THE IMPORTANCE OF SKILL MEASUREMENT FOR GROWTH ACCOUNTING

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In a growth accounting context one usually constructs a quality adjusted index of labor services by aggregating over predefined groups of workers, using the groups' relative wage bills as weights. In this article we suggest a method based on decomposing individual predicted wages into a skill-related part and a part unrelated to skill, where the former consists of both observed and unobserved components. The predicted wages, associated with individual skill attributes, are sorted and classified into deciles. The median predicted skill-related wage in each decile is used to construct an alternative skill-adjusted index of labor services. We find that total factor productivity (TFP) growth decreases significantly when using the latter method. This means that when using the alternative method one explains more of the growth in labor productivity than what a more traditional labor quality adjustment procedure does.

1. INTRODUCTION

In the growth accounting literature it has since long been acknowledged that one should pay attention to improvements in labor quality (see, for instance, Jorgenson *et al.*, 1987; Bureau of Labor Statistics, 1993). Ignoring the labor quality component when carrying out growth accounting implies that improvements in labor quality are allocated to the residual TFP growth component, which incorporates the contribution of all unobserved production factors and hence is difficult to interpret. The issue of productivity measurement with heterogeneous labor is discussed in OECD (2001, chapter 4.5), Ahmad *et al.* (2003, chapter 4.5), and Boulhol and Turner (2009). These references also provide some recommendations with regard to practical implementation.

The idea behind skill-adjusting labor is based on the fact that labor is not a homogeneous input, but differs in skill and efficiency. If one replaces a worker with a more productive one, an increase in output will, *ceteris paribus*, be the result. The question then is how to measure differences in productivity. An early idea put forward by Griliches (1960) was to look at relative wages. In a perfect labor market wage differences should mirror differences in productivity. The approach pursued in the present paper also builds on this idea, but is modified. We view variation in skill related predicted wages as more informative about variation in productivity

than the raw hourly wages. Observed wage differences not only reflect skill differences, but also variables unrelated to skill, such as regional and temporal variations in labor market conditions, rent sharing, unions' bargaining power, and transient wage fluctuations.

A common method used to construct an index of skill-adjusted labor input is to divide the workers into several groups and then let the growth in labor input services be a weighted sum of the increases in man-hours in each of the groups. As Zoghi (2010) points out, one may calculate weights in different ways. The simplest way is to utilize the observed wage bills associated with the different groups. An alternative to using observed mean wages, which may be somewhat volatile, is to employ mean predicted wages from a wage equation. Bolli and Zurlinden (2009), Lacuesta *et al.* (2008), and Schwerdt and Turunen (2007) represent, in a broad sense, recent contributions within this type of approach. These contributions focus on robustness issues in different dimensions. For instance, Bolli and Zurlinden (2009) are occupied with the implications of taking account of unobserved worker characteristics, while Lacuesta *et al.* (2008) have a special focus on selection problems caused by a substantial amount of inflow of immigrant workers to Spain.

The main contribution of the current paper is to suggest an alternative method for handling heterogeneity of labor within a growth accounting framework. We start out by estimating a wage equation at the industry level using a panel data model for 11 manufacturing industries. As explanatory variables in the equation we include variables related to individual skill or personal attributes; that is, length of education, experience, type of education, and gender. In addition we include dummies for local labor market areas and fixed effects for years. From the estimated wage equation we extract what one may label the skill component of the predicted wage, which solely captures the effects of observed and unobserved individual variables. We then sort these predicted wages in ascending order and divide them into deciles. In each year we then know which decile the worker belongs to and how many man-hours he/she contributes. This information is used to construct an index of skill-adjusted labor. The change in this index is a weighted average of the change in man-hours for each of the ten groups. To calculate the weights we use the relative median values of the skill-related predicted wages within each decile.

The estimated wage equations (one for each of the industries) are also utilized in conjunction with a benchmark method, where we divide the observations into 12 cells distinguishing between high and low education, three intervals of experience, and gender. For each year we calculate the total number of man-hours and the mean of the predicted (skill related) wages in each of the cells. This information is used to derive an index of labor services.

We consider calculation of TFP growth at the industry level when labor is treated in three different ways. In the first case labor is considered a homogeneous input variable. The second case corresponds to what we just referred to as the benchmark method, whereas in the third case we calculate TFP growth using the new method put forward in this article. We find that the TFP growth diminishes when one goes from the case with homogeneous labor to the benchmark method and even further when one goes from the benchmark method to our proposed decile-based method. For the manufacturing industry as a whole the annual mean TFP growth in the sample period is 2.5 percent when labor is treated as a

homogeneous input, 2.3 percent when skill is accounted for by the benchmark method, and 2.0 percent when using our decile-based method.

The paper proceeds as follows. In Section 2 we describe the data used in our analysis. Section 3 deals with classification of labor according to skill. In Section 4, we calculate growth in total factor productivity (TFP), applying the different ways of measuring labor input. Section 5 concludes the paper.

2. Data

For this study we use a rich employer–employee panel dataset on Norwegian firms, covering the period 1995–2005. The sample is based on information from limited dependent companies (i.e., the smallest legal unit). We have constructed panels of annual firm-level data for Norwegian firms in 11 manufacturing industries, accounting for about 90 percent of total man-hours in the manufacturing sector.

Five different sources of Norwegian micro data are used. Two of them are firm-level datasets. One of the firm-level datasets is based on the accounts statistics of limited dependent companies, and the other comprises structural statistics for different industrial activities. These data sources provide information on value-added and capital at the end of the year in constant prices (for details about the capital variable, see Raknerud *et al.*, 2007). The three remaining datasets contain individual-level data. These are the Register of Employers and Employees, the Pay Statements Register, and the National Education Database. The individual level data provide us with information on man-hours, wages (constructed as annual earnings at constant prices divided by contracted annual working hours), the worker's place of residence, length and type of education, and potential experience—calculated as a person's age minus the length of his education minus the age at which he/she started at compulsory primary school. This information makes it possible to link firm-level and individual-level information and to integrate individual-level data into a common database and then aggregate to the firm level.[1]

3. Skill Classification

We start out by classifying workers into K different skill categories, according to their relative efficiency. The categories are sorted in ascending order such that the least efficient workers are in category 1, and each category contains the same proportion of total man-hours, $100/K$ percent, over the whole sample. If $M_{(k)t}$ denotes total man-hours in skill category k, for $k = 1, \ldots K$, then total man-hours, M_t, can be written as

$$M_t = \sum_{k=1}^{K} M_{(k)t}.$$

[1]For a more detailed description of data sources used, see the Data Appendix of Nilsen *et al.* (2009).

A particular set of efficiency weights, λ_k, $k = 1, \ldots, K$, with $\lambda_{k-1} < \lambda_k$, is applied to the man-hours in each category, k, to calculate efficiency-adjusted aggregate man-hours, $\tilde{M}_t$:

$$\text{(1)} \qquad \tilde{M}_t = \sum_{k=1}^{K} \lambda_k M_{(k)t}, \quad 1 = \lambda_1 < \lambda_2 < \ldots < \lambda_K.$$

These weights are calibrated based on the assumption of perfect substitution between workers, such that relative efficiency between a worker in skill category k and 1, λ_k, is equal to their relative wage. Instead of using the actual relative wages between individuals observed in the data to calculate λ_k, we use the skill-related part of the predicted wages, as motivated by the discussion in Section 1.

The following wage equation is estimated separately for each industry (for ease of exposition we suppress the index for industry throughout the paper):

$$\text{(2)} \qquad \ln(W_{prt}) = Z_{rt}\gamma_z + X_{pt}\gamma_x + v_p + \varepsilon_{prt},$$

where W_{prt} is the hourly wage of person p working in labor market region r in year t. On the right-hand side, we specify two (row) vectors with observed variables, Z_{rt} and X_{pt}. The vector of explanatory variables Z_{rt} consists of observed variables that are related to the labor market region (r) where the individual works and the calendar year (t), and is assumed to be unrelated to the individual's skill:[2]

$$Z_{rt} = (\text{labor market region dummies, year-specific dummies}).$$

The other vector, X_{pt}, contains values of variables related to individual p's skill in year t:[3]

$$X_{pt} = (\text{years of schooling, powers of years of experience up to 4th order,}$$
$$\text{gender, type of education-dummies}).$$

The attached coefficient vectors are denoted γ_z and γ_x, respectively. The scalar v_p is an unobserved individual random effect of individual p. Finally, ε_{prt} denotes a genuine error term.

From (2) we decompose the log wage, $\ln(W_{prt})$, into three parts:

$$\ln(W_{prt}) = \omega_{pt} + Z_{rt}\gamma_2 + \varepsilon_{prt},$$

where

$$\text{(3)} \qquad \omega_{pt} \equiv X_{pt}\gamma_1 + v_p$$

[2]The definition of the seven labor market region dummies is based on characteristics such as size and centrality (see http://www.ssb.no/english/subjects/06/sos110_en/sos.110_en.pdf).
[3]The data investigation shows that mainly workers with the following three types of education are represented in the chosen industries: education in "General Programs," "Business and Administration," and education in "Natural Sciences, Vocational and Technical subjects."

is the only part which is relevant to skill measurement; while the second part is related to the variables in the vector Z_{rt}; and the third part, the transient noise ε_{prt}, does not concern skill measurement.

To calculate the weights λ_k, and to classify workers into skill categories, only the skill-related part, ω_{pt}, of the wage will be used, cf. (3). The detailed calculations are as follows. Consider all the values of ω_{pt} occurring in our sample and sort them in ascending order. To be specific, assume that $K = 10$ (deciles), which is what we actually use in our application. Then let $\omega_{(1)} < \omega_{(2)} < \ldots < \omega_{(10)}$ denote the 5, 15, 25, . . . , 95 percent quantiles in the empirical distribution of ω_{pt}. Thus $\omega_{(k)}$ is the median predicted wage (after removing the effect of noise, ε_{prt}, and labor market region and time dummies, Z_{rt}) within category k. The man-hours of person p at time t are allocated to category k iff

$$k = \arg\min_{j} |\omega_{pt} - \omega_{(j)}|.$$

Finally, we calibrate the efficiency parameters using the relative median skill-related predicted wages:

$$(4) \qquad\qquad \lambda_k = \frac{\exp(\omega_{(k)})}{\exp(\omega_{(1)})}, k = 1, \ldots, 10.$$

The median $\omega_{(k)}$ is then the middle point within the k-th decile; it is chosen as the reference point as it is not vulnerable to outliers, in contrast to the corresponding mean value of ω_{pt}. In general, the difference between $\omega_{(k)}$ and the mean value of ω_{pt} within the k-th decile is small, except for the highest decile, where the mean is influenced by a few high outliers. Of course, this framework can be used for any K, and the modified definitions of the $\omega_{(k)}$ follow straightforwardly.

In practice, $\omega_{(k)}$ and λ_k must be estimated. This is done by replacing ω_{pt} with

$$\hat{\omega}_{pt} \equiv X_{pt}\hat{\gamma}_1 + \hat{v}_p,$$

where $\hat{\gamma}_1$ denotes the estimated parameter vector and $\hat{v}_p$ is the predicted random effect of individual p based on feasible GLS estimation. In our empirical analysis, the parameters $\omega_{(k)}$ and λ_k are replaced by estimates, $\hat{\omega}_{(k)}$ and $\hat{\lambda}_k$, using $\hat{\omega}_{pt}$ instead of ω_{pt}. The unknown parameters in (2) are estimated by GLS using unbalanced panel data for each industry. The assumption that v_p is a random effect is convenient in order to identify γ_x—in particular the coefficient attached to years of schooling, which in our sample is close to being an individual-specific time-invariant variable.

An objection frequently raised against random effects models is that the GLS-estimators applied to estimate them are biased if the latent effect is correlated with the observed right-hand side variables. However, in our setting there are several problems attached to using fixed effects estimators. First, for a substantial part of the individuals there are too few observations in order to obtain precise estimates. Second, most of the observed right-hand side variables are time-invariant or nearly so, which implies a genuine identification problem.

Third, since we also apply the wage equations to predict wages for observations not included when estimating the wage equation (see below), the random effects specification seems more appropriate. In light of these three features we have chosen to stick to the random effects specification instead of the fixed effects specification.

Before we estimate the wage equation (2), we carry out some data cleaning. First, since wages of part-time workers are particularly hampered by measurement errors, we omit data for part-time workers. Second, we omit wage observations which are viewed as being either unusually high or unusually low. The corresponding cut-off values are obtained using quantile regressions. For each industry, we perform quantile regressions for the 5 and 95 percent quantiles, respectively, to estimate these quantiles conditional on labor market region and calendar year (which are the only included regressors). When estimating the wage equations, we omit observations that are characterized by either hourly wages below the conditional 5 percent or above the conditional 95 percent quantiles. This procedure ensures smoother quantiles across time and labor market region compared to the raw data quantiles.

The data cleaning referred to above has been done only when estimating the wage equation. The omitted observations are included again when performing the final TFP calculations. Based on the wage equations we predict the skill-related wages for all persons in every period they are observed. For workers not included in the estimation sample, we obtain $\hat{\omega}_{pt}$ by using the observed X_{pt} and setting $\hat{v}_p = 0$, which is the optimal *ex ante* estimate of the random effect.

The results from the wage equation estimations are reported in Table 1. We see that the marginal returns to education are approximately 5 percent, in line with other studies based on Norwegian data (see, for instance, Hægeland *et al.*, 1999). The coefficients attached to years of experience are hard to interpret directly, since the effect of experience is represented by a fourth order polynomial. If we only look at the first order term, we find returns of the same magnitude as for education. However, the marginal returns to experience is decreasing and becomes zero at around 30–32 years of experience, and negative thereafter. The effects of the other explanatory variables, such as gender, labor market region, and type of education are all in line with our prior expectations.

The calculated values of λ_k for all the manufacturing industries are displayed in Figure 1. We see that there is considerable variation in λ_k across the different industries, for a given decile k. In particular, λ_{10} is highest in the typical high-tech industry Electrical equipment (which also has the highest share of workers with at least 13 years of education; about 35 percent), especially compared to the traditional lowtech industry Wood products (where the share of workers with at least 13 years of education is about 8 percent). One also notes that the curves of Electrical equipment and Chemical products are steeper at the upper part of the distribution compared to industries characterized by a large share of low-skilled workers. Thus the high-tech industries seem to employ and reward workers with especially high productivity.

We will consider different types of benchmark methods for calculating efficiency weighted total man-hours, $\tilde{M}_t$. A trivial benchmark is, of course, to set

TABLE 1
WAGE EQUATION ESTIMATION RESULTS

Industry	Educ. Length	Experience				Gender		Educ. Type		No. of Ind.	No. of Obs.
		1. Power	2. Power[a]	3. Power[b]	4. Power[c]	Male	Gen.	BA	Sci.&Tech.		
Food etc.	0.046 (0.0005)	0.056 (0.0007)	−0.029 (0.0005)	0.007 (0.0002)	−0.006 (0.0005)	0.221 (0.0018)	0.044 (0.0022)	0.044 (0.0026)	0.035 (0.0020)	71,721	328,564
Textile etc.	0.035 (0.0015)	0.036 (0.0026)	−0.018 (0.0018)	0.004 (0.0005)	−0.004 (0.0005)	0.239 (0.0050)	0.046 (0.0063)	0.077 (0.0073)	0.036 (0.0063)	10,147	44,066
Wood etc.	0.036 (0.0008)	0.040 (0.0010)	−0.020 (0.0008)	0.005 (0.0002)	−0.044 (0.0002)	0.106 (0.0050)	0.050 (0.0038)	0.059 (0.0046)	0.027 (0.0033)	22,183	106,570
Paper etc.	0.038 (0.0005)	0.049 (0.0007)	−0.023 (0.0006)	0.005 (0.0002)	−0.004 (0.0002)	0.156 (0.0038)	0.027 (0.0027)	0.016 (0.0027)	0.021 (0.0023)	48,759	253,708
Chemical etc.	0.060 (0.0004)	0.043 (0.0007)	−0.018 (0.0005)	0.004 (0.0002)	−0.003 (0.0002)	0.131 (0.0021)	0.043 (0.0031)	0.032 (0.0034)	0.010 (0.0027)	36,059	181,448
Min. products	0.041 (0.0008)	0.039 (0.0013)	−0.017 (0.0010)	0.004 (0.0003)	−0.003 (0.0003)	0.155 (0.0025)	0.056 (0.0042)	0.048 (0.0052)	0.039 (0.0038)	14,755	71,476
Met. products	0.048 (0.0005)	0.045 (0.0006)	−0.022 (0.0005)	0.005 (0.0001)	−0.004 (0.0001)	0.112 (0.0045)	0.056 (0.0029)	0.039 (0.0035)	0.029 (0.0026)	51,666	252,227
Machinery	0.056 (0.0005)	0.048 (0.0008)	−0.023 (0.0006)	0.005 (0.0002)	−0.005 (0.0002)	0.174 (0.0027)	0.070 (0.0040)	0.047 (0.0046)	0.029 (0.0035)	38,791	173,249
El. equip.	0.064 (0.0005)	0.048 (0.0008)	−0.019 (0.0006)	0.004 (0.0002)	−0.003 (0.0002)	0.201 (0.0034)	0.065 (0.0036)	0.051 (0.0040)	0.034 (0.0032)	33,597	154,983
Transport etc.	0.055 (0.0004)	0.053 (0.0007)	−0.027 (0.0005)	0.006 (0.0002)	−0.006 (0.0002)	0.163 (0.0028)	0.082 (0.0033)	0.047 (0.0039)	0.042 (0.0028)	65,534	275,895
Furniture etc.	0.038 (0.0009)	0.045 (0.0012)	−0.023 (0.0009)	0.006 (0.0003)	−0.005 (0.0003)	0.135 (0.0034)	0.053 (0.0043)	0.076 (0.0049)	0.024 (0.0039)	20,893	93,538

Notes: For full industry names and NACE codes, see Table A1. For full names of education types, see footnote 3.
  Standard errors in parentheses. A constant term, year dummies, and regional labor market dummies are also included as regressors in the wage equation, but the estimated coefficients attached to these variables are not reported in the table.
  [a]The estimated values and standard errors have been rescaled with a multiplicative factor of 10.
  [b]The estimated values and standard errors have been rescaled with a multiplicative factor of 100.
  [c]The estimated values and standard errors have been rescaled with a multiplicative factor of 10,000.
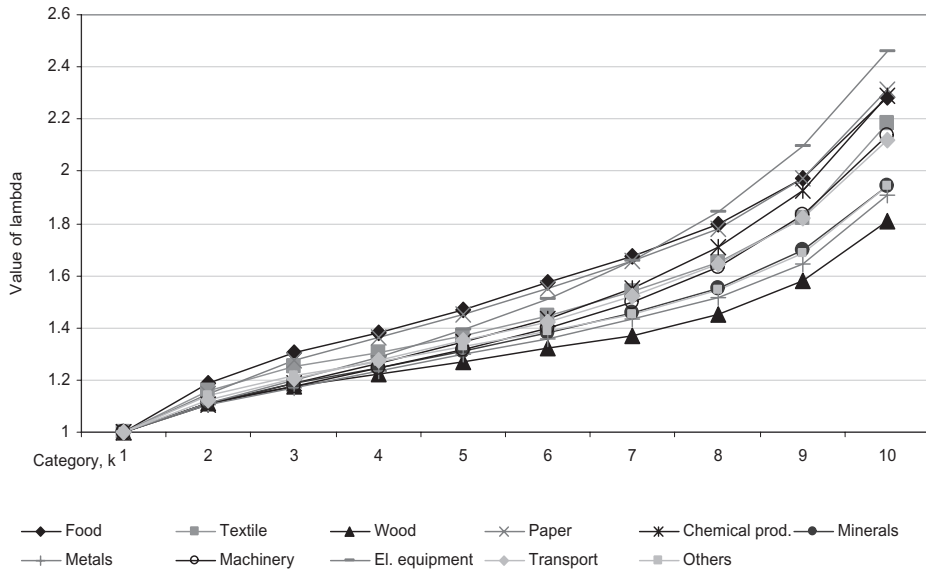
Figure 1. Estimated Efficiency Parameters, λ_k, for Different Industries

$\tilde{M}_t = M_t$, i.e., no skill adjustments. In the (more elaborate) benchmark method we will classify workers (or man-hours by a particular worker in a given year) into cells based on values of a sub-set of the covariates, X_{pt}, described above. Then we follow Zoghi (2010) and skill-adjust the change in input of labor services by calculating the change in a Törnqvist index. The weight of the workers in cell $j, j \in J$, is the skill-related wage bill for this group of workers divided by the total skill-related wage bills for all the groups. In our application we will consider a case with 12 cells. The classification is based on three variables— Education length, Experience, and Gender—where Education length has two discrete outcomes (less than 13 years, and at least 13 year), and Experience has three disjunct outcomes (experience $\leq$ 7 years, $8 \leq$ experience $\leq$ 15 years, and experience $\geq$ 16 years). A listing of the cells with definitions is given in Table A2 in the Appendix.

4. Productivity Growth Analysis

To analyze the importance of the choice of different skill measures, we consider a growth accounting framework at the industry level implicitly assuming constant returns to scale. Instead of sticking to a Cobb–Douglas production function specification with constant share-parameters, we allow for time-varying share-parameters and employ Törnqvist indices. As pointed out by Morrison Paul (1999, p. 43) and Diewert (1976), this choice is consistent with assuming a translog production function. The growth in labor productivity, $\Delta\ln(Y_t/M_t)$, where Y_t and M_t are value added and the total number of man-hours at the industry level,

respectively, is decomposed into contributions from heterogeneous labor (to be specified below), capital services, K_t, and a residual term, ΔTFP_t. The latter denotes growth in total factor productivity.[4] The expression for the relative growth in labor productivity is given by

$$(5) \qquad \Delta \ln\left(\frac{Y_t}{M_t}\right) = \alpha_t \Delta \ln\left(\frac{\tilde{M}_t}{M_t}\right) + (1 - \alpha_t)\Delta \ln\left(\frac{K_t}{M_t}\right) + \Delta TFP_t,$$

where $\tilde{M}_t$ is aggregate skill-adjusted man-hours according to our proposed method, as defined in (1) or calculated according to the benchmark method. Using the benchmark method, we follow Zoghi (2010), and define

$$(6) \qquad \Delta \ln(\tilde{M}_t) = \sum_{j \in J} 0.5\left(s_{jt} + s_{j,t-1}\right)\Delta \ln(M_{jt}),$$

where M_{jt} is the number of man-hours in cell j at time t, and the s_{jt} are weights defined as follows:

$$s_{jt} = \frac{\exp(\hat{\omega}_{jt})M_{jt}}{\sum_{j \in J}\exp(\hat{\omega}_{jt})M_{jt}},$$

where $\hat{\omega}_{jt}$ denotes the mean value of $\hat{\omega}_{pt}$ belonging to cell j in year t, cf. (3). Following the traditional approach in growth accounting, the industry level share-parameter α_t is calibrated using the arithmetic mean of the cost share of labor (i.e., the total wage bill divided by total factor costs) in period t and $t-1$.[5]

For each industry in the manufacturing sector, we compare the TFP growth obtained from (5) with two other cases: first, when $\lambda_k \equiv 1$ for all k and hence $\tilde{M}_t$ in (5) is replaced by the non-adjusted man-hours, M_t; and second, when $\Delta \ln(\tilde{M}_t)$ is calculated as in (6) based on an index set, J, consisting of 12 categories. Note that the left-hand side of (5) does not depend on the skill measure used, since M_t equals total man-hours.

We see from the results reported in Table 2 that labor costs as a share of total factor costs are approximately 70 percent on average, but vary considerably, from about 80 percent in Electrical equipment and Transport and communication to about 50 percent in Mineral products. Furthermore, labor productivity growth (3.5 percent annually, averaging over all the industries) is mainly explained by capital deepening. Growth in labor quality also contributes: regardless of which method is used to skill-adjust labor input, the growth in skill-adjusted man-hours

[4]In the TFP growth calculations we only include firms with at least three years of contiguous data and no missing variables.

[5]In the current paper we do not consider the link between TFP growth at the plant/firm and the industry levels, as discussed in Hulten (2001, pp. 38–39); cf. also Baily *et al.* (1992) and Foster *et al.* (2001).

TABLE 2
GROWTH EQUATION RESULTS

Industry[a]	Labor Prod Growth $100 \times \Delta\ln(Y_t/M_t)$	Labor Share α	Labor Quality Growth $100 \times \Delta\ln(M_t/M)$ Benchmark Method	Our Method	Capital $100 \times \Delta\ln(K/M)$	TFP Growth (%) (1)	(2)	(3)
Food etc.	2.8	0.69	0.3	0.6	3.1	1.8	1.6	1.4
Textile etc.	4.4	0.77	0.6	1.1	6.2	3.0	2.6	2.2
Wood etc.	4.0	0.75	0.2	0.4	3.4	3.1	3.0	2.9
Paper etc.	1.5	0.75	0.3	0.3	2.3	0.9	0.7	0.7
Chemical etc.	2.4	0.70	0.2	0.3	2.4	1.7	1.6	1.5
Min. products	0.8	0.50	0.1	0.4	0.7	0.5	0.4	0.3
Met. products	5.6	0.61	0.1	0.3	5.4	3.4	3.3	3.2
Machinery	3.6	0.76	0.3	0.6	4.8	2.6	2.3	2.1
El. equip.	4.9	0.80	0.5	1.0	5.8	3.7	3.3	2.9
Transport	4.8	0.80	1.0	1.5	4.7	3.7	3.3	2.9
Furniture etc.	3.8	0.77	0.2	0.5	4.2	2.8	2.7	2.4
Weighted average[b]	3.5	0.72	0.3	0.7	3.9	2.5	2.3	2.0

Notes: All figures are simple means of annual growth rates of different productivity variables over the period 1995–2005. The TFP growth is calculated using equation (5), with different skill measures: the case with no skill adjustment in column (1); the benchmark method in column (2); and our decile-based method in column (3).

[a]For full industry names and NACE codes see Table A1.
[b]The weights are based on value added.

is higher than the growth in number of man-hours (i.e., $\Delta\ln(\tilde{M}_t/M_t)$ is positive in all industries). The lower value of TFP-growth using our method compared to the benchmark method is solely accounted for by a higher growth in skill-adjusted man-hours obtained with our method.

In Table 2 we also report the mean annual growth in labor productivity over the period 1995–2005 together with the mean annual TFP growth according to (i) the case without any skill adjustment, (ii) the benchmark method, and (iii) our proposed wage equation based skill-adjusted measure of labor input.

With no skill adjustment, the mean annual TFP growth varies between 0.5 and 3.7 percent, with 2.5 as an average across the industries. Our proposed efficiency adjustment leads to an even wider difference. The latter difference varies from less than 0.1 to 0.4 percentage points. On average, our method leads to 0.5 percentage points lower TFP growth than the case with no quality adjustment, and 0.3 percentage points lower growth compared to the benchmark method. Thus, our method unambiguously leads to reduced TFP growth, by allowing more of the change in value added to be picked up by the measurable components compared to the benchmark method.

We have considered some robustness checks. First, we have added type of education as an extra dimension for the benchmark method. This variable has three outcomes: General programs; Vocational and technical subjects; and Other type of education. Thus, the benchmark method now involves 48 cells. We find for all industries that the TFP growth for this extended version of the bench-mark method is practically indistinguishable to the one obtained for the bench-

mark method using 12 cells. This resembles the conclusion obtained by Fosgerau *et al.* (2002) using Danish data. As a second robustness issue we have investigated how sensitive the results are with respect to the cut-off values used when trimming the dataset for the full-time workers. Instead of applying the thresholds corresponding to the 5 and 95 percent conditional quantiles, we have employed the 1 and 99 percent thresholds. It turns out that even though the estimates of the parameters in the wage equations are somewhat changed, the predicted values obtained from the estimated wage equations are very similar. Accordingly, the estimated TFP growth is not significantly influenced by the application of these alternative cut-off values.

As a last robustness check we have tested whether it is the effect of a decile-based classification or the effect of using only the skill-related part of the predicted wages that drives the differences in TFP growth. We do this by calculating the TFP growth using two "naïve" decile-based methods based on: (a) actual wages; and (b) detrended actual wages, i.e., no skill-correction of wages. The method (a) almost completely eliminates TFP-growth. Wages (as well as labor productivity) have a positive time trend. Thus, over time an increasing part of the man-hours will be classified in the higher deciles. Without removing this trend before applying the decile-based method, we could end up with a situation where all man-hours found in the lowest deciles were from the early sample years, while the man-hours in the upper deciles were all coming from the last years. Ignoring the positive trend for both wages and productivity implies that one will be exposed to what is known as "spurious regression" in the time series literature. To avoid spurious results, we therefore applied method (b) in order to remove the time trend from the actual wages before applying the decile-based method. We now obtain TFP growth rates that are almost identical to those of the benchmark (1) reported in Table 2 (without any skill-adjustment of man-hours). From these two tests we conclude that including only the skill-related predicted wages (removing, for example, the unexplained time trend) is crucial for the decile-based method to be both economically sound and empirically successful.

Why does our method for skill adjustment yield a higher increase in labor quality growth than what is obtained using the benchmark method? We have seen that this has nothing to do with the number of cells used in connection with the benchmark method. There are two main differences between the methods that may explain the difference in labor quality growth. First, a person-specific unobserved effect is included in the skill-related part of the wage equation. Hence the categorization of persons into efficiency deciles partly reflects an unobserved component which plays no role in the benchmark method. Second, it is an empirical fact that the probability that an individual moves to another decile is larger than the probability that he/she moves to another cell (see Tables A3 and A4 in the Appendix, which show transition rates between deciles and cells of the benchmark, respectively). Note that transitions from one decile to another are caused by changes in the skill-related variables occurring in the wage equation, most importantly experience.[6] The decrease in the (residual) TFP-growth term when switching

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[6]Note that this mobility has nothing to do with a general positive trend in wages, since this trend is captured by the time dummies of the wage equation, which are not included in the quality index.

from the benchmark method to our decile-based method shows that the increased variability in skill-adjusted man-hours using the latter method instead of the former method enables us to explain labor productivity growth in a better way.

A final important question is whether the differences in the mean TFP growth using the various skill measures are statistically significant. To answer this question we provide standard errors of the mean difference in TFP growth by means of bootstrapping. The bootstrap works as follows. From the dataset used to produce the TFP growth estimates reported in Table 2 we draw a sample of N firms (with replacement). For each of these N firms we use the entire time series of output, wage costs, hours of work, and capital. In each replication we calculate the difference between the mean TFP growth obtained using our decile-based method and the benchmark method. After 250 bootstrap replications, we calculate the standard deviation of the differences in mean TFP growth over the bootstrap sample and take this as an estimate of the standard error of the difference in mean TFP growth. We find that the difference in estimated TFP growth between the quantile-based method and the benchmark method is statistically significant (the estimated standard error of the difference equals 0.09 percentage points). If we now consider a 50-year horizon as an example, which is not uncommon in long-run projections, a constant annual TFP growth rate of 2.0 instead of 2.3 percent implies a 42 percentage point lower TFP growth over such a time span. Thus, an improved measure of labor input has non-negligible effects when considering growth accounting in the long term.

5. Concluding Remarks

In this paper we have proposed a new method for constructing an index of labor services. Extracting and classifying skill-related predicted wages plays a decisive role in our quantile (decile)-based method. We calculate the growth of TFP for 11 manufacturing industries using this new measure of labor services and compare the results with what is obtained using (i) a more traditional method for accounting for labor heterogeneity within a growth accounting framework, and (ii) assuming homogeneous labor. We find that the new method gives a lower growth in TFP than both (i) and (ii). For the manufacturing sector as a whole we find that the mean annual growth in TFP is 0.3 percentage points lower using the new measure of labor services instead of the more traditional measure (i) based on a set of predefined cells, which we have exemplified by dividing the observations into 12 cells according to length of education, working experience, and gender. This can be interpreted as the measure put forward in this paper captures more of the growth in labor quality than the more traditional measure.

While our main concern in the present paper has been to assess the importance of skill adjustment for calculating growth in TFP, elaborations of our approach should be of interest, given the importance of the issue discussed. Perhaps the most natural one is to extend the information set used in the estimation of the wage equations with firm-specific variables, for example represented by dummy variables of firms such as in Abowd *et al.* (1999). Another relevant topic is to relax the constant returns to scale restriction when decomposing the growth in labor productivity.

REFERENCES

Abowd, J. M., F. Kramarz, and D. N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 67, 251–333, 1999.

Ahmad, N., F. Lequiller, P. Marianna, D. Pilat, P. Schreyer, and A. Wölfl, "Comparing Labour Productivity Growth in the OECD Area: The Role of Measurement," OECD Statistics Working Papers 2003/5, OECD, Paris, 2003.

Baily, M. N., C. Hulten, and D. Campbell, "Productivity Dynamics in Manufacturing Plants," *Brookings Papers on Economic Activity, Microeconomics*, 187–267, 1992 (with discussion).

Bolli, T. and M. Zurlinden, "Measurement of Labor Quality Growth caused by Unobservable Characteristics," Swiss National Bank Working Papers 2009-1, 2009.

Boulhol, H. and L. Turner, "Employment–Productivity Trade-Off and Labour Composition," Working Paper No. 698, Economics Department, OECD, 2009.

Bureau of Labor Statistics, "Labor Composition and U.S. Productivity Growth, 1948–90," Bulletin 2426, U.S. Department of Labor, Bureau of Labor Statistics, December, 1993.

Diewert, W. E. "Exact and Superlative Index Numbers," *Journal of Econometrics*, 4, 115–45, 1976.

Fosgerau, M., S. E. Hougaard Jensen, and A. Sørensen, "Measuring Educational Heterogeneity and Labor Quality: A Note," *Review of Income and Wealth*, 48, 261–9, 2002.

Foster, L., J. Haltiwanger, and C. J. Krizan, "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in C. R. Hulten, E. R. Dean, and M. J. Harper (eds), *New Developments in Productivity Analysis*, Chicago University Press, Chicago, 303–63, 2001.

Griliches, Z., "Measuring Inputs in Agriculture: A Critical Survey," *Journal of Farm Economics*, 42, 1411–33, 1960.

Hægeland, T., T. J. Klette, and K. G. Salvanes, "Declining Returns to Education in Norway? Comparing Estimates across Cohorts, Sectors and Over Time," *Scandinavian Journal of Economics*, 101, 555–76, 1999.

Hulten, C., "Total Factor Productivity: A Short Biography," in C. R. Hulten, E. R. Dean, and M.·J. Harper (eds), *New Developments in Productivity Analysis*, Chicago University Press, Chicago, 1–47, 2001.

Jorgenson, D. W., F. M. Gollop, and B. M. Fraumeni, *Productivity and U.S. Economic Growth*, Harvard University Press, Cambridge, MA, 1987.

Lacuesta, A., S. Puente, and P. Cuadrado, "Omitted Variables in the Measure of a Labour Quality Index: The case of Spain," Bank of Spain Working Paper 08/35, 2008 (forthcoming in *Review of Income and Wealth*).

Morrison Paul, C. J., *Cost Structure and the Measurement of Economic Performance: Productivity, Utilization, Cost Economics and Related Performance Indicators*, Kluwer Academic Publishers, London, 1999.

Nilsen, Ø., A. Raknerud, M. Rybalka, and T. Skjerpen, "Lumpy Investments, Factor Adjustments, and Labour Productivity," *Oxford Economic Papers*, 61, 104–27, 2009.

OECD, *Measuring Productivity OECD Manual: Measurement of Aggregate and Industry-Level Productivity Growth*, OECD, Paris, 2001.

Raknerud, A., D. Rønningen, and T. Skjerpen, "A Method for Improved Capital Measurement by Combining Accounts and Firm Investment Data," *Review of Income and Wealth*, 53, 397–421, 2007.

Schwerdt, G. and J. Turunen, "Growth in Euro Area Labor Quality," *Review of Income and Wealth*, 53, 716–34, 2007.

Zoghi, C., "Measuring Labor Composition: A Comparison of Alternate Methodologies," in R. Abraham, K. G. Spletzer, and M. J. Harper (eds), *Labor in the New Economy*, Chicago University Press, Chicago, 457–92, 2010.

SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

Appendix: Supplementary Tables.

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