time workers not excluded due to unrealistic low or high hourly wages (by the previously described quantile regression procedure), we include the predicted value of the random effect, whereas for individuals not involved in the estimation of the wage equations the random effect is set to zero.

The thresholds for distinguishing high- and low-skilled workers in a particular industry are constructed by using the wage equation for that industry. First, we calculate a predicted wage for a synthetic person with 13 years of education in the reference year (1995) and in the reference labour market area (Region 6) using weighted mean values of experience, type of education and gender of workers in this subsample. To calculate the weights we use man-hours.[11] The characteristics of the synthetic person and his predicted hourly wage are presented in Table 6. In accordance with our criterion a worker (in Region 6 in 1995) is classified as high skilled if his hourly wage is higher than the hourly wage of the synthetic person, i.e., about 116 and 122 NOK in Machinery

[11]Since we have rather few persons with this education length in the relevant sub population, persons with 12, 13 and 14 years of education are used for setting the values of experience, type of education and gender of the synthetic person.

and Electrical Equipment, respectively. The thresholds corresponding to other combinations of labour market region and year are obtained by accounting for the region specific and time specific effects in the model. An overview of all thresholds in the two sectors is provided in tables 7 and 8 below.

<Tables 6, 7 and 8 about here>

Mainly, we can distinguish between three cases: (i) The worker is low skilled from the start and stays in this group all the years he/she is in the sample, (ii) the worker is high skilled from the start and stays in this group all the years he/she is in the sample and (iii) the worker is low skilled but switches to high skilled in one of the years during the sample period.[12]

Table 9 shows the correspondence between definitions of high-skilled and high-educated persons. We see that some of the highly educated individuals (13 years or more) are classified as low-skilled. This is due do to the short experience they have. At the same time some workers with low education but long experience are classified as high skilled. This is especially evident in the case of Machinery, where more than half of the high-skilled workers have low education but long experience.

<Table 9 about here>

To obtain a wage for high-skilled at the firm level in a certain period we calculate a weighted mean of predicted hourly wages for the workers belonging to this skill group, where the weight for a specific person is his share of worked man-hours within the group of high-skilled workers. The firm-level wage of low skilled is calculated in an analogous fashion. According to our classification criterion a substantial part of the firms makes only use of low-skilled workers. For such firms the above procedure cannot be applied to produce a firm-specific wage rate for high-skilled which they are assumed to face when they decide on labour input. For these firms one may set the firm-specific wage equal to the median wage of the sector in the actual year.

[12]There are also a few examples of the opposite transition, i.e., the worker switches from being high- to being low-skilled. This feature is related to the fact that the effect of experience is represented by a fourth order polynomial in the wage equation. For older workers an increase in experience yields a negative effect on the wage level and may as such bring the predicted wage below the threshold value. Usually it happens around the pension age.

Table 10 gives the summary statistics of predicted wages for two skill groups and share of man hours worked by high-skilled workers at the industry level. W^h and W^l are the means of the estimated wages at the firm level weighted by man hours, worked by high skilled and low skilled in the given firm in a given period correspondingly. The share of H shows the share of man hours worked by high-skilled workers in the industry.

<Table 10 about here>

5 Construction of labour quality indices

Assume that the firms are allowed to have different skill compositions within each skill group (H and L), with firm–specific hourly wages, denoted w_{it}^h and w_{it}^l. In the production function, we consider both H_{it} and L_{it} as aggregates of heterogeneous man-hours. The simplest way of incorporating such heterogeneity is to assume that

$$\begin{aligned}\overline{H}_{it} &= \sum_k \lambda_k H_{(k)it} \\ \overline{L}_{it} &= \sum_k \mu_k L_{(k)it},\end{aligned}$$

where, for high-skilled and low-skilled workers, respectively, $H_{(k)it}$ and $L_{(k)it}$ are the number of man-hours in sub-skill category k, and λ_k and μ_k are corresponding efficiency parameters. We have normalized λ_k and μ_k by setting $\lambda_1 = \mu_1 = 1$. Due to the high-skill labour augmenting factor β_{it} in the production function, this normalization entails no loss of generality. Thus we obtain:

$$\begin{aligned}\overline{H}_{it} &= H_{it}\chi_{it}^h, \text{ with } \chi_{it}^h = \sum_k \lambda_k h_{(k)it} \\ \overline{L}_{it} &= L_{it}\chi_{it}^l, \text{ with } \chi_{it}^l = \sum_k \mu_k l_{(k)it},\end{aligned}$$

where, for high-skilled and low-skilled workers, respectively, H_{it} and L_{it} are total man-hours, χ_{it}^h and χ_{it}^l are labour quality indices, and $h_{(k)it}$ and $l_{(k)it}$ are the shares of man-hours in sub-category k (all variables refer to firm i in year t).

Because workers are perfect substitutes within the two skill groups, an optimizing firm will choose $H_{(k)it} > 0$ and $H_{(m)it} > 0$ only if

$$\lambda_k = \frac{w^h_{(k)rt}}{w^h_{(1)rt}},$$

where $w^h_{(k)rt}$ is the wage cost of an employee in efficiency category k in region r in year t. Similarly

$$\mu_k = \frac{w^l_{(k)rt}}{w^l_{(1)rt}}.$$

Thus relative productivity is assumed to be equal to relative (predicted) wage. This suggests that we use the old idea (cf. for instance Griliches, 1960) of ordering the man hours according to wages. Note that the parameters λ_k and μ_k do not depend on time (t) or labour market region (r) even if the wages do so. The reason is that time effects and region-effects affect $w^h_{(k)rt}$ and $w^l_{(k)rt}$ proportionally, due to the log-linear form of the wage equation, and hence cancel out when forming the ratio λ_k.

We apply the following approach for estimating λ_k: Let z^h_{krt} be the k'th *quintile* in the wage distribution (across workers in the industry in labour market region r in year t) defined by

$$P(w^h_{pit} \leq z^h_{krt}) = \frac{k}{5},\ k = 1, ..., 5,$$

where w^h_{pit} is the wage of high-skilled worker p in firm i at time t. A man-hour with wage w^h_{pit} is then classified into category k if $w^h_{pit} \in (z^h_{k-1,rt}, z^h_{krt}]$. The wage distribution is then characterized by a histogram, where the k'th bar in the histogram contains all the wages in the interval $(z^h_{k-1,t}, z^h_{k,t}]$, the corresponding man-hours make up 20 percent of all man-hours (in year t and region r), and these man-hours are assigned the same wage, $w^h_{(k)rt}$ – the median wage in $(z^h_{k-1,rt}, z^h_{krt}]$. In Table 11 we report, for both industries, the values of the efficiency parameters λ_k and μ_k.

<Table 11 about here>

6 Empirical results

Table 12 contains the estimates of the labour demand equation (6). We first see that the estimated elasticity of substitution between high- and low-skilled workers is -0.65

in Machinery and -0.50 in Electrical equipment, respectively. Both estimates are plausible, but very uncertain according to the estimated standard errors. The main reason for this is that the quality adjusted wage ratio, $w_{it}^h \chi_{it}^l / w_{it}^l \chi_{it}^h$, does not vary much, neither across firms, nor over time. In fact, most of the variation in relative wages w_{it}^h / w_{it}^l is accounted for by the quality index ratio $\chi_{it}^h / \chi_{it}^l$, as the correlation coefficient between these two ratios is more than 0.95 in both industries. The regression model gives a very good fit to the data with an R^2 equal to 0.99.

<Table 12 about here>

The coefficients $-r \ln(\beta_{t+1}/\beta_t)$ can be interpreted as the industry-wide skill biased technical change from t to $t+1$ given on a logarithmic scale. The corresponding indices are depicted in Figure 1, together with the indices for the share of high-skilled man hours in the industry (the ratio of high skilled to total man hours relative to the ratio in 1996) and the industry-wide average wage ratios w_{it}^h / w_{it}^l. The figure shows that in both industries, the share of high-skilled man-hours has increased by 20 per cent from 1996 to 2004. Moreover, in Electrical equipment all of the increase is accounted for by skill-biased technical change, compared to about 50 per cent in Machinery. On the other hand, the relative wage between high skilled and low skilled is almost constant over the 9-year period.

Turning to the estimates of the full system (8) in Table 13, we first note that the estimated coefficient of $\ln c_{it}$ is negative in both industries: In Machinery the common coefficient attached to $\ln c_{it}$ in the sales and labour demand equations is estimated to -0.34, while the estimated coefficient in the capital equation is -0.10. The corresponding estimates in Electrical equipments are -0.70 and -0.16, respectively. Thus there is a significant negative relation between relative wages and relative labour demand. With regard to the equations for sales and labour demand, the estimated loading coefficients of $\ln A_{it}$ are very similar in both industries: 0.21 and 0.22.

<Table 13 about here>

According to our structural model, the coefficient of lagged capital, $\ln K_{i,t-1}$, in equations S, H and L is equal to $\gamma(e-1)/(\varepsilon + e - e\varepsilon)$, which must be less than one for profit maximization to be well-defined. The estimates are depicted in the last column of Table 13, and they are equal to 0.16 and 0.15 in the two industries, which gives evidence that either the elasticity of scale $\gamma + \varepsilon < 1$ or $e < \infty$ (firms have market power). These results are consistent with those of Klette (1999). Note that neither γ, ε nor e are identifiable without further restrictions, such as e.g. $\gamma + \varepsilon = 1$.

Let us then turn to the results of the equation for $\ln K_{it}$, i.e., the capital accumulation equation. From the estimated loading coefficients, we see that capital accumulation is affected mainly by shocks in $\ln A_{it}$. In both industries, we see that the estimated loading coefficient of $\ln A_{it}$ is .07 in the capital equation, which is about 1/3 of the estimated loading coefficient of equations S, H and L. Moreover, from (9), we can see that a shock $\Delta \ln A_{it}$ leads to a shift in the equilibrium level of capital equal to $\kappa_A \times \Delta \ln A_{it}$ and a short-run effect on sales and factor costs equal to $(e-1)/(\varepsilon + e - e\varepsilon) \times \Delta \ln A_{it}$. The ratio of the coefficients $(e-1)/(\varepsilon + e - e\varepsilon)$ and κ_A (cf. 13), tells us how many per cent the capital stock will increase in the long run as a result of a Hicks-neutral innovation that increases sales and factor costs by 1 percent in the short run. These estimated ratios are equal to $(.07/(1-.77) =).30/.21 = 1.4$ per cent for Machinery and $(.07/(1-.74) =).27/.22 = 1.2$ per cent for Electical equipment. Thus, our results show a strong link between innovations and investments in the long run, although the speed of adjustment of capital towards the equilibrium path, K^*_{it}, is quite slow.

7 Concluding remarks

Using matched employer-employee data from two narrowly defined Norwegian industries, Machinery - a traditional manufacturing industry, and Electrical equipment and optical equipment - a high-tech industry, we analyse the effect of technological change on firms' skill composition. Contrary to a major part of the existing literature, we define high skilled and low skilled based on not only education, but creates an index based on predicted wages. Other variables than educational level, observed and unobserved, may also affect skill-levels and wages. Moreover, educational length does not vary much over time for a given individual, which makes it a rather restrictive measure of skill. On the other hand, observed wage differences do not only reflect skill differences, but also variables unrelated to skill, such as, regional and temporal variations in labour market conditions, rent sharing, workers' bargaining power, and transient fluctuations. Thus, using predicted wages to classify a worker, controlling for variables that are unrelated to skill, such as time and regional effects, seems to be appropriate. In our econometric model, it is assumed that the high- and low-skilled workers are imperfect substitutes. We take into account heterogeneity within the two groups of workers by constructing quality adjusted man-hours for each of them. Thus, within the groups of either high skilled or low skilled it is assumed that the workers are perfect substitutes after correction for efficiency differences.

Using a rather simple, structural model based on a production function in which capital – assumed to be quasi-fixed – and two types of labour are used as inputs, we have a model at hand in which the skill composition of the workers and their relative wages depend on both demand- and supply-side changes. The firms face two types of technological changes; one skill-neutral and one skill-biased. Using this model we quantify an index for skill-biased technical change at the industry level.

The descriptive statistics show that in both industries, the share of high-skilled man-hours has increased by 20 per cent from 1996 to 2004 while the relative wage between high skilled and low skilled was rather constant. Using our model, we find that in Electrical equipment and optical equipment all of the increase in relative demand for high skilled is accounted for by skill-biased technical change. For the more traditional manufacturing industry - Machinery – only 50 per cent of the increase in the relative demand for high-skilled workers is accounted for by skill-biased technical change. Thus, it seems that the existing technology level in an industry is an important factor explaining the effect of skill-biased technological changes. Finally, the results show a strong link between innovations and investments in the long run, although the speed of adjustment of capital towards the equilibrium path is quite slow.

There is a set of issues we have not addressed and that need to be explored in future work. As already mentioned in the introduction, it is relevant to extend our study by analyzing the relation between the estimated skilled-biased technology index and some proxies of R&D intensity at the industry level as a robustness check of our existing findings. In addition, we will carry out a decomposition of productivity growth to analyze the contribution of skill-biased technological change, as opposed to neutral technical change. Furthermore, it would be useful to look at more industries to see whether our finding that there is a strong link between the overall technology-level and the effect of skill-biased technical change is robust.

We do think that to understand the nature of the increased demand for skills and the importance of worker skills for economic performance, one needs a skill-measure that takes into account several attributes. OECD (2007) highlights the puzzling feature that Norway has high productivity growth while innovative activity measured e.g. by R&D intensity, is low. Furthermore, the role of technology adoption in productivity growth is not well understood. Investment in new capital is known to be a driving force behind productivity growth at the industry level, but recent microeconometric studies find that the immediate impact of large investments on productivity at the firm level is small, or even negative. This may reflect adjustment costs due to the disruption of production. Thus, a useful extension of our study would be to allow the desired capital level to be affected by quality-adjusted relative wages for high- vs. low-skilled workers. In this way we can distinguish between neutral and skilled-biased technology shocks, and learn more about the relationship between new capital, which embody technological progress, and the skill composition at the firm-level.

8 Figures and tables

Table 1: Variables and data sources.

Variable	Interpretation	Data source(s)
S	sales	accounts statistics
K	capital	accounts statistics, structural statistics
H	man-hours worked by high-skilled workers	REE, NED
L	man-hours worked by low-skilled workers	REE, NED
w^h	hourly wage for high-skilled workers	REE, NED
w^l	hourly wage for low-skilled workers	REE, NED

Note: S and K are in 1000 NOK. The hourly wages are in NOK.

Table 2: Classification of economic regions by 7 typologies

Code	Characteristic of the region
1	The capital region
2	Regional metropolises
3	Regional centres
4	Medium-sized towns and regions
5	Small labour areas
6	Micro labour areas

Table 3: Summary statistics of hourly wage, education length and experience

	Machinery				Electrical equipment			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
edu	11.726	2.078	6	20	12.417	2.614	6	20
ex	22.797	11.964	0	52	20.487	12.218	0	51
W	145.00	42.63	48.78	326.60	150.71	57.14	13.20	419.84
No. of obs.	157,948				210,754			

Notes: The reported numbers refers to the sample used for wage equation estimations

Table 4: Summary statistics of the dummy variables occuring in the wage equations

Variable	Machinery	Electrical equipment
1995	0.103	0.098
1996	0.109	0.103
1997	0.092	0.110
1998	0.100	0.111
1999	0.104	0.110
2000	0.096	0.096
2001	0.102	0.103
2002	0.102	0.096
2003	0.096	0.090
2004	0.095	0.084
$reg1$	0.100	0.248
$reg2$	0.157	0.201
$reg3$	0.320	0.405
$reg4$	0.148	0.037
$reg5$	0.210	0.079
$male$	0.893	0.727
$edutype0$	0.208	0.222
$edutype4$	0.080	0.117
$edutype5$	0.657	0.551

Table 5: Estimated wage equation

	Machinery		Electrical equipment	
Variable	Estimate	Std. error	Estimate	Std. error
edu	0.0562	0.0006	0.0672	0.0005
ex	0.0526	0.0009	0.0516	0.0009
$(ex)^2$	-0.0027	0.0001	-0.0021	0.0001
$(ex)^3$	6.42×10^{-5}	0.21×10^{-5}	4.19×10^{-5}	0.22×10^{-5}
$(ex)^4$	-5.87×10^{-7}	0.21×10^{-7}	-3.49×10^{-7}	0.23×10^{-7}
$male$	0.1686	0.0036	0.1967	0.0029
$reg1$	0.1320	0.0039	0.0983	0.0051
$reg2$	0.1270	0.0039	0.0869	0.0054
$reg3$	0.0849	0.0035	0.0748	0.0051
$reg4$	0.0475	0.0042	-0.0127	0.0066
$reg5$	0.1147	0.0039	0.0897	0.0057
$Edutype0$	0.0631	0.0042	0.0616	0.0038
$Edutype4$	0.0449	0.0049	0.0497	0.0042
$Edutype5$	0.0356	0.0037	0.0396	0.0034
1996	0.0235	0.0012	0.0197	0.0012
1997	0.0885	0.0013	0.0732	0.0013
1998	0.1428	0.0013	0.1313	0.0013
1999	0.1659	0.0013	0.1665	0.0013
2000	0.1802	0.0014	0.1973	0.0014
2001	0.2490	0.0014	0.2492	0.0014
2002	0.2905	0.0014	0.2836	0.0015
2003	0.3162	0.0015	0.3062	0.0015
2004	0.3386	0.0016	0.3360	0.0016
$Constant$	3.4529	0.0097	3.2995	0.0098
σ_v^2/σ_u^2	0.7688		0.7963	
R^2 $(overall)$	0.4322		0.5433	
Number of workers	37,432		32,688	
Number of obs.	157,948		141,986	

Note: For definition of R^2 see Statacorp. (2005, p. 302)

Table 6: Characteristics of the synthetic person with 13 years of education in 1995 in Region 6 in the two industries

	Variables in wage equation						
Industry	ex	$edutype0$	$edutype4$	$edutype5$	$male$	ν_p	Hourly wage
Machinery	16.4	0.052	0.064	0.839	0.917	0	115.68
El.equipment	16.8	0.101	0.081	0.686	0.807	0	122.35

Table 7: Year/region-specific threshold values of predicted hourly wage for classification of workers as low- and high-skilled. Machinery

Year	Ref. region	Region 1	Region 2	Region 3	Region 4	Region 5
1995	115.68	132.00	131.34	125.93	121.31	129.73
1996	118.43	135.14	134.46	128.92	124.19	132.82
1997	126.38	144.22	143.49	137.58	132.53	141.74
1998	133.44	152.27	151.50	145.26	139.93	149.65
1999	136.54	155.81	155.03	148.65	143.19	153.14
2000	138.51	158.06	157.26	150.79	145.25	155.34
2001	148.38	169.32	168.46	161.53	155.60	166.41
2002	154.67	176.49	175.60	168.37	162.19	173.46
2003	158.70	181.10	180.18	172.76	166.42	177.98
2004	162.29	185.19	184.26	176.67	170.19	182.01

Table 8: Year/region-specific threshold values of predicted hourly wage for classification of workers as low- and high-skilled. Electrical eqiupment

Year	Ref. region	Region 1	Region 2	Region 3	Region 4	Region 5
1995	122.35	134.99	133.46	131.85	120.81	133.84
1996	124.79	137.68	136.11	134.48	123.21	136.50
1997	131.64	145.24	143.59	141.86	129.98	144.00
1998	139.51	153.92	152.18	150.34	137.75	152.61
1999	144.53	159.45	157.64	155.74	142.70	158.09
2000	149.04	164.43	162.57	160.61	147.16	163.03
2001	156.98	173.18	171.22	169.16	154.99	171.71
2002	162.47	179.25	177.22	175.08	160.42	177.72
2003	166.19	183.35	181.27	179.09	164.09	181.79
2004	171.22	188.89	186.75	184.51	169.05	187.29

Table 9: Correspondence between high-educated and high-skilled. Number of man-years in the industry

	Machinery				Electrical equipment			
Education	low-skilled		high-skilled		low-skilled		high-skilled	
<13 years	169,935	(64.9%)	43,642	(16.7%)	129,459	(55.3%)	30,329	(13.0%)
>=13 years	14,200	(5.4%)	33,973	(13.0%)	20,685	(8.8%)	53,674	(22.9%)

Note: Shares of the total number of employees in parentheses

Table 10: Predicted real wages for two skill groups and share of man hours worked by high-skilled workers at the industry level

	Machinery				Electrical equipment			
Year	W^h	W^l	W^h/W^l	Share of H	W^h	W^l	W^h/W^l	Share of H
1995	152.55	101.99	1.496	0.299	165.40	102.45	1.614	0.360
1996	154.25	102.91	1.499	0.304	167.34	103.65	1.614	0.361
1997	160.14	107.21	1.494	0.303	173.21	106.85	1.621	0.371
1998	164.58	110.42	1.490	0.291	179.60	110.12	1.631	0.359
1999	165.76	110.62	1.498	0.309	182.55	111.72	1.634	0.380
2000	164.15	108.89	1.507	0.323	182.80	112.12	1.630	0.387
2001	171.33	113.74	1.506	0.348	188.62	114.90	1.642	0.401
2002	176.65	117.52	1.503	0.350	192.77	117.91	1.635	0.411
2003	177.43	118.15	1.502	0.361	193.51	118.56	1.632	0.426
2004	180.66	120.60	1.498	0.368	198.28	121.86	1.627	0.428

Notes: Predicted wages based on wage-equation regressions. The wages in the wage equations are measured in nominal NOK. The predicted wages are then deflated using CPI (1995 = 1.000)

The share of H is the share of man hours worked by high-skilled employees in the given industry.

Table 11: Efficiency parameters related to quality adjustment of man-hours worked by low and high skilled

	Machinery		El. equipment	
skill category, k	λ_k	μ_k	λ_k	μ_k
1	1	1	1	1
2	1.065	1.123	1.084	1.126
3	1.142	1.215	1.183	1.235
4	1.243	1.311	1.315	1.361
5	1.380	1.440	1.488	1.516

Table 12: **Estimates of elasticity of substitution ($r-1$), and skill-biased technical change.** St.err. in parentheses

Coefficient	Machinery	El.equipment
$r-1$	−0.65(0.35)	−0.50(0.41)
$-r\ln(\beta_{1997}/\beta_{1996})$	−0.02(0.02)	0.00(0.02)
$-r\ln(\beta_{1998}/\beta_{1997})$	−0.01(0.02)	−0.04(0.02)
$-r\ln(\beta_{1999}/\beta_{1998})$	0.01(0.02)	0.03(0.02)
$-r\ln(\beta_{2000}/\beta_{1999})$	0.04(0.02)	0.05(0.02)
$-r\ln(\beta_{2001}/\beta_{2000})$	0.01(0.02)	0.01(0.02)
$-r\ln(\beta_{2001}/\beta_{2002})$	−0.02(0.02)	0.07(0.02)
$-r\ln(\beta_{2003}/\beta_{2002})$	0.05(0.02)	0.02(0.02)
$-r\ln(\beta_{2004}/\beta_{2003})$	0.04(0.02)	0.04(0.02)
R^2	0.99	0.99
No. of firms	841	560

Table 13: Estimates of coefficients in system of equations for sales and labour demand

Industry	Equation	Coefficient of: $\ln A_{it}$	$\ln c_{it}$	$\ln K_{i,t-1}$
Machinery	S	0.21 (0.01)	−0.34 (0.01)	0.16 (0.01)
	H	0.21	−0.34	0.16
	L	0.21	−0.34	0.16
	K	0.07 (0.01)	−0.10 (0.01)	0.77 (0.09)
El. equipment	S	0.22 (0.01)	−0.70 (0.11)	0.15 (0.02)
	H	0.22	−0.70	0.15
	L	0.22	−0.70	0.15
	K	0.07 (0.01)	−0.16 (0.04)	0.74 (0.03)

Standard errors in parentheses are obtained from the inverse
Hessian of the log-likelihood function

Table 14: Educational levels

Tripartition of levels	Level	Class level
	0	Under school age
Primary education	1	1st – 6th
Secondary education	2	7th – 9th
	3	10th
	4	11th – 12th
Post-secondary education	5	13th – 14th
	6	15th – 16th
	7	17th – 18th
	8	19th+
	9	Unspecified

Table 15: Types of education in Norwegian classification of education

Code	**Description**
0	General programs
1	Humanities and Arts
2	Teacher Training and Pedagogy
3	Social Sciences and Law
4	Business and Administration
5	Natural Sciences, Vocational and Technical subjects
6	Health, Welfare and Sport
7	Primary Industries
8	Transport an Communications, Safety and Security
9	Unspecified

Table 16: Quantile regression estimates

	Machinery		Electrical equipment	
Variable	0.05 quantile	0.95 quantile	0.05 quantile	0.95 quantile
Constant	3.895 (0.021)	5.186 (0.010)	3.931 (0.021)	5.151 (0.013)
1996	-0.008 (0.019)	0.032 (0.009)	-0.019 (0.014)	0.025 (0.009)
1997	0.010 (0.019)	0.075 (0.009)	0.067 (0.014)	0.096 (0.009)
1998	0.054 (0.019)	0.142 (0.009)	0.081 (0.014)	0.157 (0.009)
1999	0.064 (0.019)	0.188 (0.009)	0.128 (0.014)	0.219 (0.009)
2000	0.067 (0.019)	0.229 (0.009)	0.157 (0.014)	0.260 (0.009)
2001	0.205 (0.019)	0.305 (0.009)	0.243 (0.014)	0.317 (0.009)
2002	0.238 (0.019)	0.356 (0.009)	0.317 (0.014)	0.361 (0.009)
2003	0.238 (0.019)	0.406 (0.009)	0.332 (0.014)	0.418 (0.009)
2004	0.256 (0.019)	0.429 (0.009)	0.313 (0.014)	0.447 (0.009)
$reg1$	0.454 (0.022)	0.175 (0.010)	0.418 (0.020)	0.330 (0.013)
$reg2$	0.421 (0.020)	0.136 (0.009)	0.339 (0.020)	0.216 (0.013)
$reg3$	0.293 (0.019)	0.098 (0.009)	0.324 (0.020)	0.181 (0.012)
$reg4$	0.302 (0.020)	0.007 (0.009)	0.067 (0.025)	-0.008 (0.016)
$reg5$	0.440 (0.019)	0.135 (0.010)	0.334 (0.022)	0.317 (0.014)

Note: Standard errors in parentheses.

Table 17: Year/labour area specific threshold values of trimming of wages according to quantile regression results. Machinery

Year	Thresholds	Ref. region	Region 1	Region 2	Region 3	Region 4	Region 5
1995	Lower	49.156	77.401	74.888	65.891	66.487	76.325
	Upper	178.752	212.938	204.793	197.157	180.008	204.588
1996	Lower	48.764	76.784	74.292	65.366	65.957	75.717
	Upper	184.565	219.862	211.452	203.568	185.861	211.241
1997	Lower	49.650	78.179	75.641	66.553	67.155	77.092
	Upper	192.674	229.522	220.743	212.512	194.028	220.523
1998	Lower	51.883	81.696	79.044	69.547	70.176	80.560
	Upper	206.026	245.227	236.040	227.238	207.473	235.804
1999	Lower	52.405	82.517	79.838	70.246	70.881	81.369
	Upper	215.724	256.980	247.151	237.936	217.239	246.904
2000	Lower	52.562	82.765	80.078	70.457	71.094	81.614
	Upper	224.753	267.736	257.495	247.894	226.331	257.238
2001	Lower	60.340	95.012	91.927	80.883	81.614	93.691
	Upper	242.500	288.877	277.827	267.468	244.203	277.550
2002	Lower	62.365	98.199	95.012	83.596	84.352	96.834
	Upper	255.188	303.992	292.364	281.463	256.980	292.072
2003	Lower	62.365	98.199	95.012	83.596	84.352	96.834
	Upper	268.272	319.578	307.354	295.894	270.156	307.047
2004	Lower	63.497	99.983	96.737	85.115	85.884	98.593
	Upper	274.513	327.013	314.505	302.778	276.442	314.191

Table 18: Year/labour area specific threshold values for trimming of wages according to quantile regression results. Electrical Equipment

Year	Thresholds	Ref. region	Region 1	Region 2	Region 3	Region 4	Region 5
1995	Lower	50.958	77.401	71.522	70.457	54.449	71.165
	Upper	172.604	240.087	214.219	206.851	171.229	236.986
1996	Lower	49.999	75.944	70.176	69.131	53.464	69.826
	Upper	176.973	246.164	219.642	212.088	175.563	242.985
1997	Lower	54.489	82.765	76.478	75.339	58.265	76.096
	Upper	189.995	264.278	235.804	227.693	188.482	260.864
1998	Lower	55.257	83.931	77.556	76.401	59.086	77.169
	Upper	201.946	280.900	250.636	242.015	200.337	277.272
1999	Lower	57.916	87.970	81.288	80.078	61.930	80.883
	Upper	214.863	298.867	266.667	257.495	213.151	295.007
2000	Lower	59.621	90.559	83.680	82.434	63.752	83.263
	Upper	223.855	311.376	277.827	268.272	222.072	307.354
2001	Lower	64.975	98.692	91.195	89.837	69.477	90.740
	Upper	236.986	329.640	294.124	284.007	235.097	325.382
2002	Lower	69.965	106.272	98.199	96.737	74.814	97.710
	Upper	247.646	344.468	307.354	296.783	245.673	340.018
2003	Lower	71.023	107.878	99.683	98.199	75.944	99.186
	Upper	262.172	364.673	325.382	314.191	260.083	359.963
2004	Lower	79.686	105.848	97.807	96.351	74.515	97.320
	Upper	269.886	375.403	334.956	323.436	267.736	370.554

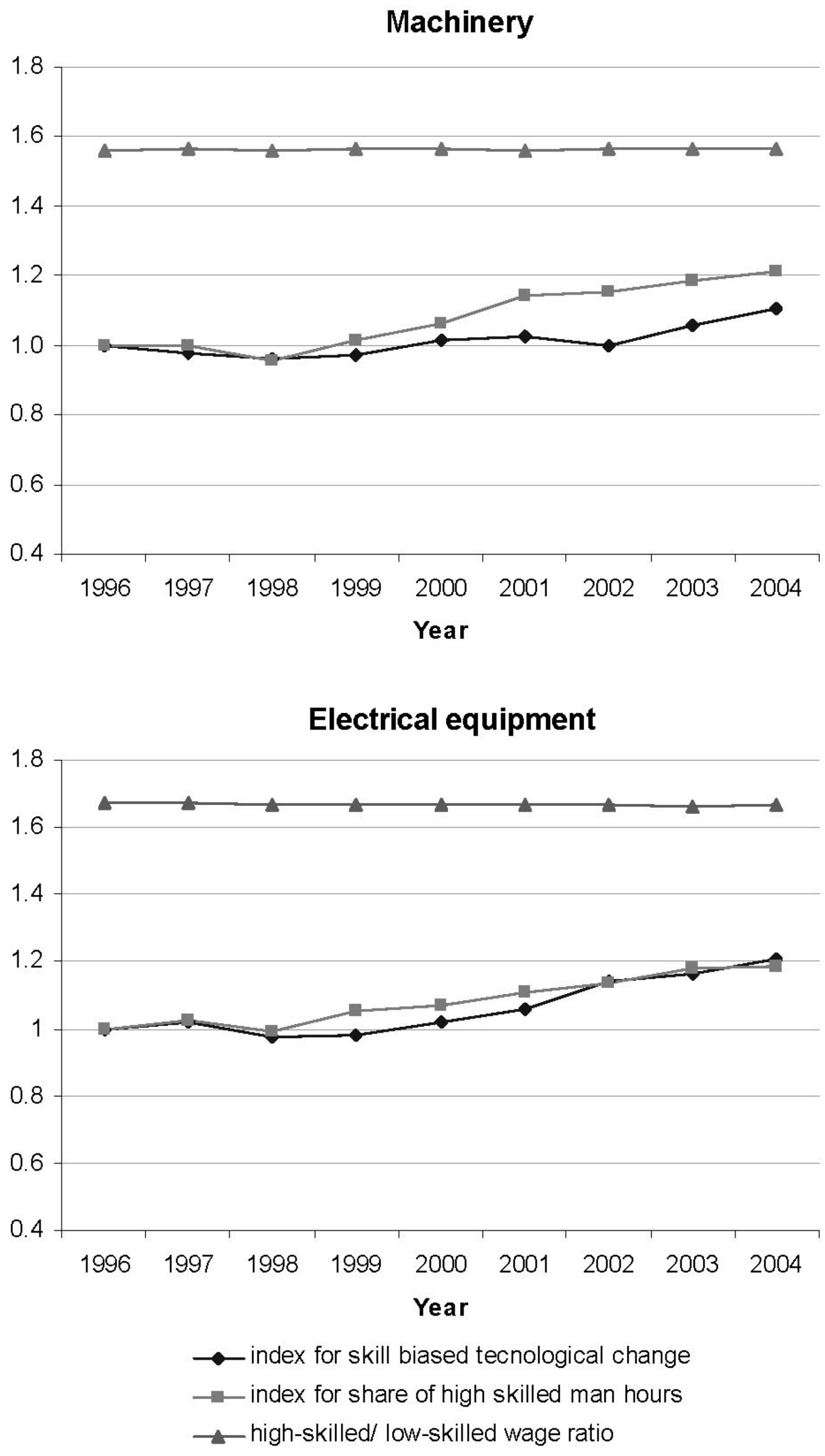

Figure 1: Index for skill biased technical change, share of man hours by high skilled workers and average wage ratio between high- and low-skilled workers

References

[1] Autor, D.H., L.F. Katz, and M.S. Kearney (2007): Trends in U.S. Wage Inequality: Revising the Revisionists. Mimeo. *Review of Economics and Statistics*, 90(2), 300–323.

[2] Bloom, N., S. Bond and J. van Reenen (2007): Uncertainty and Investment Dynamics. *Review of Economic Studies*, 74, 391–415.

[3] Borghans, L., F. Green, and K. Mayhew (2001): Skills measurement and economic analysis: an introduction. *Oxford Economic Papers* 53(3), 375–384.

[4] Dixit, A.K. and J.E. Stiglitz (1977): Monopolistic Competition and Optimum Product Diversity, *American Economic Review*, 67, 297–308.

[5] Edvardsson, I.R., E. Heikkilä, M. Johansson, L.O. Persson, T.D. Schmidt and L.S. Stambøl (2004): Economic renewal and demographic change. Evaluation of policies for well functioning local labour markets in the Nordic countries. Paper presented at the 44th Congress of the European Regional Science Association, Porto, Portugal, 25 - 29 August 2004.

[6] Griliches, Z. (1960): Measuring Inputs in Agriculture: A Critical Survey. *Journal of Farm Economics*, 42(5), 1411–1433.

[7] Hawkins, D.F. (1986): Corporate financial reporting and analysis: Text and cases. The Robert N. Anthony/Williard J. Graham Series in Accounting, Irwin, Homewood.

[8] Hægeland, T. and T.J. Klette (1999): Do higher wages reflect higher productivity? Education, gender and experience premiums in a matched plant-worker panel data set. Ch. 11 in Haltiwanger, J.C., J.L. Lane, J.R. Spletzer, J.J.M. Theeuwes and K.R. Troske (Eds.) *The creation and analysis of employer-employee data.* Amsterdam: North-Holland.

[9] Hægeland, T., T.J. Klette, and K.G. Salvanes (1999): Declining Returns to Education in Norway? Comparing Estimates across Cohorts, Sectors and over Time. *Scandinavian Journal of Economics* 101 (4), 555–576.

[10] Kahn, L.M. (1998): Against the Wind: Bargaining Recentralisation and Wage Inequality in Norway 1987–1991. *Economic Journal* 108, 603–645.

[11] Klette, T.J., (1999): Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data, *Journal of Industrial Economics* 47, 451–476.

[12] Machin, S. (2003): Skill-Biased Technical Change in the New Economy. In D. Jones (Ed.): *New Economy Handbook*. Amsterdam: Elsevier.

[13] Nelson, R. and E. Phelps (1966): Investment in Humans, Technological Diffusions, and Economic Growth, *American Economic Review*, 61, 69–75

[14] Nilsen, Ø.A., A. Raknerud, M. Rybalka and T. Skjerpen (2008): Lumpy Investments, Factor Adjustments. and Labour Productivity, *Oxford Economic Papers* 61, 104–127.

[15] Nilsen, Ø.A., A. Raknerud, M. Rybalka and T. Skjerpen (2009): The importance of skill measurement for growth accounting. Shortened and revised version of Discussion Paper 531, Statistics Norway. (Under review in *Review of Income and Wealth*).

[16] OECD (2001): Manual, Measuring Capital: A Manual on the Measurement of Capital Stocks, Consumption of Fixed Capital Services, Paris and Washington, 17th September.

[17] OECD (2007): Encouraging innovation, *OECD Economic Surveys Norway*, 136–166.

[18] Persson, L.O. (ed.), I.R. Edvardsson, E. Heikkilä, M. Johansson, S. Korkalainen, T.D. Schmidt and L.S. Stambøl (2004): *Economic renewal and demographic change. An evaluation of local labour market performance in the Nordic countries.* Report 2004:8, Nordregio, Stockholm.

[19] Raknerud, A., D. Rønningen and T. Skjerpen (2007): A Method for Improved Capital Measurement by combining Accounts and Firm Investment Data. *Review of Income and Wealth*, 53(3), 397–421.

[20] Stambøl, L. S. (2006): Urban and Regional Labour Market Mobility in Norway, *Social and Economic Studies no.* 110/2006, Statistics Norway.

[21] StataCorp (1995): Stata Longitudinal/Panel. Reference manual. Release 9. College Station, TX: Stata Press.

[22] Statistics Norway (2000): Accounts Statistics, Official Statistics of Norway, D 249, Oslo/Kongsvinger.

Appendix A: Technical details

A.1 The derivation of (5) From (3)-(4) and Shephard's lemma

$$\begin{aligned}\ln H_{it} &= \frac{1}{\varepsilon}(\ln Q_{it} - \ln A_{it}) - \frac{\gamma}{\varepsilon}\ln K_{it} + \ln \partial c_{it}/\partial w_t^h \\ \ln L_{it} &= \frac{1}{\varepsilon}(\ln Q_{it} - \ln A_{it}) - \frac{\gamma}{\varepsilon}\ln K_{it} + \ln \partial c_{it}/\partial w_t^l.\end{aligned}$$

Straightforward calculations then give

$$\begin{aligned}\ln H_{it} &= \frac{1}{\varepsilon}(\ln Q_{it} - \ln A_{it}) - \frac{\gamma}{\varepsilon}\ln K_{i,t-1} + (1-r)\ln c_{it} \\ &\quad -(1-r)\ln w_{it}^h - r\ln(\beta_{it}\chi_{it}^h) + e_{it,H}, \\ \ln L_{it} &= \frac{1}{\varepsilon}(\ln Q_{it} - \ln A_{it}) - \frac{\gamma}{\varepsilon}\ln K_{i,t-1} + (1-r)\ln c_{it} \\ &\quad -(1-r)\ln w_{it}^l - r\ln(\chi_{it}^l) + e_{it,L},\end{aligned} \tag{16}$$

and (5) follows directly.

A.2 The derivation of frictionless capital Now consider the problem of finding frictionless capital K_{it}^*. First we can find the cost minimizing level of capital, $\widetilde{K}_{it}$, defined as

$$\begin{aligned}\widetilde{K}_{it} &= \arg\min_{K_{it}} q_{Kt}K_{it} + C(K_{it}, Q_{it}) \\ &= \arg\min_{K_{it}} q_{Kt}K_{it} + c_{it}\left(\frac{Q_{it}}{A_{it}K_{it}^{\gamma}}\right)^{\frac{1}{\varepsilon}}\end{aligned}$$

The 1. order condition of this problem is

$$\ln \widetilde{K}_{it} = \theta_1 + \frac{1}{\gamma+\varepsilon}(\ln Q_{it} - \ln A_{it}) + \frac{\varepsilon}{\gamma+\varepsilon}\ln c_{it} - \frac{\varepsilon}{\gamma+\varepsilon}\ln q_{Kt}, \tag{17}$$

where θ_1 is a constant. This leads to the following cost function:

$$\begin{aligned}
C_{it}(Q_{it}) &= c_{it}\left(\frac{Q_{it}}{A_{it}\widetilde{K}_{it}^{\gamma}}\right)^{\frac{1}{\varepsilon}} + q_{Kt}\widetilde{K}_{it} \\
&= \left(\frac{c_{it}^{\varepsilon}Q_{it}}{A_{it}\exp(\gamma\theta_1)\left[Q_{it}^{\frac{\gamma}{\gamma+\varepsilon}}A_{it}^{\frac{-\gamma}{\gamma+\varepsilon}}c_{it}^{\frac{\gamma\varepsilon}{\gamma+\varepsilon}}q_{kt}^{\frac{-\gamma\varepsilon}{\gamma+\varepsilon}}\right]}\right)^{\frac{1}{\varepsilon}} + \exp(\gamma\theta_1)\times q_{Kt}\left[Q_{it}^{\frac{1}{\gamma+\varepsilon}}A_{it}^{\frac{-1}{\gamma+\varepsilon}}c_{it}^{\frac{\varepsilon}{\gamma+\varepsilon}}q_{kt}^{\frac{-\varepsilon}{\gamma+\varepsilon}}\right] \\
&= \theta_2\times q_{kt}^{\frac{\gamma}{\gamma+\varepsilon}}c_{it}^{\frac{\varepsilon}{\gamma+\varepsilon}}A_{it}^{\frac{-1}{\gamma+\varepsilon}}Q_{it}^{\frac{1}{\gamma+\varepsilon}},
\end{aligned}$$

where θ_2 is constant.

Frictionless capital, K_{it}^* is now found from (17) by replacing Q_{it} with Q_{it}^*, which corresponds to the optimal output in the case where all inputs are assumed to be flexible and fully adjusted immediately:

$$\begin{aligned}
Q_{it}^* &= \arg\max_{Q_{it}} P_{it}Q_{it} - C(Q_{it}) \\
&= \arg\max_{Q_{it}} \Phi_t^{\frac{1}{e}}Q_{it}^{\frac{e-1}{e}} - \theta_{2kt}^{\frac{\gamma}{\gamma+\varepsilon}}c_{it}^{\frac{\varepsilon}{\gamma+\varepsilon}}A_{it}^{\frac{-1}{\gamma+\varepsilon}}Q_{it}^{\frac{1}{\gamma+\varepsilon}}.
\end{aligned}$$

Let $\varpi = e+\gamma+\varepsilon-e(\gamma+\varepsilon)$. Then the 1. order condition is

$$\begin{aligned}
& \frac{e-1}{e}Q_{it}^{\frac{-1}{e}}\Phi_t^{\frac{1}{e}} - \theta_2 q_{kt}^{\frac{\gamma}{\gamma+\varepsilon}}c_{it}^{\frac{\varepsilon}{\gamma+\varepsilon}}A_{it}^{\frac{-1}{\gamma+\varepsilon}}\frac{1}{\gamma+\varepsilon}Q_{it}^{\frac{1-\gamma-\varepsilon}{\gamma+\varepsilon}} = 0 \\
& \Updownarrow \\
Q_{it}^{\frac{-1}{e}-\frac{1-\gamma-\varepsilon}{\gamma+\varepsilon}} \equiv\ & Q_{it}^{\frac{-\varpi}{e(\gamma+\varepsilon)}} = \frac{e}{e-1}\frac{\theta_2}{\gamma+\varepsilon}\Phi_t^{\frac{-1}{e}}q_{kt}^{\frac{\gamma}{\gamma+\varepsilon}}c_{it}^{\frac{\varepsilon}{\gamma+\varepsilon}}A_{it}^{\frac{-1}{\gamma+\varepsilon}} \\
& \Updownarrow \\
Q_{it} =\ & \theta_3\Phi_t^{\frac{e(\gamma+\varepsilon)}{\varepsilon\varpi}}q_{kt}^{\frac{-\gamma e}{\varpi}}c_{it}^{\frac{-\varepsilon e}{\varpi}}A_{it}^{\frac{e}{\varpi}} \\
& \Updownarrow \\
\ln Q_{it} =\ & \theta_4 + \frac{e(\gamma+\varepsilon)}{\varepsilon\varpi}\ln\Phi_t - \frac{\gamma e}{\varpi}\ln q_{Kt} \\
& -\frac{\varepsilon e}{\varpi}\ln c_{it} + \frac{e}{\varpi}\ln A_{it}. \qquad (18)
\end{aligned}$$

Inserting (18) into (17) gives

$$
\begin{aligned}
\ln K_{it}^{*} &= \frac{1}{\gamma+\varepsilon}\left(\ln Q_{it}-\ln A_{it}\right)+\frac{\varepsilon}{\gamma+\varepsilon}\ln c_{it}-\frac{\varepsilon}{\gamma+\varepsilon}\ln q_{Kt} \\
&= \theta_5+\frac{-e\varepsilon-e\gamma}{\varepsilon\nu}\ln\Phi_t \\
&\quad +\frac{-\varepsilon^2\gamma+\varepsilon^3 e+\varepsilon^2 e\gamma-\varepsilon^3}{\varepsilon\nu}\ln c_{it} \\
&\quad +\frac{-\varepsilon^3 e+\varepsilon^3+e\varepsilon^2+\varepsilon^2\gamma+\gamma e\varepsilon-\varepsilon^2 e\gamma}{\varepsilon\nu}\ln q_{Kt} \\
&\quad +\frac{\varepsilon\gamma-\varepsilon^2 e+-e\varepsilon\gamma+\varepsilon^2}{\varepsilon\nu}\ln A_{it},
\end{aligned}
$$

where θ_3, θ_4 and θ_5 are constants and $\nu=-(\varepsilon+\gamma)\varpi$. Note that when $\gamma+\varepsilon=1$, $\nu=-1$, and hence one obtains

$$
\ln K_{it}^{*}=\theta+(e-1)\ln A_{it}+\varepsilon(1-e)\ln c_{it}+\frac{e}{\varepsilon}\ln\Phi_t+(e\varepsilon-e-\varepsilon)\ln q_{Kt}.
$$

Appendix B. Data issues

B.1 Data sources *Accounts statistics:* All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, in particular, the information about operating revenues, operating costs and operating result, labour costs, the book values of a firm's tangible fixed assets at the end of a year, their depreciation and write-downs.

The structural statistics: The term "structural statistics" is a general name for the different industrial activities statistics, such as Manufacturing statistics, Building and construction statistics, Wholesale and retail trade statistics, etc. They all have the same structure and include information about production, input factors and investments at the firm level. The structural statistics are organised according to the NACE standard and are based on General Trading Statements, which are given in an appendix to the tax return. In addition to some variables, which are common to those in the accounts statistics, the structural statistics contain data about purchases of tangible fixed assets and operational leasing. These data were matched with the data from the accounts statistics. As the firm identification number here and further we use the number given to the firm under registration in the Register of Enterprises, one of the Brønnøysund registers, which is operative from 1995.

The Register of Employers and Employees (REE): The REE contains information obtained from employers. All employers are obliged to send information to the REE about each individual employee's contract start and end, working hours, overtime and occupation. An exception is made only if a person works less than four hours per week in a given firm and/or was employed for less than six days. In addition, this register contains identification numbers for the firm and the employee, hence, the data can easily be aggregated to the firm level.

The National Education Database (NED): The NED gathers all individually based statistics on education from primary to tertiary education and have been provided by Statistics Norway since 1970. We use this data set to identify the length and the type of education. For this purpose, we utilize the first two digits of the NUS variable. This variable is constructed on the basis of the Norwegian Standard Classification of Education and is a six-digit number, the leading digit of which is the code of the educational level of the person and the second is the code of the type of education. According to the Norwegian standard classification of education (NUS89), there are nine educational levels in addition to the major group for "unspecified length of education". The educational levels are given in Table 14. The types of education are described in Table 15.

<Tables 14 and 15 about here>

B.2 Data trimming using quantile regressions For the wage equation estimation we carry out some data trimming, i.e., we omit observations which are viewed as either unusual high or unusual low wage rates. The threshold values are obtained using quantile regressions for the two sectors. We perform quantile regression based on the 5 and 95 per cent quantiles, respectively. The expression below corresponds to conditional expecation given the explanatory variables in usual mean regressions. It shows how regressor variables influence the conditional θ-quantile of the response variable.

$$q_\theta\left(\log(W_{pt})|reg1_{pt},...,reg6_{pt};\kappa_t^\theta,c^\theta,\tau_1^\theta,...,\tau_6^\theta\right)=c^\theta+\kappa_t^\theta+\sum_{j=1}^{6}\tau_j^\theta regj_{pt};\ \theta=0.05,\ 0.95.$$

The obtained parameter estimates are reported in Table 16 below.

<Table 16 about here>

For Machinery the lower and upper threshold values for the reference region in the reference year are exp(3.895)=49.2 and exp(5.186)=178.8. The corresponding numbers for Electrical Equipment are exp(3.931) = 51 and exp(5.151) = 172.6. The thresholds for the untransformed wage in different years and labour market areas are reported in tables 17 and **??**. To obtain the final samples, i.e., the sample we use when estimating the wage equations, we remove all observations which are either lower than the lower threshold or higher than the upper threshold.

<Tables 17 and 18 about here>