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Discussion paper

Skill composition: Exploring a wage-based skill measure

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Skill composition: Exploring a wage-based skill measure

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Abstract:
This study explores a wage-based skill measure using information from a wage equation. Evidence from matched employer-employee data show that skill is attributable to variables other than educational length, for instance experience and type of education. Applying our wage-based skill measure to TFP growth analysis, the TFP growth decreases, indicating that more of the change in value-added is picked up by our skill measure than when using a purely education-based skill measure.

JEL classification: C23, D24, J31
Keywords: Skill composition, wages, TFP.

1 Introduction

To account for labor heterogeneity one commonly classify workers as high skilled or low skilled based on their years of schooling. Another method is based on the assumption that one may calculate efficiency-adjusted man-hours such that the relative efficiency of any two workers equals their wage ratio (see Griliches, 1960). Both methods have obvious shortcomings. Years of schooling may be too

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approximate a proxy for skill. Observed wage differences also reflect variables unrelated to skill, such as regional and temporal variations in labor market conditions, rent sharing, bargaining power, and transient fluctuations.

This study utilizes a wage equation framework and decomposes a worker's wage into two parts: (i) a function of variables related to the worker's skill (observed and unobserved personal characteristics) and (ii) inter alia labor market, time specific characteristics and transient errors.[1] Each observation is then allocated to a skill group according to the size of the first part of the wage equation. We explore the implications of this wage-based skill measure for labor composition and relative wages in the firms. Furthermore, we adjust man-hours according to the worker's efficiency. The importance of the various skill measures is illustrated in an analysis of TFP growth. The TFP growth is lower when skill is represented by a wage-based skill measure rather than the educational length.

2 Skill classification

To classify a worker in a particular year as high or low skilled, we use information from an industry specific wage equation:

$$\ln(W_{pt}) = X_{1pt}\gamma_1 + X_{2pt}\gamma_2 + \nu_p + \varepsilon_{pt} \tag{1}$$

where W_{pt} is the hourly wage of person *p* in year *t* in a given industry. On the right hand side, we specify two (row) vectors with observed variables, X_{1pt} and X_{2pt}. X_{1pt} contains values of variables describing the individual's skill, i.e., educational length,

[1] Our method has similarities with the ones used by Abowd et al. (1999), Iranzo et al. (2006) and Hellerstein and Neumark (2007), but is simpler since we do not explicitly account for firm effects.

powers of experience up to the fourth order, type of education (represented by dummies) and gender. X_{2pt} consists of year-specific dummies and dummies related to local labor regions (based on workers' place of residence), i.e., observed variables that are assumed to be unrelated to an individual's skill. The corresponding coefficient vectors are denoted γ_1 and γ_2, respectively. The scalar v_p is an unobserved random effect and ε_{pt} is a genuine error term. Equation (1) is estimated by GLS using matched employer–employee data from the Norwegian manufacturing industries, covering the period 1995-2005.[2]

We compare the predicted value of

$$\omega_{pt} \equiv X_{1pt}\hat{\gamma}_1 + \hat{v}_p, \tag{2}$$

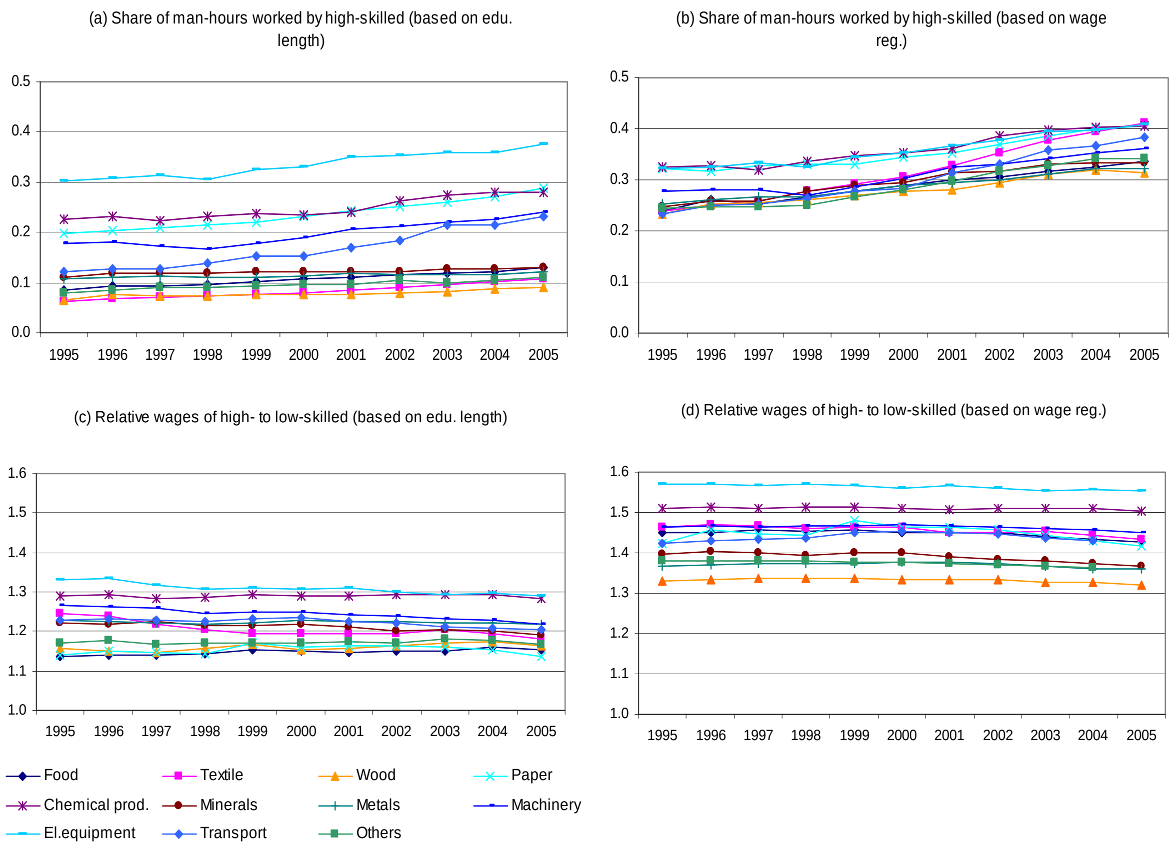
i.e. the part of the wage equation relevant to skill measurement, with a threshold value, ω^{ref}, related to a hypothetical reference person defined as having 13 years of education and industry specific mean values (conditional on 13 years of education) for experience, type of education, gender and $\hat{v}_p$. Since we correct for the effect of time and local labor market areas through X_{2pt}, the threshold value ω^{ref} has no subscripts. A person *p* in period *t* is classified as high skilled if $\omega_{pt} > \omega^{ref}$.

Figure 1 depicts the averages (weighted by man-hours) across firms with respect to skill composition (panels a and b) and relative wages (panels c and d). The results of our wage-based skill measure are compared with those of the traditional education-based definition. There is an upward trend in the use of high-skilled workers, but relative wages are more or less constant. With the education-based skill

[2] For a more detailed description of data sources and estimation issues, see Nilsen et al. (2008).

measure, the proportion of high skilled workers is much smaller relative to the case of our wage-based skill measure. Thus, experience plays an important role when one applies our wage-based skill measure. Moreover, the relative wage differences between high and low skilled are much smaller with the education-based skill measure. Again, this indicates that skill premiums are not only attributable to educational length.

Figure 1 Proportion of man-hours and relative wages of high skilled workers using different skill measures



As a refined classification, we also divide workers within each of the skill groups into subcategories according to their efficiency, assuming that workers within each group m are perfect substitutes when adjusted for efficiency differences. Let $M^{m}_{(k)it}$ denote the number of man-hours worked in subcategory k in skill group m, where k =

1,2,...,5. The categories are sorted with respect to efficiency such that the least efficient workers are in subcategory 1, and each of the five subcategories contains 20 percent of total man-hours. The efficiency-adjusted aggregate man-hours can be written as

$$\tilde{M}_{it}^{m} = \sum_{k=1}^{5} \lambda_k^m M_{(k)it}^m,\ \lambda_1^m < \lambda_2^m < \ldots < \lambda_5^m, m = h, l, \tag{3}$$

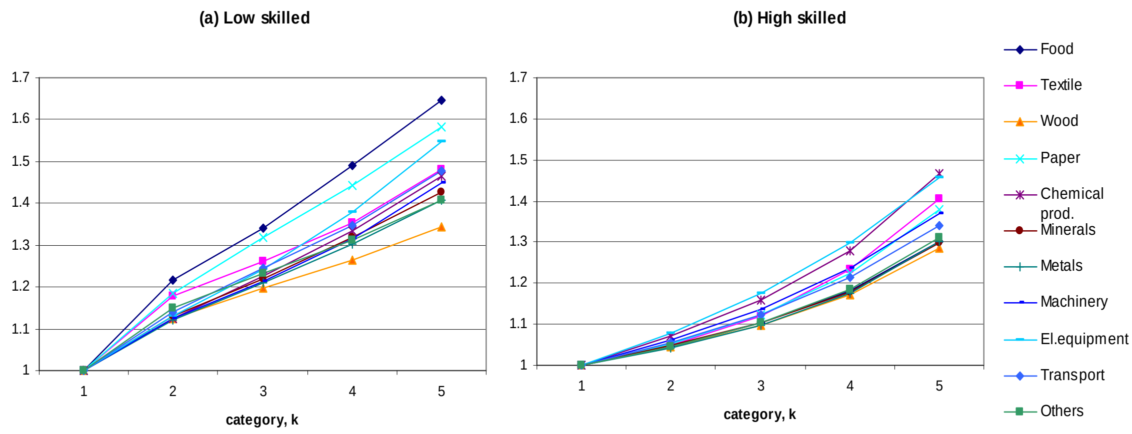
where λ_k^m are efficiency parameters, which are calibrated as follows. Within each skill group, we collect the skill-related part of the predicted log wage, ω_{pt}^m, (see equation (2)), for all persons in all periods, sort them, and divide them into five categories of equal size. Let $\omega_{(k)}^m$ denote the median value of all the ω_{pt}^m that are contained in the *k*'th category for skill group *m*. We then calibrate the efficiency parameters as

$$\lambda_k^m = \frac{\exp(\omega_{(k)}^m)}{\exp(\omega_{(1)}^m)}, k = 1, \ldots, 5, m = h, l.$$

The formula for λ_k^m can be derived from the assumption of perfect substitution within skill group *m*, so that relative wage equals relative productivity of any two workers from different categories within the same skill group and with the same values of X_{2pt}.

The calculated values of λ_k^m are displayed in Figure 2. If we consider λ_5^m, representing the relative wage of the most and the least effective workers within skill group m, one sees that the wage gap is generally larger for low skilled than for high skilled workers.

Figure 2: The efficiency parameters for low and high skilled workers



3 Productivity growth and different skill measures

The importance of the skill measure is illustrated with a simple example. Consider the following decomposition of the growth in labor productivity, $\Delta \ln(Y_t / L_t)$, at the industry level

$$\Delta \ln\left(\frac{Y_t}{L_t}\right) = \alpha_{ht} \Delta \ln\left(\frac{\tilde{M}_t^h}{L_t}\right) + \alpha_{lt} \Delta \ln\left(\frac{\tilde{M}_t^l}{L_t}\right) + (1 - \alpha_{ht} - \alpha_{lt}) \Delta \ln\left(\frac{K_t}{L_t}\right) + \Delta TFP_t \quad (4)$$

Here Y_t, L_t and K_t denote value-added, total man-hours and the capital stock at the end of period t, respectively.[3] $\tilde{M}_t^m$ (m = h, l) denote efficiency-adjusted man-hour aggregates, defined as

[3] We retain value-added as the output concept at the disaggregate industry level even though there are arguments for using gross output instead, as discussed in Jorgenson et al. (1987). Furthermore, 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).

$$\tilde{M}_t^m = \sum_{i=1}^{N_t} \tilde{M}_{it}^m, m = h, l,$$

where N_t denotes the number of firms in the industry in period *t*. Note that if $\lambda_k^m = 1$ for all *k*, $\tilde{M}_t^m$ coincides with a pure aggregate of man-hours in a given period. The term ΔTFP_t denotes growth in total factor productivity. We assume constant returns to scale, i.e., that the value of production equals total costs. The weights related to the two labor inputs are denoted by α_{ht} and α_{lt}, respectively, given as the arithmetic means of the income shares (the wage bill related to the skill group divided by value added) in the periods *t* and *t-1*.

In Table 1 we report the mean annual growth in labor productivity together with the mean annual TFP growth according to three skill measures; column (i) the education-based skill measure, column (ii) the wage-based skill measure without efficiency adjustment, i.e. setting $\lambda_k^m = 1$ in equation (3) for all *k*, and finally, column (iii) the wage-based skill measure with efficiency differences.

Table 1. Different skill measures and TFP growth[a]

Industry (NACE-codes)	Growth in labor productivity (%)	TFP growth (%)		
		(i)	(ii)	(iii)
Food, beverages and tobacco (15-16)	2.79	1.06	0.95	0.83
Textile and leather products (17-19)	4.45	1.19	0.86	0.70
Wood and wood products (20)	4.00	2.35	2.24	2.18
Paper and publishing (21-22)	-0.00	0.41	0.34	0.28
Chemical and plastic products (23-25)	2.53	1.14	1.11	1.02
Mineral products (26)	0.86	0.36	0.28	0.24
Metal products (27-28)	5.58	1.97	1.91	1.87
Machinery (29)	3.57	0.53	0.48	0.39
Electrical equipment (30-33)	4.92	1.50	1.30	1.15
Transport and communication (34-35)	4.78	2.07	1.88	1.75
Furniture and others (36-37)	3.86	1.72	1.53	1.47
Average for manufacturing (15-37)[b]	3.22	1.26	1.16	1.07

[a] All figures are simple means of annual growth rates over 1995-2005. The TFP growth is calculated using Equation (4) with different skill measures; the education-based in column (i), the wage-based in column (ii), and the wage-based with efficiency adjustment in column (iii).
[b] Weights based on value added.

Using the education-based skill measure, the mean annual TFP growth varies between 0.36 and 2.35 percent. In all the industries the mean annual TFP growth is lower using the two wage-based skill measures compared to the education-based one. Comparing the two last columns of the table, we find that the TFP growth is somewhat lower when we also adjust for efficiency differences within the two skill groups. These results support that more appropriate ways of dealing with labor heterogeneity decrease TFP growth, since more of the change in value-added is picked up by the measurable components.

We have calculated the TFP growth for the entire manufacturing industry, assuming homogeneous labor, to be 1.30 percent.[4] Compared with this benchmark, the TFP growth is 0.04 percentage points lower when heterogeneity in labor input is represented by educational length (see the column (i), last row of Table 1). The use of a wage-based skill measure with efficiency adjustment, column (iii), decreases the TFP growth further with 0.2 percentage points. The difference between our efficiency-adjusted wage-based skill measure, column (iii), and the education-based measure, column (i), is statistically significant when sampling uncertainty is taken into account (the estimated standard error equals 0.08 percentage points).[5] Consider now a 50-years horizon, common in long-run projections. An annual TFP growth rate of 1.07 instead of 1.26 percent implies a 10 percent lower TFP level after such a time span. Thus, an improved skill measure may have non-negligible effects.

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[4] This is rather close to calculations using Norwegian national accounts data for the manufacturing industry showing an annual TFP growth of 1.5 percent. The EU-KLEMS project (see http://www.euklems.net/) reports (implicitly) that the (valued-added based) average TFP growth for a subgroup of the EU countries is on the short side of 1.

[5] We use the following bootstrap procedure. From the dataset used in Table 1, we draw a sample of N firms (with replacement). For each of these N firms we use the entire time series of output, efficiency-adjusted man-hours, and capital. In each replication we calculate the difference between the mean TFP growth using the two skill measures. The standard error of these differences after 250 replications is used as the relevant estimate.

4 Conclusion

The relative wage differences between high skilled and low skilled workers are much smaller using only educational attainment for classification instead of our wage-based measure. This indicates that skill is attributable to many other factors than educational length. Applying our wage-based skill measure to TFP growth analysis, it appears that a wage-based skill measure that in addition accounts for efficiency differences within skill groups, is a more appropriate measure of skill than a measure based on only educational attainment.

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