The Multi-Dimensional Nature of Labor Demand and Skill-Biased Technical Change*

Erik Mellander†

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Abstract

Investigating the robustness of the skill-biased technical change hypothesis, this analysis incorporates two novel features. First, effective labor is modeled as the product of a quantity measure – number of employees with a given level of education – and a quality index, depending on, i.a., demographic characteristics and fields-of-study. Second, low-skilled labor is more disaggregated than in earlier studies. A fully specified structural model is used, containing demand equations for four categories of labor, two types of capital and intermediate goods. The empirical application covers 24 industries in the Swedish manufacturing sector 1985–1995. The skill-bias is further corroborated: it is confirmed although the specification of effective labor is supported. Substantial differences are, however, found among the low-skilled.

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†*Research Institute of Industrial Economics (IUI)*, Box 5501, SE – 114 85 Stockholm, Sweden, Fax: +46 - 8 - 661 79 69, Email: erikm@iui.se & *Office of Labour Market Policy Evaluation (IFAU)*, Box 513, SE – 751 20 Uppsala, Sweden, Fax: +46 - 18 - 471 70 75, Email: erik.mellander@ifau.uu.se.

1. Introduction

As documented by Nickell and Bell (1995), unemployment rates for unskilled workers in the OECD have been increasing since the beginning of the 1980's. Arguing that the supply of lower educated workers has fallen, as a consequence of the expansion of higher and further education, they attribute the increased unemployment to a substantial decrease in demand.

Berman, Bound and Griliches (1994) consider two alternative explanations to this development: skill-biased technical change increasing the relative demand for skilled workers, and competition from the Third World.[1] To assess the relative importance of these two driving forces, they first decompose the changes in the employment shares of low- and high-skilled workers into between- and within-industry components. The former component is identified with international competition while the latter is associated with skill-biased technical change. For U.S. manufacturing, they find that within-industry changes, i.e. technical change, is by far the most important component.

In a second step they derive a labor demand equation, explaining changes in skilled workers' share in total labor cost as a function of the relative wage for non-skilled vs skilled workers, the capital/output ratio and a constant, measuring the skill-bias in technical change. In the empirical implementation the relative wage is excluded, in order to avoid endogeneity problems and a bias arising from the definitional relationship between the dependent variable (i.e. skilled workers share in the wage bill) and the relative wage. The estimated skill-bias is positive

[1] Recently, related explanations have been put forward by Lindbeck and Snower (1999) and Dinopoulos and Segerstrom (1999). The former analysis considers the reorganization of work within firms and fits with the skill-biased technical change explanation; changes in work organization can be viewed as the outcome of (disembodied) technical change. The latter study relates to the trade explanation, but offers a North-North trade explanation rather than the North-South explanations suggested in earlier analyses.

and significant, supporting the skill-bias hypothesis. Adding explicit indicators of technical change – computer investments and R&D expenditures – they find these also positively related to the skilled workers' share in total wages.

These results are confirmed by Hansson (1996, 1998) and Machin (1996), who apply the same framework to Swedish and U.K. data, respectively. Using similar approaches and internationally comparable data for several countries, Machin and Van Reenan (1998) and Berman, Bound, and Machin (1998) lend further support to the skill-bias hypothesis. Indeed, the large similarities across countries observed in the latter study have led the authors to launch the extended hypothesis that skill biased technical change has been *pervasive*, i.e. that the same kinds of changes have occurred in many countries simultaneously.

A drawback with a majority of these studies is that they use very crude labor data: mostly only production versus non-production workers are considered, as in, e.g., Berman et al. (1994). For the U.S. and the U.K., Machin, Ryan and Van Reenan (1996) disaggregated employment into three educational categories: i) at most high school, ii) some college, and iii) college degree. Morrison and Siegel (1997) disaggregate labor even further, by splitting the first group into "no high school diploma" and "high school diploma". Still, even in these studies the most low-skilled category of labor is large and, presumably, quite heterogenous.[2] Furthermore, no account is taken of the fact that there are numerous other dimensions to labor beside the level of education, such as, e.g., demographic characteristics.

Another somewhat unsatisfactory feature of the aforementioned analyses, with the exception of the Morrison and Siegel (op.cit.) study, is that they attempt to estimate demand functions – supposed to describe the relation between prices and quantities – without using data on prices, i.e. wages. Certainly, the argument that wages are endogenous should be taken seriously. However, the exclusion of the rel-

[2] That heterogeneity among the low-skilled might be of importance in analyses of labor demand is indicated in a study on job competition by van Ours and Ridder (1995). They find substantial differences in the results for workers with primary and secondary education, respectively.

ative wage from the demand equation effectively amounts to use a constant as an instrument. While a constant obviously fulfills one of the two basic requirements of a valid instrument, namely that of being uncorrelated the equation's residual, it fails completely with respect to the other criterion, i.e. that it be highly correlated with the variable it replaces. Morrison and Siegel (op.cit.) instead construct instruments using lagged values of the arguments in the cost function from which labor demand has been derived. While these instruments are guaranteed to do worse with respect to the first requirement, they are also certain to do much better with respect to the second requirement.[3]

Moreover, the Morrison and Siegel estimate a complete system of input demand equations, i.e. not just a labor demand function. This eliminates the above mentioned problem with the definitional relationship between the dependent variable and the relative wage in the single-equation context.

Despite the methodological differences, the results obtained by Morrison and Siegel are not much different from the findings discussed above. Including external indicators of technical change, trade, and outsourcing they find skill–biased technical change to have strong negative impacts on the two least educated categories of labor and almost equally strong positive impacts on the demands for workers with at least some college. Trade has similar, but much weaker effects. Outsourcing does not seem to affect relative labor demands.

While the recent literature just considered emphasizes the importance of external factors in the explanation of relative labor demands, the earlier literature stresses internal, endogenous, factors. In particular, a well-known motivation for estimating labor demand by educational and/or skill categories originates from the capital-skill complementarity hypothesis put forward by Griliches (1969). In the stylized form of this hypothesis, the firm's choice of capital affects relative labor demands because capital and well educated (skilled) labor are complements

[3]Unfortunately, the results reported by Morrison and Siegel do not make it possible to judge the validity of the instruments they use.

while capital and labor with little education (unskilled labor) are substitutes. There is also a weaker version, according to which skilled labor and capital may also be substitutes but weaker substitutes than capital and unskilled labor. Many empirical tests support the capital-skill complementarity hypothesis.[4]

The basic notion underlying the capital-skill complementarity hypothesis can easily be extended. For instance, it is of interest to analyze how demands for different categories of labor relate to the firm's demand for intermediate goods. This is so because at the firm level trade effects and outsourcing will manifest themselves in an increasing demand for intermediate goods. Whether this will decrease or increase the demand for labor with a given skill level depends on whether this labor category and intermediate goods are substitutes or complements.[5]

Finally, there are, of course, connections between external and internal factors. For example, the effects of skill-biased technical change may be exacerbated if high-skilled and low-skilled labor are substitutes.

The main contribution of this paper is to (further) investigate the robustness of the skill-biased technical change hypothesis. To this end, the analysis incorporates two novel features. First, a multi-dimensional specification of labor is developed where effective labor is given by the product of a quantity measure of labor – number of employees with a given level of education – and a quality index, which depends on demographic characteristics, immigrant status, work hours, and fields-of-study. The latter information makes it possible to account for the *nature*, as

[4] Numerous studies have found capital-skill complementarity in the U.S.; see, e.g., Griliches (1969), Fallon and Layard (1975), Morrison and Berndt (1981), and Bartel and Lichtenberg (1987). In contrast, Berger (1983), Gyapong and Brempong (1988). See Hamermesh (1993) for a review. Morrison and Siegel (1997) estimate capital and skilled labor to be substitutes. Berman et al. (op.cit.) find complementarity with respect to the aggregate capital stock but not for equipment capital. With respect other countries, Machin and Van Reenan (1998) report capital-skill complementarity for Denmark, Sweden, and the UK but not for Japan.

[5] The trade and utsourcing effects reported by Morrison and Siegel (1997) are external effects and measure to what extent aggregate trade and outsourcing (at the 2-digit industrial level) affect labor demands at the disaggregate (4-digit) level. That these effects are weak does not preclude that trade and outsourcing as internal phenomena might be of importance.

well as the level, of education. Using the fact that effective labor can equivalently be expressed in terms of "quality-adjusted" wages, this specification is integrated into a flexible cost function, representing the firm's production technology. The labor quality indexes make it possible to check whether previous estimates of skill-biased technical change have picked up changes in other characteristics of labor, as measured by the quality indexes. The second novel feature is to use a very fine disaggregation of labor at the lower end of the educational spectrum. In contrast to preceding studies, two categories of labor are distinguished whose levels of education are below upper secondary school. This makes it possible to investigate possible aggregation bias with respect to the low-skilled.

As a by-product of the specification of effective labor, improved instruments for the possibly endogenously determined wages are derived. These instruments include all of the information in the labor quality indexes and do so in a way that is consistent with the "quality-adjusted" wages.

Like in Morrison and Siegel (op.cit.) the analysis is based on a fully specified structural model, similar to the one they use. The demands for four types of labor, classified by educational levels, are modeled together with the demands for capital and intermediate goods. Also, a distinction is made between short run and long run effects by allowing for the fact that (part of) the capital stock may be fixed in the short run.

The empirical application covers 24 industries in the Swedish manufacturing sector, observed annually 1985–1995.[6]

The paper unfolds as follows. A brief general description of the data is given in Section 2. In Section 3 the labor data are examined in more detail. The model is specified in Section 4, while Section 5 discusses its estimation. Results are provided in Section 6 and conclusions in Section 7.

[6] Lack of data has hitherto hindered applications to other countries. A study based on data for France is currently being undertaken, however.

2. The data

The data set contains annual observation on 24 industries in the Swedish manufacturing sector 1985–1995. It has been constructed by merging Swedish National Accounts (SNA) data with data from the Swedish Register of Employment (SRE).

The SNA provides industry data on gross output and four inputs – labor, intermediate goods, and two types of capital; equipment and structures. The SRE contains data on all employed individuals.[7] For these, there is information about, *i.a.*, education, wage income, demographic characteristics, and industry.

The level of aggregation has been determined by the SNA; it is the most disaggregate level for which complete production data are provided. The starting point, 1985, equals the first year of the SRE. The endpoint is due to a major change in the industrial classification used in the SNA. Under the old classification, there are published data up to and including 1994 and estimates can be constructed for 1995 as well. Estimates for the period after 1995 would be unreliable, however.

In the merging of the SNA and SRE data sets, the aggregate labor data in the SNA have been replaced by the more detailed information in the SRE. The labor data will be further discussed in the following section.

The break-down of the manufacturing sector into the 24 industries is spelled out in Table 1. Table 1 also provides the industry shares in total manufacturing employment in 1991. The year 1991 is chosen for two reason: it is located approximately in the middle of the sample period and, following the SNA, it is the base-year in the empirical analysis.

Volume measure for output and intermediate goods are given by expenditures in 1991 year prices. Corresponding price indexes are obtained by dividing expenditures in current prices by expenditures in 1991 year prices, yielding Paasche price indexes with base-year 1991.

[7] To be counted as employed the individuals have to satisfy a minimum earnings criterion, the effect of which is to exclude individuals with very limited part-time employment.

Table 1: The industries considered and their shares in total manufacturing employment in 1991

SNI69 code[a]	**Industry**	**Employment share 1991, %**
3110[b]	Food	8.6
3130	Tobacco & Beverages	0.8
3200	Textile, Apparel & Leather	3.0
3310	Saw Mills & Planing Mills	2.2
3320	Other Wood Products	6.3
3410	Pulp	0.6
3420	Paper & Paperboard	4.1
3430	Products made of Pulp, Paper & Paperboard	1.9
3440	Printing & Publishing	8.1
3510	Industrial Chemicals incl. Plastic Materials	2.2
3520	Other Chemical Products	2.5
3530	Petroleum Refineries, Petroleum & Coal Products	0.3
3550	Rubber Products	0.9
3560	Plastic Products	2.0
3600	Non-Metallic Mineral Products	3.3
3710	Iron & Steel	3.0
3720	Non-Ferrous Metals	1.0
3810	Metal Products	11.5
3820	Machinery & Equipment, not elsewhere classified	13.5
3830	Electrical Machinery, not elsewhere classified	8.1
3840	Transport Equipment, except Shipyards	12.3
3850	Instruments, Photographic & Optical Devices	2.2
3860	Shipyards	0.8
3900	Other Manufacturing	0.8
3000	Total Manufacturing	100.0

Notes:
a) The SNI69 codes correspond very closely to the ISIC codes.
b) The Food industry used to be broken down into two subindustries, the "sheltered" food industry, protected from foreign competition, and a subindustry subject to international competition. Both of these are included in 3110.

The capital stocks are from the SNA.[8] The method used for their computation is a variant of the perpetual inventory method which implies depreciation rates that vary slightly over time. However, compared to the variation across industries and types of capital (equipment and structures) the time variation is negligible. The capital stocks can therefore be very closely approximated by means of the following accumulation formula

$$K_{ij,t} = \left(1 - \overline{\delta}_{ij}\right) K_{ij,t-1} + I_{ij,t-1} \tag{2.1}$$

where K_{ijt} is the capital stock of type i, in industry j, at the beginning of period t. The $\overline{\delta}_{ij}$ is the time-average of the SNA depreciation rate for capital of type i in industry j, over the period 1985-1995.[9] Finally, $I_{ij,t-1}$ denotes gross investments in capital of type i in industry j during period $t-1$.

The rental price for capital can be written

$$P_{K_{ij,t}} = P_{I_{ij,t-1}} \left[r_{t-1} + \overline{\delta}_{ij} \frac{\left(P_{I_{ij,t|t-1}}\right)^e}{P_{I_{ij,t-1}}} - \left(\frac{\left(P_{I_{ij,t|t-1}}\right)^e - P_{I_{ij,t-1}}}{P_{I_{ij,t-1}}} \right) \right] \tag{2.2}$$

where $P_{K_{ij,t}}$ denotes the rental price for type i capital, in industry j, at the beginning of period t, $P_{I_{ij,t-1}}$ is the gross investment price index for period $t-1$, r_{t-1} is a long-term interest rate measured at the very end of period $t-1$, and $\left(P_{I_{ij,t|t-1}}\right)^e$ is the expected value of the investment price index for period t, given information about this index up to period $t-1$. The difference $\left(P_{I_{ij,t|t-1}}\right)^e - P_{I_{ij,t-1}}$ measures the expected windfall profit (loss) that accrues to the owner of the capital asset through an increase (decrease) in the renewal cost.[10]

[8]The SNA provides "gross" capital stocks and "net" capital stocks. The net stocks are used here. For these the rates of depreciation are consistently higher than for the gross stocks.

[9]The $\overline{\delta}_{ij}$, vary between types of capital and across industries. The depreciation rates for equipment range between 7.7 percent (in the Paper and Paperboard industry) and 21.4 percent (in Electrical Machinery). For structures the smallest and largest rates are 3.7 percent (in Other Wood Products) and 7.6 percent (in Textile, Apparel & Leather), respectively.

[10]As discussed in Harper, Berndt and Wood (1989), (2.2) is a discrete time approximation to

The P_I are obtained from the SNA. The interest rate r is measured by means of the nominal rate on Swedish long-term industrial bonds. The expectational variables $\left(P_{I_{ij,t|t-1}}\right)^e$ are implemented by means of univariate Kalman filter.[11]

3. A first look at employment by educational level

For each industry, labor is broken down by four successively higher levels of education:

1 = Elementary school (compulsory shorter than 9 years).

2 = 9 year compulsory school.

3 = Upper secondary school.

4 = Tertiary and postgraduate education.[12]

This classification is clearly more disaggregated at the lower end of the educational spectrum than at the upper end. Due to the small numbers of highly educated employees in Swedish manufacturing an attempt to, e.g., separate individuals holding at least a Bachelor's degree from the category 4 employees would for many industries result in numbers too small to admit meaningful statistical analyses.

Level 1 differs from the other levels because there is practically no inflow into level 1 during the 1985-95 period. The 9 year compulsory school was successively introduced in the 1960s and from 1968 it became the minimum schooling requirement in Sweden. The last students to finish their education in Sweden with

the more well–known continuous time formula $P_K = P_I \left[r + \delta - \left(\partial P_I / \partial t\right) / P_I\right]$.

[11] This filter amounts to modeling the investment price index by means of a transition equation and a measurement equation. The former models the "true" investment price index as a random walk, incorporating a drift in the form of a quadratic deterministic time trend. The measurement equation models the observed price index as the sum of the "true" index and a random error.

[12] These categories have been constructed from the Swedish Standard Classification of Education (SUN). The following equalities define the categories in terms of the SUN codes, and the corresponding UNESCO International Standard Classification of Education (ISCED) codes: Level 1 = SUN 1 = ISCED 0 + ISCED 1, Level 2 = SUN 2 = ISCED 2; Level 3 = SUN 3 + SUN 4 = ISCED 3; Level 4 = SUN 5 + SUN 6 + SUN 7 = ISCED 5 + ISCED 6 + ISCED 7.

elementary school only were born in the early 50s. Thus, apart from immigrants (and a small number of drop-outs from 9 year compulsory school) level 1 workers were all well over 40 years old during the period studied.

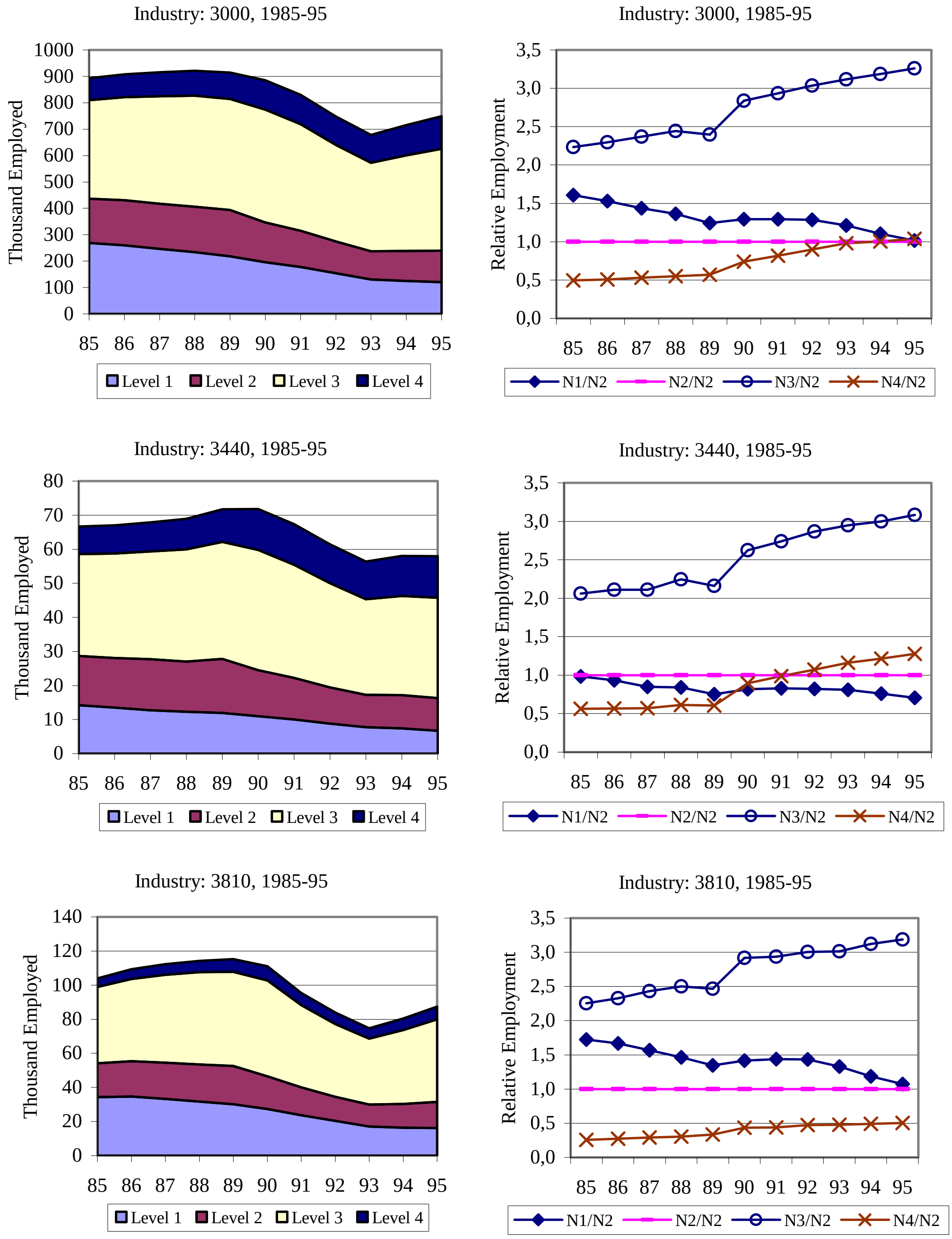
In Diagram 1 the distribution over the four categories are illustrated for the entire manufacturing sector (Industry 3000) as well as for two of the 24 industries that we consider, namely the Printing and Publishing industry (Industry 3440) and the Metal industry (Industry 3810). The former industry has been chosen because it has undergone large changes in production methods and technology during the 1985-95 period while the latter is an example of a more "mature" industry where changes have been less dramatic.[13]

The charts to the left, showing employment in absolute terms, all reflect the underlying business cycle; during the period the turning points were 1985 (trough), 1988 (peak), 1993 (trough), and 1994 (peak)

As can be seen from the upper left chart, workers with at most 9 years of education (Level 1 + Level 2) accounted for a very large, albeit rapidly decreasing, share of employment in the manufacturing sector. In 1985, they made up nearly 450 000 individuals and accounted for almost 1/2 of employment. By 1995 their numbers had shrunk dramatically to well below 250 000, corresponding to less than 1/3 of employment. During the same period, the number of workers in the most well-educated category, i.e. Level 4, increased from about 85 000 to almost 125 000, which meant that their share in employment rose from 10 percent to over 15 percent. The development of relative employment is also illustrated in the upper right chart. It is evident that employment in the Level 3 category and, in particular, Level 4 has increased dramatically compared to Level 2, which is the reference category in the diagram. At the same time, the relative employment of Level 1 workers has decreased markedly. This decrease is to a large extent explained by Level 1 individuals entering retirement; cf. above.

[13] In the econometric analysis data for all of the 24 industries are used, of course.

Diagram 1: Employment by educational level, in absolute and relative terms, for the whole manufacturing sector and two selected industries.



The variation across industries is illustrated in the middle and lower charts. In Printing and Publishing (Industry 3440) Level 4 workers constitute a large and rapidly increasing share of employment; their share rose from 12 percent in 1985 to 21 percent in 1995. Employment rose from around 8 000 to about 12 000, i.e. by 50 %. Taken together, Level 1 and Level 2 workers reduced their share from 42 percent to 28 percent. From the middle right chart it can be seen that the ratio between Level 4 and Level 2 workers almost tripled over the period.

In the Metal Products industry (Industry 3810), Level 1 and Level 2 workers together made up more than 1/3 of the workforce even in 1995. The number of Level 4 employees increased only very slightly. Nevertheless, they increased their share from 5 to 9 percent, due to the declining number of low-educated workers.

For comparative purposes, the Berman et al. (1994) decomposition of changes in employment shares into within- and between-industry changes is provided in Appendix A. Just like in earlier studies, the between-industry changes are completely dominated by the within-industry changes.

The employment data are not adjusted for incidence of part-time work. This is due to what is probably the only drawback with the SRE: there are no data on work hours. In the empirical analysis, this shortcoming is taken into account by allowing the labor quality indexes considered in Section 4.1 to depend on industry level data on work hours. These data, from the Swedish Labor Force Survey, provide information, by sex, about three classes of weekly work hours: 0–19, 20-34, and 34– hours. The 1991 distributions are given in Table 2, which also contains distributions over age, sex, immigrant status, and fields-of-study.

To save space, Table 2, like Diagram 1, only considers the entire manufacturing sector (Industry 3000), and the Printing and Publishing (3440) and Metal Products (3810) industries, and, moreover, only for 1991. The table indicates that the age distributions vary substantially between different levels of education, but not so much across industries. Focusing, therefore, on the manufacturing sector

Table 2: Distributions over demographic characteristics, fields-of-study, and work hours, by level of education, 1991, for the whole manufacturing sector and two selected industries. Shares in %.

Industry 3000		Level of Education			
		1	2	3	4
Age	16-29	1.0	33.5	36.3	28.3
	30-39	4.9	37.1	23.0	31.3
	40-49	34.7	20.3	23.4	26.6
	50-74	59.4	9.0	17.4	13.8
Sex	Male	69.2	66.1	73.4	77.2
	Female	30.8	33.9	26.6	22.8
Immigrant	No	94.9	93.0	94.4	93.0
	Yes	5.1	7.0	5.6	7.0
Fields-of-Study[1]	FoS1	100.0	100.0	9.2	0.0
	FoS2	0.0	0.0	18.8	24.9
	FoS3	0.0	0.0	59.3	60.1
	FoS4	0.0	0.0	12.7	15.0
Weekly Hours	1-19	1.8	2.1	1.8	1.6
	20-34	12.6	13.2	11.3	10.1
	35-	85.6	84.7	86.9	88.3

Industry 3440		Level of Education			
		1	2	3	4
Age	16-29	0.7	30.8	33.0	18.7
	30-39	3.6	31.3	21.7	30.4
	40-49	32.0	23.2	23.8	31.8
	50-74	63.7	14.7	21.4	19.1
Sex	Male	60.2	59.4	58.2	57.1
	Female	39.8	40.6	41.8	42.9
Immigrant	No	96.2	95.6	96.0	94.2
	Yes	3.8	4.4	4 .0	5.8
Fields-of-Study[1]	FoS1	100.0	100.0	20.2	0.0
	FoS2	0.0	0.0	30.0	49.4
	FoS3	0.0	0.0	36.1	16.1
	FoS4	0.0	0.0	13.7	34.5
Weekly Hours	1-19	7.2	7.2	7.2	7.2
	20-34	15.3	15.4	15.7	15.9
	35-	77.5	77.4	77.1	76.8

Industry 3810		Level of Education			
		1	2	3	4
Age	16-29	1.0	32.8	34.7	28.2
	30-39	5.3	38.8	23.2	28.7
	40-49	35.4	20.3	24.7	27.7
	50-74	58.3	8.1	17.4	15.4
Sex	Male	74	73.1	80.3	83.0
	Female	26	26.9	19.7	17.0
Immigrant	No	94.5	93.4	94.2	91.9
	Yes	5.5	6.6	5.8	8.1
Fields-of-Study[1]	FoS1	100.0	100.0	5.7	0.0
	FoS2	0.0	0.0	13.8	23.5
	FoS3	0.0	0.0	69.7	63.6
	FoS4	0.0	0.0	10.8	12.9
Weekly Hours	1-19	1.7	1.7	1.4	1.3
	20-34	12.6	12.9	11.1	10.4
	35-	85.7	85.4	87.5	88.3

[1] FoS1 = General education, FoS2 = Administration, economics, social science and law, FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

as a whole (Industry 3000), we note that:

– for level 1, almost 95 % of the individuals are at least 40 years old.

– for level 2, more than 70 % of the individuals are *below* 40.

– for level 3, the youngest individuals, aged 16-29, make up more than 1/3.

– for level 4, the majority of the individuals are 30-49 year old.

The huge differences between levels 1 and 2 are especially noteworthy, of course.

With respect to sex there are large differences, both across educational levels and, in particular, between industries. For Printing and Publishing (3440) the female share is at least 40 % and rising with education. In Metal Products (3810) the female share is about 26 % at levels 1 and 2 and much lower at levels 3 and 4.

Immigrants constitute a minor share of the workforce, across all industries. For the manufacturing sector as a whole, they make up about 5 % of employment at educational levels 1 and 3 with slightly higher proportions at levels 2 and 4.[14]

Concerning fields-of-study there are (non-degenerate) distributions only for educational levels 3 and 4. For these, there are notable differences between the Printing and Publishing (3440) and the Metal Products (3810) industries. In 3810 the totally dominating field-of-study is FoS3, i.e. essentially engineering. In 3440, FoS2, covering various dimensions of business administration, is of almost equal importance at educational level 3 and much more important at level 4.

As noted above, work hours are not available by level of education, only by sex. The differences in the work hour distributions across educational levels that can be seen in Table 2 are thus due to differences in gender compositions.

Table 3 shows how the various worker characteristics in Table 2 have changed between 1985 and 1995.

[14]Due to data constraints, an individual is classified as an immigrant if he/she immigrated to Sweden at most 17 years before the year of observation. Accordingly, those classified as immigrants in Table 3 came to Sweden in 1974 or later. In a definitional sense, the immigrant shares will thus be understated. However, the individual's origin is not of primary interest in the present context, but rather whether he/she can be considered to be reasonably assimilated in the Swedish society. For this purpose, the "moving window" definition is more appropriate.

Table 3: Changes in the sample shares corresponding to demographic characteristics, fields-of-study, and work hours between 1985 and 1995 by level of education, in % per annum.

Industry 3000		Level of Education			
		1	2	3	4
Age	16-29	-0.02	-2.80	-0.53	-0.51
	30-39	-1.35	+0.28	+0.17	-0.21
	40-49	-0.73	+1.99	+0.06	+0.34
	50-74	+2.10	+0.53	+0.30	+0.38
Sex	Male	+0.18	+0.20	-0.20	-0.62
	Female	-0.18	-0.20	+0.20	+0.62
Immigrant	No	+0.23	+0.16	+0.20	-0.04
	Yes	-0.23	-0.16	-0.20	+0.04
Fields-of-Study[1]	FoS1	0.0	0.0	-0.12	--
	FoS2	--	--	-0.09	+0.09
	FoS3	--	--	-0.03	+0.02
	FoS4	--	--	+0.24	-0.11
Weekly Hours	1-19	-0.25	-0.24	-0.22	-0.19
	20-34	-0.41	-0.43	-0.39	-0.31
	35-	+0.66	+0.67	+0.61	+0.50

Industry 3440		Level of Education			
		1	2	3	4
Age	16-29	-1.21	-2.58	-0.27	+0.34
	30-39	0.0	-0.06	+0.07	-0.73
	40-49	-1.15	+1.85	-0.09	-0.07
	50-74	+2.37	+0.80	+0.28	+0.45
Sex	Male	+0.45	+0.44	-0.18	-0.54
	Female	-0.45	-0.44	+0.18	+0.54
Immigrant	No	-0.08	+0.12	+0.11	+0.18
	Yes	+0.08	-0.12	-0.11	-0.18
Fields-of-Study[1]	FoS1	0.0	0.0	-0.20	--
	FoS2	--	--	+0.06	+0.46
	FoS3	--	--	-0.06	+0.15
	FoS4	--	--	+0.19	-0.61
Weekly Hours	1-19	+0.26	+0.26	+0.28	+0.29
	20-34	-0.74	-0.74	-0.63	-0.56
	35-	+0.49	+0.49	+0.36	+0.28

Industry 3810		Level of Education			
		1	2	3	4
Age	16-29	-0.78	-2.67	-0.49	+0.03
	30-39	+0.01	+0.21	+0.11	-0.67
	40-49	-1.48	+1.92	0.0	+0.23
	50-74	+2.25	+0.54	+0.39	-0.41
Sex	Male	+0.20	+0.20	+0.10	-0.16
	Female	-0.20	-0.20	-0.10	+0.16
Immigrant	No	+0.09	+0.06	+0.24	-0.15
	Yes	-0.09	-0.06	-0.24	+0.15
Fields-of-Study[1]	FoS1	0.0	0.0	-0.06	--
	FoS2	--	--	-0.17	-0.40
	FoS3	--	--	-0.04	+0.45
	FoS4	--	--	+0.27	-0.05
Weekly Hours	1-19	-0.24	-0.24	-0.22	-0.20
	20-34	-0.23	-0.23	-0.26	-0.21
	35-	+0.47	+0.48	+0.48	+0.42

[1] FoS1 = General education, FoS2 = Administration, economics, social science and law, FoS3 = Industry, crafts, natural sciences and technology, FoS4 = Other fields-of-study.

Regarding the age structure, we see that for manufacturing as a whole the shares of 16-29 year olds have decreased at each educational level, which implies that the overall share of this age group in manufacturing employment must have decreased, too. For 50-74 year olds the opposite development has taken place.

The changes in the gender structure have had the effect of increasing the female representation at higher educational levels (levels 3 and 4) and decreasing it at the lower levels. A similar development can be seen for immigrants.

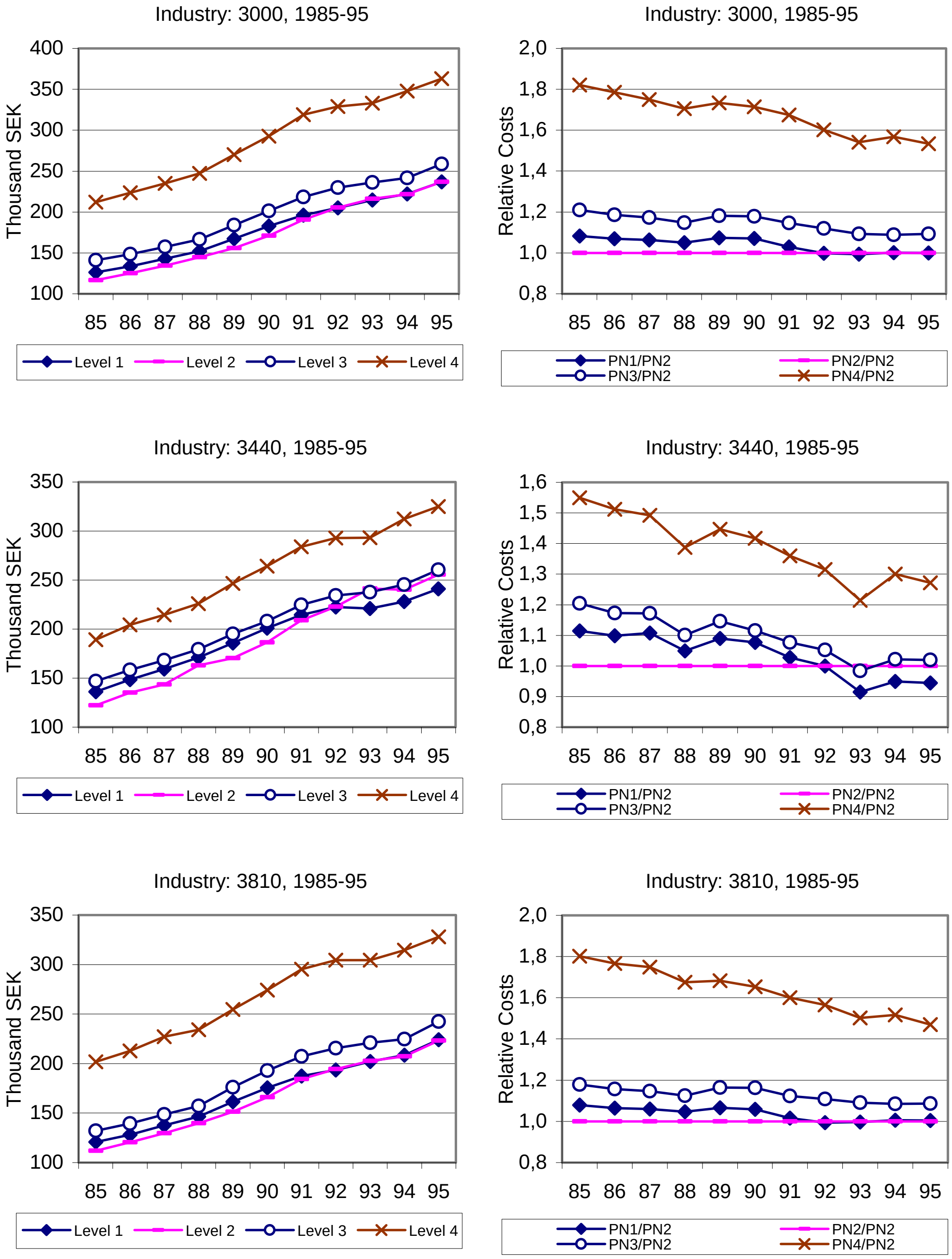
With respect to fields-of-study, the share changes are not very large for manufacturing as whole. However, in 3440 and 3810 substantial, and quite different, changes have occurred at the highest level of education. Concerning work hours, is clear that those working full time, i.e. at least 35 hours a week, have increased their shares, at all levels of education and across industries.

We now turn from labor quantities to labor costs. To compute these, payroll tax rates for white-collar and blue-collar workers have been applied to the SRE data.[15] The blue-collar rates have been applied to Level 1 and Level 2 workers, while the white-collar rates have been used for the Level 4 employees. With respect to Level 3, the blue-collar rates have been applied to workers with at most 2 years of upper secondary education and the white-collar rates have been used for those with 3 years of upper secondary education. This partition is motivated by the fact that the majority of the 2 year programs involve vocational training while the 3 year programs are more theoretically oriented.

From Diagram 2 it can be seen that the relative changes in employment shown in Diagram 1 are mirrored by changes in relative labor costs in the opposite direction. Thus, e.g., the employment increase for Level 4 labor, compared to Level 2 labor, corresponds to falling labor costs for Level 4, relative to Level 2. Judging from the charts to the right, the relative decrease has been substantial.

[15] The payroll taxes are from *Näringslivets Ekonomifakta*, a private statistical agency, and include both compulsory payroll taxes and non-compulsory payroll fees agreed upon in employer/union negotiations. During the sample period the rates varied between 37.00 % and 43.47 % for blue-collar workers and between 38.55 % and 46.57 % for white-collar workers.

Diagram 2: Average yearly labor costs by educational level, in absolute and relative terms, for the whole manufacturing sector and two selected industries.



For the manufacturing sector as a whole (Industry 3000) the fall is almost 20 percent, for Printing and Publishing (3440) slightly less and in Metal Products (3810) even more. The relative costs for Levels 3 and 1 have decreased as well, but, except for industry 3440, less dramatically.

From a microeconomic perspective, the declining relative labor costs and the increase in relative employment for high–skilled workers is very natural. This development differs, however, from U.K. and U.S. experiences where the employment shares of the high-skilled have been constant or increasing in spite of successively higher relative wages for high-skilled labor [Machin and Van Reenan (1998)].

Since the relative labor costs in Diagram 2 are simply based on average labor costs by educational level, the decreasing relative wages might be reflecting differences in age structure across levels and differences with respect to, e.g., gender and immigrant/non-immigrant status. To check this, Diagram 3 has been constructed like Diagram 2 but for Swedish males aged 40–49 only.[16]

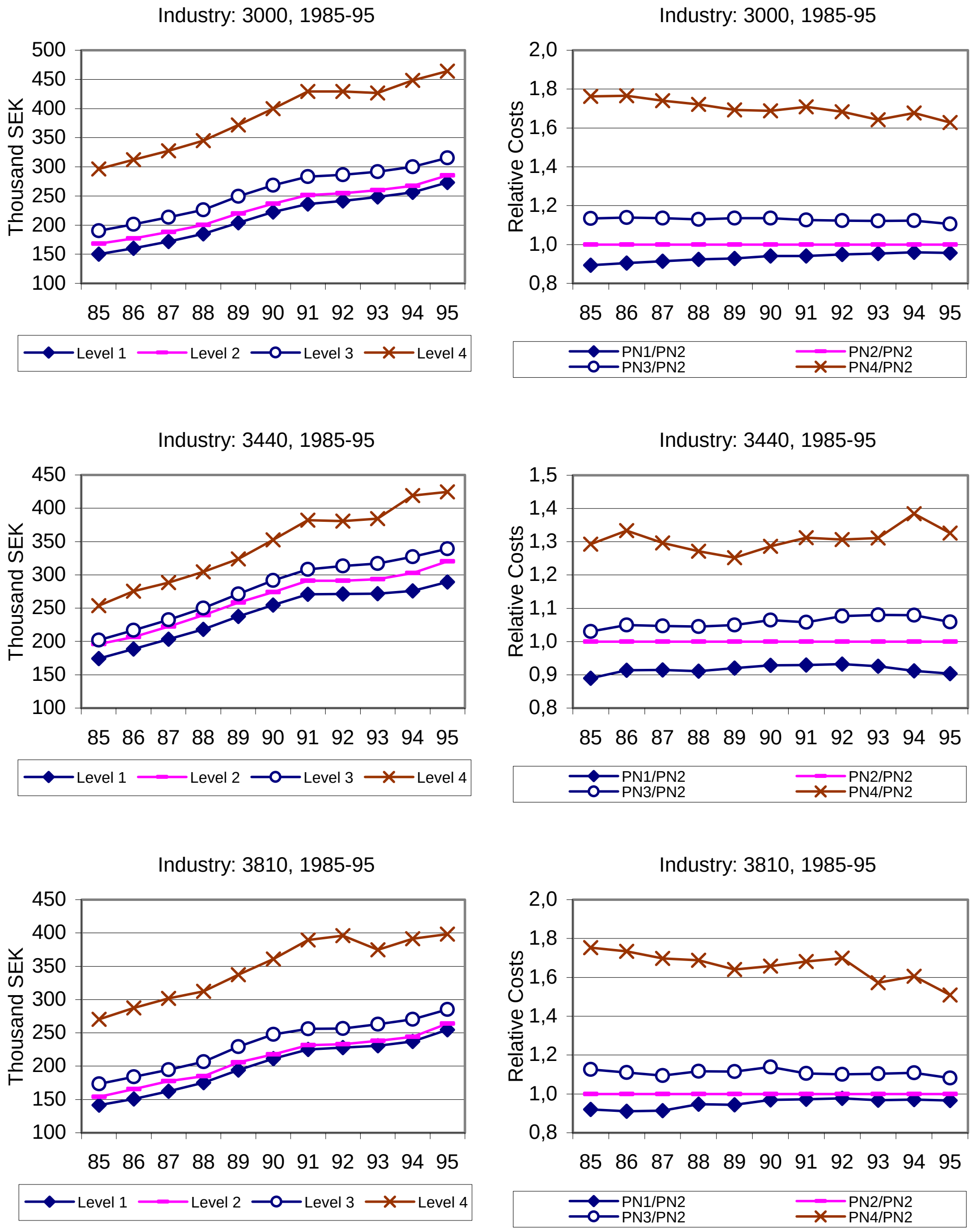
For the manufacturing sector as a whole, the relative wage of level 4 workers has decreased over time, even for Swedish 40–49 year old men. The decline is smaller than in Diagram 2, however. Also, the charts for Printing and Publishing (3440) and Metal Products (3810) indicate that there are large differences across industries. In 3440, the relative wage of university educated workers has been fairly constant while in 3810 it has decreased markedly.

For individuals with upper secondary school, the downward trending relative wages in Diagram 2 have been replaced by constant relative wages in Diagram 3.

With respect to level 1 workers, average labor costs *increase* relative to the higher Level 2 education, which is in contrast to Diagram 2. Inspection of Table 4 indicates, however, that this apparent anomaly can be explained by differences in (average) work experience. At Level 2, the number of individuals aged 40–49

[16] Of course, due to differences in length of education, individuals in the 40–49 age interval can differ markedly with respect to work experience. In contrast to younger individuals, all workers aged 40 or above should have at least some work experience, however.

Diagram 3: Average yearly labor costs by educational level, in absolute and relative terms, for the whole manufacturing sector and two selected industries, *for Swedish males aged 40-49.*



has been increasing rapidly, while the opposite is true for Level 1. Accordingly, at Level 1 the mean age of the 40–49 year olds is likely be closer to 49 than to 40. At Level 2, by contrast, the mean age is probably close to 40.

The comparison of Diagrams 2 and 3 show the importance of labor dimensions beside the level of education. A simple way to account for these is considered next.

4. The model

To avoid excessive notation, the model discussion will be carried out in terms of a single firm, at a single point in time.

4.1. The specification of effective labor input

For simplicity, assume that, at a given level of education, the number of employees is multiplicatively separable from the other properties of the workers.[17] [18] Let N_i be the number of employees with educational level i and B_i an index controlling for the characteristics in Table 2. The measure L_i of *effective labor* is

$$L_i = N_i \times B_i, \qquad i = 1, 2, 3, 4. \tag{4.1}$$

Clearly, (4.1) specializes to a purely quantitative measure of labor when $B_i = 1$.[19]

To derive the price of effective labor, P_{L_i}, consider labor costs:

$$P_{L_i} L_i = P_{L_i} N_i B_i = (P_{L_i} B_i)\, N_i = P_{N_i} N_i\,, \qquad i = 1, 2, 3, 4. \tag{4.2}$$

[17] For a discussion of the notion of separability, cf. Blackorby, Primont and Russell (1978).

[18] Alternatively, labor can be disaggregated by both level of education and other dimensions; see Berger (1983) for a simple example. The problem with this approach is that the number of labor categories soon becomes very large. For instance, our four levels of education and the characteristics in Table 2 would yield 1728 categories of labor.

[19] A specification similar to (4.1) was used by Morrison and Berndt (1981) who multiplied work hours by an exogenously determined index of educational attainment, to account for quality changes over time. In Kazamaki Ottersten, Lindh, and Mellander (1999) a labor quality index is instead estimated and this approach will be taken here, too.

where P_{N_i} is defined as total labor costs for labor category i, divided by the number of employees in this category. From (4.2) it follows that the price of effective labor, P_{L_i}, can be written

$$P_{L_i} = P_{N_i} B_i^{-1}, \qquad i = 1, 2, 3, 4. \tag{4.3}$$

Thus, the adjustment by B_i affects the volume and the price of efficient labor inversely: if the correction amounts to a quantity increase, it will have a corresponding decreasing effect on the price of effective labor.

The B_i are modeled by means of the distributions in Table 2. The underlying idea is best conveyed by means of a simple example. Assume that the only distribution considered is the workers' age distribution. Denote the shares of the four age categories by H_{i1}, H_{i2}, H_{i3}, H_{i4}. If the contributions to effective labor from the different age groups exactly matches the corresponding number of workers then

$$L_i = N_i \times B_i = N_i \times (H_{i1} + H_{i2} + H_{i3} + H_{i4}) = N_i \times 1. \tag{4.4}$$

This is the standard assumption. To account for possible differences across age groups with respect to their contributions to effective labor, we can specify that

$$L_i = N_i \times \left[(1 + \theta_{i1}) H_{i1} + (1 + \theta_{i2}) H_{i2} + (1 + \theta_{i3}) H_{i3} + (1 + \theta_{i4}) H_{i4} \right]. \tag{4.5}$$

Since the contribution to effective labor from a given age group can be both larger and smaller than the corresponding share the θ_{ik}, $k = 1, 2, 3, 4$, can be either positive or negative. They should, however, normally be larger than -1, to ascertain that the contributions from all age groups are positive.

As the shares are linearly dependent, it necessary to impose one constraint on the θ_{ik}. For this purpose, we normalize the effect of the age distribution to unity in the base–year (i.e. in 1991) so that

$$B_{i0} = (1+\theta_{i1})\,H_{i10} + (1+\theta_{i2})\,H_{i20} + (1+\theta_{i3})\,H_{i30} + (1+\theta_{i4})\,H_{i40} = 1, \quad (4.6)$$

where subindex 0 denotes base-year values. Solving for, e.g., θ_{i4}we get

$$\theta_{i4} = \frac{1 - \sum_{k=1}^{3}(1+\theta_{ik})\,H_{ik0}}{H_{i40}} - 1. \quad (4.7)$$

The normalization means that labor quality is measured relative to the base–year. This is a more realistic ambition than to try to determine the level of effective labor. Given the normalization, the N_i are implicitly expressed in terms of workers with the base–year age distribution.

In the general case, with many characteristics, there are two additional problems. The first is how to weigh different distributions together. The second relates to substitutability: to what extent are, e.g., gender and age characteristics interchangeable? A simple way to address these issues is to specify B_i as a CES aggregator function. Denote different distributions by subindex j, $j = 1, 2, ..., J_i$ and the number of categories associated with the jth distribution by K_{j_i}.[20] Then

$$B_i = \left[\sum_{j=1}^{J_i} \nu_{ij}\left(\sum_{k=1}^{K_{ji}}(1+\theta_{ijk})\,H_{ijk}\right)^{-\rho_i}\right]^{-\frac{1}{\rho_i}}, \quad (4.8)$$

where the ν_{ij} are the weights attached to the different distributions; $\sum_{j=1}^{J_i}\nu_{ij} = 1$, and ρ_i is the substitution parameter. The elasticity of substitution, σ_i, between

[20]The number of characteristics accounted for by the B_i differ by level of education. As fields-of-study distributions are available only for the two highest levels of education, $J_1 = J_2 = 4$ and $J_3 = J_4 = 5$. Moreover, with respect to fields-of-study, the number of shares also differ between these two levels of education; as seen in Table 2 the fields-of-study distribution contains four categories at educational level 3 and three categories at level 4. Thus, letting field-of-study be the fourth characteristic so that $j = 4$ we have $K_{43} = 4$ and $K_{44} = 3$.

different characteristics in the quality index is given by

$$\sigma_i = \frac{1}{1+\rho_i} \qquad (\rho_i > -1)\,. \tag{4.9}$$

A reasonable conjecture would be that $0 < \sigma_i < 1$, i.e. there are some possibilities of substitution but that these are rather limited. This implies that $0 < \rho_i < \infty$.

It should be noted that in addition to the parameters, the θ_{ijk}, ν_{ij}, and ρ_i, the L_i and the P_{L_i} are unknown as well. To estimate these, the specification of effective labor has to be integrated into a representation of the firm's technology.

4.2. Representing the production technology

The restricted Generalized Leontief (GL) cost function suggested by Morrison (1988), is a flexible, second order, representation of the production technology. Like, e.g., the translog cost function it allows some inputs to be substitutes and others to be complements, in accordance with the capital–skill complementarity hypothesis. It also allows quasi–fixed inputs, which are the source of the distinction between short-run and long–run effects. Unlike the translog, Morrison's function provides analytical solutions for the long run, equilibrium, values of the quasi-fixed inputs, making it.easy to compare short-run and long-run effects.

Six variable inputs are considered: the four categories of labor, L_1, L_2, L_3, and L_4, equipment capital, E, and intermediate goods, M. Structure capital, S, is treated as quasi-fixed, i.e. fixed in the short run, which is here one year.

Variable costs are determined by the level of output, Y, the prices of the variable inputs, P_i, structure capital, S, and a time index, t, representing the state of the technology. Given long–run constant returns to scale, the variable cost function, VC, can be written:

$$
\begin{aligned}
VC &= Y \cdot \; \sum_i \sum_j \alpha_{ij} P_i^{\frac{1}{2}} P_j^{\frac{1}{2}} + \gamma_{SS} \sum_i P_i \left(\frac{S}{Y}\right) \\
&\quad + \sum_i \delta_{iS} P_i \left(\frac{S}{Y}\right)^{\frac{1}{2}} \Big] \quad i,j = L_1, L_2, L_3, L_4, E, M,
\end{aligned} \tag{4.10}
$$

where

$$
\alpha_{ii} = \lambda_{i0} + \lambda_{it} t\,. \tag{4.11}
$$

The main difference between (4.10) and Morrison's (1988) long run constant returns to scale specification lies in the specification of technical change, where Parks' (1971) more easily interpretable formulation (4.11) has been used.[21]

Using a time index might seem a crude way to capture technical change. However, problems are associated with using, e.g., measures information technology (IT) use or R&D expenditures is . First, by construction, such specific indicators only consider certain aspects of technical change. IT and R&D variables cannot capture the effects of changes in work organization, which may be important skill-biased technical changes; cf. Lindbeck and Snower (1999). Second, there are econometric problems. Implicitly, it is assumed that employment of IT and spendings on R&D are exogenously determined. However, computers are part of the (equipment) capital stock, which is endogenous, and R&D outlays are dominated by wages to high-skilled workers, the demand for which is endogenous, too.[22]

Deviations from constant returns to scale are allowed in the short run, as a consequence of non-optimal levels of the quasi-fixed input. That is to say, non–constant returns to scale are not taken to be an intrinsic feature of the technology

[21] Another difference relative to Morrison's specification is that the interaction effects between technical change and short-run returns to scale are disregarded. This is to lessen the well-known problem of separating technical change and return to scale effects.

[22] Accordingly, if one is interested in the effects of IT specifically the appropriate way is to break down the equipment capital stock into computers and non-computer equipment. Likewise, R&D workers should preferably be separated from other (high-skilled) workers.

but arise through the constraints facing the firm in the form of quasi-fixed inputs.

To be a proper representation of an underlying production technology (4.10) must be increasing and concave in the P_i and decreasing and convex in S.

The short run demand equations for the variable inputs can be derived from VC by application of Shephard's lemma to (4.10) and subsequent application of the equalities (4.11), (4.1), and (4.3). For labor this yields

$$\begin{aligned}\frac{N_i}{Y} &= B_i^{-1}\cdot\left[\lambda_{L_i0}+\lambda_{L_it}t+\sum_{j\neq i}\alpha_{L_iL_j}\left(\frac{P_{N_j}B_j^{-1}}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}+\alpha_{L_iE}\left(\frac{P_E}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}\right.\\ &\quad\left.+\alpha_{L_iM}\left(\frac{P_M}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}+\gamma_{SS}\left(\frac{S}{Y}\right)+\delta_{L_iS}\left(\frac{S}{Y}\right)^{\frac{1}{2}}\right],\quad i=1,2,3,4,\end{aligned}\tag{4.12}$$

These labor demand equations imply that the quantities of labor with base-year characteristics, the N_i, are endogenously determined, while deviations in labor characteristics relative to the base-year, the B_i are treated as predetermined.

The demand equations for equipment capital and intermediate goods are:

$$\begin{aligned}\frac{E}{Y} &= \lambda_{E0}+\lambda_{Et}t+\sum_{i=1}^{4}\alpha_{L_iE}\left(\frac{P_{N_1}B_1^{-1}}{P_E}\right)^{\frac{1}{2}}+\alpha_{EM}\left(\frac{P_M}{P_E}\right)^{\frac{1}{2}}\\ &\quad+\gamma_{SS}\left(\frac{S}{Y}\right)+\delta_{ES}\left(\frac{S}{Y}\right)^{\frac{1}{2}},\end{aligned}\tag{4.13}$$

$$\begin{aligned}\frac{M}{Y} &= \lambda_{M0}+\lambda_{Mt}t+\sum_{i=1}^{4}\alpha_{L_iM}\left(\frac{P_{N_1}B_1^{-1}}{P_M}\right)^{\frac{1}{2}}+\alpha_{EM}\left(\frac{P_E}{P_M}\right)^{\frac{1}{2}}\\ &\quad+\gamma_{SS}\left(\frac{S}{Y}\right)+\delta_{MS}\left(\frac{S}{Y}\right)^{\frac{1}{2}}.\end{aligned}\tag{4.14}$$

Finally, assuming perfect competition on the output market we can append an equation for the shadow value of the quasi–fixed input to the above system.

The shadow value, Z_s is given by the partial derivative $-\partial VC/\partial S$. Thus

$$\begin{aligned} Z_S &= -\gamma_{SS}\left(\sum_{i=1}^{4} P_{N_i} B_i^{-1} + P_E + P_M\right) \\ &\quad - \frac{1}{2}\left(\frac{S}{Y}\right)^{-\frac{1}{2}}\left(\sum_{i=1}^{4} \delta_{iS} P_{N_i} B_i^{-1} + \delta_{ES} P_E + \delta_{MS} P_M\right). \end{aligned} \tag{4.15}$$

Under perfect competition, after payments to all variable inputs have been made, returns to the firm can be attributed to the fixed input. In this case, the shadow value can be made operational by means of the ex post return to S, i.e.

$$Z_S = \frac{P_Y Y - P_{N_1} N_1 - P_{N_2} N_2 - P_{N_3} N_3 - P_{N_4} N_4 - P_E E - P_M M}{S} \tag{4.16}$$

where P_Y is the price of output.

The long–run cost function can be derived from the short run total costs

$$TC = VC + P_S S, \tag{4.17}$$

where P_S is the rental price for structures, by recognition of the fact that in equilibrium the quasi–fixed factor must be employed at its optimal level. By the envelope theorem, the optimal level, S^*, is obtained by minimizing (4.10) with respect to S. The first–order condition requires that the shadow price Z_S be equal to the market price P_S. Using this condition, we can solve for S from (4.15):

$$S^* = S^*(Y, \mathbf{P}) = Y \cdot \frac{\left[-\frac{1}{2}\left(\sum_{i=1}^{4} \delta_{iS} P_{N_i} B_i^{-1} + \delta_{ES} P_E + \delta_{MS} P_M\right)\right]^2}{\left[P_S + \gamma_{SS}\left(\sum_{i=1}^{4} P_{N_i} B_i^{-1} + P_E + P_M\right)\right]^2}. \tag{4.18}$$

The long–run cost function, TC^*, is given by (4.17), evaluated at $S = S^*$, i.e.

$$TC^* = VC^* + P_S S^*. \tag{4.19}$$

Similarly, evaluating (4.12)−(4.14) at $S = S^*$ yields long-run input demands.

4.3. Labor demands, demand elasticities, and skill biases

The empirical analysis generates two kinds of labor demand estimates: the number of employees and the volumes of effective labor. For both of these, short-run and long-run estimates are obtained, yielding four different demand estimates for each level of education, i.e. 16 estimates altogether.[23] To simplify the notation, define

$$\begin{aligned} X_i^{SR} \equiv\ & \lambda_{L_i0} + \lambda_{L_it}t + \sum_{j\neq i} \alpha_{L_iL_j}\left(\frac{P_{N_j}B_j^{-1}}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}} + \alpha_{L_iE}\left(\frac{P_E}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}} \\ & + \alpha_{L_iM}\left(\frac{P_M}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}} + \gamma_{SS}\left(\frac{S}{Y}\right) + \delta_{L_iS}\left(\frac{S}{Y}\right)^{\frac{1}{2}}, \quad i = 1,2,3,4, \end{aligned} \tag{4.20}$$

where superindex SR denotes Short Run. The long run, equilibrium, variable is

$$X_i^{LR} = X_i^{SR}\Big|_{S=S^*}, \quad i = 1,2,3,4. \tag{4.21}$$

Using (4.20) and (4.21), labor demand in number of employees can be written

$$N_i^{\Phi R} = Y \cdot B_i^{-1} \cdot X_i^{\Phi R}, \quad \Phi = S, L, \quad i = 1,2,3,4, \tag{4.22}$$

and the demands expressed in terms of efficient labor are given by

$$L_i^{\Phi R} = Y \cdot X_i^{\Phi R}, \quad \Phi = S, L, \quad i = 1,2,3,4. \tag{4.23}$$

The demand measures (4.22) are especially interesting, because they can be used to evaluate the effects of changes in, e.g., demographic characteristics or fields-of-study distributions on the number of individuals demanded. The evaluation of such changes is not entirely straightforward, however, because they involve changes in distributions. For example, a marginal change in the share of one age

[23] These 16 estimates refer to a given industry, at a given point in time. Different estimates are generated for each of the 24 industries and for each year.

group will involve changes in the shares for the other groups, too. Moreover, if the number of individuals in one group changes, *ceteris paribus*, this involves a change in the size of the population, of the same magnitude. In the present context it is important to separate changes in the size of the population, which are endogenously determined, from changes in the population's composition, which are predetermined. The problem is considered in detail in Appendix B. Here, a shorthand notation is used where

$$\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{\Phi R}}}\right), \qquad \Phi = S, L \tag{4.24}$$

denotes the effect on B_i of a marginal change in the jth distribution, represented by the shares H_{ijk}, $k = 1, ..., K_{j_i}$, at a given number of employees, $\overline{N_i^{\Phi R}}$.

The short run relative effect of a marginal change in the jth distribution on the number demanded with educational level i can be written:

$$\frac{\partial N_i^{SR}}{\partial B_i}\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{SR}}}\right)\frac{1}{N_i^{SR}} = -B_i^{-1}\left(1 - e_{N_iN_i}^{SR}\right)\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{SR}}}\right) \tag{4.25}$$

where $e_{N_iN_i}^{SR}$ is the short run own-price elasticity of N_i, i.e

$$\begin{aligned} e_{N_iN_i}^{SR} &= \frac{\partial N_i^{SR}}{\partial P_{N_i}}\frac{P_{N_i}}{N_i^{SR}} = e_{L_iL_i}^{SR} \\ &= -\left[\frac{\sum_{h\neq i}\alpha_{L_iL_h}\left(\frac{P_{N_h}B_h^{-1}}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}}{2\cdot X_i^{SR}} + \frac{\alpha_{L_iE}\left(\frac{P_E}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}}{2\cdot X_i^{SR}} + \frac{\alpha_{L_iM}\left(\frac{P_M}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}}{2\cdot X_i^{SR}}\right] \end{aligned} \tag{4.26}$$

Since B_i should be positive and $e_{N_iN_i}^{SR}$ should be negative[24] it follows that

$$\text{sign}\left[\frac{\partial N_i^{SR}}{\partial B_i}\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{SR}}}\right)\frac{1}{N_i^{SR}}\right] = -\,\text{sign}\left[\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{SR}}}\right)\right]. \tag{4.27}$$

[24]Negative own-price elasticities are necessary for the cost function to be concave in prices.

Long run effects are obtained as

$$\frac{\partial N_i^{LR}}{\partial B_i}\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{LR}}}\right)\frac{1}{N_i^{LR}} = -B_i^{-1}\left(1 - e_{N_iN_i}^{LR}\right)\left(\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{LR}}}\right), \tag{4.28}$$

The long run own-price elasticity is given by

$$e_{N_iN_i}^{LR} = e_{N_iN_i}^{SR} + \eta_{N_iS^*}^{LR} \cdot e_{S^*N_i}^{LR} \tag{4.29}$$

where

$$\eta_{N_iS^*}^{LR} = \frac{\partial N_i^{LR}}{\partial S^*}\frac{S^*}{N_i^{LR}} = \frac{\gamma_{SS}\left(\frac{S^*}{Y}\right) + \frac{1}{2}\delta_{L_iS}\left(\frac{S^*}{Y}\right)^{\frac{1}{2}}}{X_i^{LR}} \tag{4.30}$$

and

$$e_{S^*N_i}^{LR} \equiv \frac{\partial S^*}{\partial P_{N_i}}\frac{P_{N_i}}{S^*} = e_{S^*L_i}^{LR} = -P_{N_i}B_i^{-1}\left(\frac{\delta_{L_iS}}{F} + \frac{2\gamma_{SS}}{G}\right) \tag{4.31}$$

the F and G in (4.31) being defined according to

$$\begin{aligned} F \equiv\; & -\tfrac{1}{2}\left(\delta_{L_1S}P_{N_1}B_1^{-1} + \delta_{L_2S}P_{N_2}B_2^{-1} + \delta_{L_3S}P_{N_3}B_3^{-1} + \delta_{L_4S}P_{N_4}B_4^{-1}\right. \\ & \left. + \delta_{ES}P_E + \delta_{MS}P_S\right), \end{aligned} \tag{4.32}$$

and

$$G \equiv P_S + \gamma_{SS}\left(P_{N_1}B_1^{-1} + P_{N_2}B_2^{-1} + P_{N_3}B_3^{-1} + P_{N_4}B_4^{-1} + P_E + P_M\right). \tag{4.33}$$

With respect to changes in relative prices, cross-price elasticities of demand are of interest, too. The short run price elasticity of N_i with respect to P_{N_h} is

$$e_{N_iN_h}^{SR} \equiv \frac{\partial N_i}{\partial P_{N_h}}\frac{P_{N_h}}{N_i} = e_{L_iL_h}^{SR} = \frac{1}{2}\frac{\alpha_{L_iL_h}\left(\frac{P_{N_h}B_h^{-1}}{P_{N_i}B_i^{-1}}\right)^{\frac{1}{2}}}{X_i^{SR}}. \tag{4.34}$$

If $\alpha_{L_iL_h}$ and, hence, $e_{N_iN_h}^{SR}$, is positive (negative) if level i and level h labor are substitutes (complements). The long run cross–price elasticity is

$$e^{LR}_{N_iN_h} = e^{SR}_{N_iN_h} + \eta^{LR}_{N_iS^*} \cdot e^{LR}_{S^*N_h} \tag{4.35}$$

where $e^{SR}_{N_iN_h}$ and $\eta^{LR}_{N_iS^*}$ are given by (4.34) and (4.30), respectively, and $e^{LR}_{S^*N_h}$ can be obtained from (4.31) by substituting h for i.

To compute the skill biases in technical change, we first need the rates of cost diminution induced by technical change. These are defined according to

$$\tau^{SR}_C \equiv \frac{\partial VC}{\partial t}\frac{1}{VC} \tag{4.36}$$

and

$$\tau^{LR}_C \equiv \frac{\partial TC^*}{\partial t}\frac{1}{TC^*} \tag{4.37}$$

in the short run and long run respectively.[25] Secondly, we need the changes in the demand for the various categories of labor, induced by technical change:

$$\tau^{\Phi R}_i \equiv \frac{\partial L^{\Phi R}_i}{\partial t}\frac{1}{L^{\Phi R}_i} = \frac{\partial N^{\Phi R}_i}{\partial t}\frac{1}{N^{\Phi R}_i} = \frac{\lambda_{L_it}}{X^{\Phi R}_i}, \quad \Phi = S, L, \quad i = 1, 2, 3, 4. \tag{4.38}$$

Thus, the estimate of λ_{L_it} indicates whether technical change has increased or decreased the demand for labor in category i. The skill biases (SB) are

$$SB^{\Phi R}_i \equiv \tau^{\Phi R}_i - \tau^{\Phi R}_C, \quad \Phi = S, L, \quad i = 1, 2, 3, 4. \tag{4.39}$$

A negative skill bias means that technical change decreases the demand for level i labor at a faster rate than it saves on costs. Equivalently, technical change

[25] The negatives of (4.36) and (4.37) are the short run and long run *dual rates of technical change*, respectively. These are closely related to the short and long run rates of growth in total factor productivity, (TFP). Indeed, due to the assumption of long run returns to scale, the long run rate of growth in TFP is equal to (4.37). The short run rate of growth in TFP is obtained by multiplying (4.36) with the *dual rate of return to scale*, given by the inverse of the elasticity of variable cost with respect to output, i.e. $[(\partial VC/\partial Y)(Y/VC)]^{-1}$. On these equalities, see Ohta (1975).

reduces the demand for type i labor more than it reduces the demand for all inputs, weighted by their respective cost shares. A positive bias implies that technical change increases demand relative to a cost-share weighted average of all inputs. Note that the bias may be positive even if $\tau_i^{\Phi R} < 0$.

5. The estimation procedure

While the theoretical model concerns a single firm, the application will be to aggregates of firms, belonging to different industries. Due to the assumption of long-run constant returns to scale, this is not a problem with respect to aggregation conditions. Industry-specific characteristics must be allowed for, however.

The estimation of the model raises two problems. First, the analysis is partial in nature, in that only the demand side is modeled. This makes endogeneity problems highly likely. In particular, the model's assumption of exogenously given input prices and level of output can be questioned. Second, the model is strongly non-linear in the parameters, due to the specification of effective labor.

A two-stage approach is used that takes care of both of these problems. In the first step, instruments and the labor quality indexes are estimated simultaneously. This yields improved instruments and, moreover, second stage input demand equations that are linear in the parameters.

5.1. Estimation of instruments and quality indexes

Instruments are constructed for output and all variable input prices, except the price for equipment capital. By construction, the capital prices only incorporate historical information, cf. (2.2), and can thus be treated as predetermined.[26]

Explanatory variables in the instrument equations are t, S, P_E, once-lagged

[26] Regarding output, most Swedish manufacturing firms compete in world markets for (relatively) homogenous goods, where output *prices* can be taken as exogenously given. The firm's output choice must thus concern the volume of output which, hence, becomes endogenous.

values of the P_{N_i}, P_M and Y, and the variables used to model the B_i indexes. The latter variables could, in principle, be included linearly in the regressions. However, to ascertain that the equality (4.3) holds, the wage instruments are first specified in terms of effective labor costs, the P_{L_i}, and then respecified in terms of the observed labor costs, the P_{N_i}. We thus start with the following system:

$$\begin{bmatrix} P_{L_1} \\ P_{L_2} \\ P_{L_3} \\ P_{L_4} \\ P_M \\ Y \end{bmatrix} = \mathbf{A} \begin{bmatrix} 1 \\ t \\ S \\ P_E \\ L(P_{L_1}) \\ L(P_{L_2}) \\ L(P_{L_3}) \\ L(P_{L_4}) \\ L(P_M) \\ L(Y) \end{bmatrix} + \mathbf{u} \tag{5.1}$$

where $\mathbf{A}$ is a 6×10 matrix of coefficients, L is the lag operator, and $\mathbf{u}$ is a 6×1 vector of residuals. By means of (4.3), we can rewrite (5.1) according to

$$\begin{bmatrix} P_{N_1} \\ P_{N_2} \\ P_{N_3} \\ P_{N_4} \\ P_M \\ Y \end{bmatrix} = \begin{bmatrix} B_1 \mathbf{a}_{1\bullet} \\ B_2 \mathbf{a}_{2\bullet} \\ B_3 \mathbf{a}_{3\bullet} \\ B_4 \mathbf{a}_{4\bullet} \\ \mathbf{a}_{5\bullet} \\ \mathbf{a}_{6\bullet} \end{bmatrix} \begin{bmatrix} 1 \\ t \\ S \\ P_E \\ L(P_{N_1}/B_1) \\ L(P_{N_2}/B_2) \\ L(P_{N_3}/B_3) \\ L(P_{N_4}/B_4) \\ L(P_M) \\ L(Y) \end{bmatrix} + \begin{bmatrix} B_1 u_1 \\ B_2 u_2 \\ B_3 u_3 \\ B_4 u_4 \\ u_5 \\ u_6 \end{bmatrix} \tag{5.2}$$

where the B_i are given by (4.8) and $\mathbf{a}_{k\bullet}$ denotes the kth row of the matrix $\mathbf{A}$. In contrast to (5.1) this system is expressed in terms of observable variables only.

The substitution of $P_{N_i}B_i^{-1}$ for P_{L_i} $i = 1, 2, 3, 4$, imposes cross-equation constraints on the system (5.2), through the B_i. To take these into account, the estimation is carried out by means of full information maximum likelihood *(FIML)*, under the assumption that the disturbances are joint normally distributed.[27]

To ascertain that the B_i indexes are equal to unity in the base-year, constraints like (4.7) are imposed on the parameters of each of the distributions included in the indexes. This involves a choice of the share whose parameter is to be solved for. For a given distribution, the share has been chosen so as to minimize the multicollinearity among the remaining shares.[28]

The parameters of the B_i indexes are allowed to vary with across educational levels, with one exception, the distributions over work hours. The reason is that the only variation in these distributions between levels of education come from differences in gender composition; cf. Section 3.

Two constraints have also been imposed on the general form (4.8) of the B_i, in order to facilitate the estimation and the interpretation of the results. First, for a given B_i, the included distributions have all been given the same weight, i.e. $\nu_{ij} = \frac{1}{J_i}, \quad j = 1, ..., J_i, \quad i = 1, 2, 3, 4$. Accordingly, for B_3 and B_4, $\nu_{3j} = \nu_{4j} = \frac{1}{5} = 0.2$ while, for B_1 and B_2, $\nu_{1j} = \nu_{2j} = \frac{1}{4} = 0.25$ because the fields-of-study distributions for educational levels 1 and 2 are degenerate; cf. Table 2. Second, the elasticity of substitution between different characteristics has been set equal across educational levels, i.e. $\rho_i = \rho, \quad i = 1, 2, 3, 4$, and ρ has been estimated by

[27] The transformation of the system (5.1) into (5.2) also makes the residuals in the latter system heteroscedastic. The heteroscedasticity will, however, be disregarded, as it does not affect the consistency of the estimates, but only their efficiency.

[28] In practice, for a n-category distribution there are $\binom{n}{n-1} \times \binom{n-1}{n-2}$ possible regression where one of n shares can be regressed on $n-2$ of the other shares. For instance, for the age distributions there are $\binom{4}{3} \times \binom{3}{2} = 12$ possible regressions where one share can be regressed on two other shares. Given these regressions we have applied a minimax criterion (minimize the maximal R^2 among the other shares) to determine the share whose parameter is to be constrained.

means of a grid search procedure.[29]

Given these constraints, the system (5.2) contains altogether 87 parameters. The number of degrees of freedom available for their estimation is given by: # equations × # industries × # years, i.e. $6 \times 24 \times 10 = 1440$.

5.2. Estimation of the cost function

To obtain the cost function's parameters, the instruments (i.e. the predicted values) $\hat{P}_{N_i}$, $i = 1, ..., 4$, $\hat{P}_M$, and $\hat{Y}$ are substituted in the equations (4.12)–(4.15), together with the estimated B_i indexes.

The parameters λ_{L_i0}, $i = 1, 2, 3, 4$, λ_{E0}, and λ_{M0} are allowed to vary across industries, to capture industry-specific fixed effects. The shadow price equation contains no industry-specific parameters. However, it has been necessary to include an *a priori* intercept in this equation.[30] This is so because the ex post return (4.16) used for the shadow price is sometimes negative, which is inconsistent with the underlying theory. Presumably, this is due to the costs for intermediate goods being overestimated in the national accounts.[31] Assuming that this error only has a level effect on the shadow price we impose a negative intercept (equal to -0.03) that has the effect of making the *predicted* shadow prices positive.

Including dummy variables in labor demand equations to adjust for reclassifications that have taken place in the labor statistics during the period (in 1989 and 1990), the seven equation system contains about 180 parameters to estimate. The available degrees of freedom, computed in analogy with the previous subsection, are equal to $7 \times 24 \times 10 = 1680$. The estimation is carried out using $FIML$, assuming the residuals to be joint normally distributed.

[29] This amounts to carrying out the estimation of the system (5.2) with ρ set to different values and choosing the value at which the likelihood for the entire system is maximized.

[30] Note that, as specified in (4.15) the shadow price equation contains no intercept.

[31] Discussions with Statistics Sweden support this conjecture.

6. Results

6.1. Parameter estimates and goodness-of-fit measures

The results from the estimation of the system (5.2) are provided in Tables 4a-b. With respect to Table 4a, two things can be noted. First, goodness-of-fit, as measured by Haessel's R2, is high, implying that the instruments fulfill the requirements that they be highly correlated with the variables they replace.[32]

Table 4a: Results for the instruments regressions; the coefficients of the A matrix. Standard errors in parenthesis.

	Dependent variables					
	P_{N1}	P_{N2}	P_{N3}	P_{N4}	P_M	Y
Constant	-2.33*** (0.302)	-1.53*** (0.297)	-2.20*** (0.289)	-2.03*** (0.433)	-4.41*** (0.694)	11553 (50081)
t	2.71*** (0.351)	1.79*** (0.344)	2.58*** (0.335)	2.52*** (0.503)	5.60*** (0.805)	-1486 (57899)
S	2.2 E-6 (2.9 E-6)	-5.6 E-8 (3.0 E-6)	8.7 E-7 (2.9 E-6)	-3.3 E-6 (4.2 E-6)	7.9 E-6 (7.0 E-6)	-0.636 (0.503)
P_E	0.015 (0.011)	0.022** (0.011)	0.029*** (0.011)	0.028* (0.016)	-0.033 (0.026)	-5978*** (1869)
$L(P_{N1}/B_1)$	0.933*** (0.088)	0.200** (0.090)	0.055 (0.086)	0.034 (0.126)	0.160 (0.209)	67735*** (14996)
$L(P_{N2}/B_2)$	-0.268*** (0.071)	0.364*** (0.075)	-0.2666*** (0.072)	-0.197* (0.106)	0.155 (0.173)	27867** (12385)
$L(P_{N3}/B_3)$	-0.230** (0.100)	-0.054 (0.101)	0.538*** (0.097)	-0.192 (0.143)	-1.164*** (0.231)	-102806*** (16504)
$L(P_{N4}/B_4)$	0.178*** (0.046)	0.242*** (0.047)	0.246*** (0.046)	0.768*** (0.066)	0.371*** (0.111)	-2966 (7955)
$L(P_M)$	0.027 (0.017)	0.011 (0.047)	0.041** (0.017)	0.055** (0.025)	0.263*** (0.041)	4150 (2923)
L(Y)	-5.9 E-8 (1.1 E-7)	1.3 E-8 (1.2 E-7)	-9.5 E-9 (1.1 E-7)	2.3 E-7 (1.6 E-7)	-2.9 E-7 (2.7 E-7)	1.044*** (0.019)
N Haessel's R^2	240 0.99	240 0.99	240 0.99	240 0.98	240 0.90	240 0.99

Note:

a) Significance level are denoted according to * = 10%, ** = 5%, *** = 1%.

[32] Unlike the conventional R2, the R2 measure suggested by Haessel (1978) is applicable non-linear as well as linear models and has the advantage of always belonging to the [0,1] interval.

Secondly, the table gives some indication about the validity of using lagged variables as instruments. For a given equation, a coeffcient of the lagged endoge-nous variable close to one signals a high degree of autocorrelation in the variable. This puts the validity of using the lagged variable as an instrument into question. Only in the equations for P_{N1} and Y are the coeffcients for the lagged variables close to 1. And in these equations there are several other significant variables, beside the lagged endogenous variables, which should mitigate the problem. Table 4b shows that the age distributions are important for the quality indexes.

Table 4b: Results for the instruments regressions; the coefficients of the B_i indexes. Standard errors in parenthesis.

	B1	B2	B3	B4
Age				
16-29	2.21 (1.52)	*-0.99*	*-1.23*	*-2.44*
30-39	1.61** (0.66)	0.78*** (0.13)	0.27 (0.32)	-0.37 (0.39)
40-49	0.63*** (0.14)	-0.69** (0.19)	1.52*** (0.32)	2.13*** (0.46)
50-74	*-0.54*	1.87*** (0.41)	0.09 (0.28)	1.40** (0.63)
Sex				
Male	0.13*** (0.04)	0.18*** (0.07)	0.48*** (0.09)	0.11 (0.16)
Female	*-0.38*	*-0.43*	*-1.60*	*-0.47*
Immigrant				
No	0.01 (0.02)	0.03 (0.03)	-0.16*** (0.04)	0.07 (0.07)
Yes	*-0.31*	*-0.46*	*3.04*	*-0.98*
Fields-of-Study				
FoS1	--	--	1.68** (0.67)	--
FoS2	--	--	-0.71 (0.54)	1.50*** (0.29)
FoS3	--	--	*0.14*	*0.43*
FoS4	--	--	-0.78 (0.57)	-3.28*** (0.60)
Weekly Hours				
1-19	-0.20 (0.56)	-0.20 (0.56)	-0.20 (0.56)	-0.20 (0.56)
20-34	0.10 (0.22)	0.10 (0.22)	0.10 (0.22)	0.10 (0.56)
35-	*-0.01*	*-0.01*	*-0.01*	*-0.01*

Notes:

a) Significance level are denoted according to * = 10%, ** = 5%, *** = 1%.

b) By italics are denoted weighted averages of the industry-specific constrained estimates in each distribution. Relevant employment shares in 1991 have been used as weights.

c) Regarding the distribution weights and the substitution elasticity parameter, see the text.

The 40–49 year olds are especially noteworthy: at all levels of education their contribution to effective labor differs significantly from their weight in the age distribution. At all levels but level 2 they contribute more than indicated by their share in employment. The gender and fields-of-study distributions also affect the indexes. The immigrant/non-immigrant and, in particular, the work hour distributions are not important for the indexes, however. Thus, controlling for the other characteristics, it does not seem necessary to account for part-time work in the sense that those working part-time contribute to effective labor in accordance with their share in employment.[33]

The substitution parameter ρ is found to be 0.45. By (4.9), this translates into an elasticity of substitution approximately equal to 0.69, implying that there is a non-negligible degree of substitutability between different characteristics.

The estimates of the cost function's parameters are provided in Table 5. Most of the parameters are precisely estimated. Haessel's R^2 measures indicate that the model fits the data very well, especially with respect to the labor demand equations (the $N_i/Y-$ equations) and the equation for equipment demand (E/Y). With respect to the intermediate goods (M/Y) and the shadow price equations (Z_S) the R^2's are somewhat less impressive but, nevertheless, quite high considering the fact that the modeling of industry-specific effects is limited to allowing the intercepts in the first seven equations to vary by industry.[34]

The estimates of the $\lambda_{L_i t}$, which determine the effects of technical change on labor demands, are all significant. Their signs indicate that technical change is reducing the demand for workers with the three lowest levels of education. Only for individuals with some university education does technical change increase demand. These results support the skill-biased technical change hypothesis.

[33] Unfortunately, three estimates are well below -1; the coefficient for females in index B_3 and, in index B_4, the coefficients for 16–29 year olds and the fields-of-study category FoS4. The implication is that these categories contribute negatively to effective labor. These counter-intuitive results have probably been caused by multicollinearity among the different characteristics.

[34] More precisely, the $\lambda_{L_i 0}$, $i = 1, 2, 3, 4$, the $\lambda_{E 0}$, and the $\lambda_{M 0}$ are industry-specific.

Table 5: The cost function parameters. Standard errors in parentheses.

λ_{L_1t}	-0.00441^{***}	α_{L_1E}	0.00807	α_{L_4M}	0.05972^{**}
	(0.00071)		(0.00560)		(0.02741)
λ_{L_2t}	-0.00165^{***}	α_{L_1M}	$= 0.0$	α_{EM}	$= \alpha_{L_2M}$
	(0.00033)	$\alpha_{L_2L_3}$	-0.02009	γ_{SS}	0.01024^{***}
λ_{L_3t}	-0.00287^{***}		(0.02343)		(0.00188)
	(0.00089)	$\alpha_{L_2L_4}$	0.01410	δ_{L_1S}	-0.13420^{***}
λ_{L_4t}	0.00111^{*}		(0.01681)		(0.01450)
	(0.00061)	α_{L_2E}	0.00834^{***}	δ_{L_2S}	0.00630
λ_{Et}	-0.00022		(0.00274)		(0.00612)
	(0.00041)	α_{L_2M}	-0.01757^{**}	δ_{L_3S}	0.13072^{***}
λ_{Mt}	-0.00740^{***}		(0.00801)		(0.01865)
	(0.00024)	$\alpha_{L_3L_4}$	0.05144	δ_{L_4S}	0.04888^{***}
$\alpha_{L_1L_2}$	0.09035^{***}		(0.03899)		(0.01602)
	(0.02143)	α_{L_3E}	0.01858^{**}	δ_{ES}	0.00983
$\alpha_{L_1L_3}$	0.17898^{***}		(0.00735)		(0.00677)
	(0.06209)	α_{L_3M}	$= 0.0$	δ_{MS}	-0.10149^{***}
$\alpha_{L_1L_4}$	-0.10101^{***}	α_{L_4E}	0.00037		(0.01598)
	(0.03448)		(0.00560)		

Haessel's	N_1/Y	0.898	E/Y	0.929
(1978)	N_2/Y	0.906	M/Y	0.620
R^2 :	N_3/Y	0.888	Z_S	0.555
	N_4/Y	0.960		

Notes:
a) *, **, and *** denote signicantly different from 0 at the 10%, 5%, and 1% level.
b) To save space, the industry-specific estimates of λ_{L_i0}, $i = 1, 2, 3, 4$, λ_{E0}, and λ_{M0}, and coefficients adjusting for reclassifications in the labor statistics are not reported.
c) The parameters $\alpha_{L_1M}, \alpha_{L_3M}$ and α_{EM} are constrained, as indicated in the table.

The short-run cross-price elasticities of demand are determined by the $\alpha-$ parameters; if $\alpha_{ij} > 0$ (< 0) for $i \neq j$ then the inputs i and j are short-run substitutes (complements); cf. (4.34). The precision in the estimates of these parameters give a good indication of the precision in the estimated short-run cross-price elasticities. Regarding the α_{L_iM}, it can be seen that $\alpha_{L_2M} < 0$ and significant, indicating short-run complementarity between level 2 workers and intermediate goods. To the extent that imports from low-wage countries constitute a non-negligible share of intermediate goods this result is not in line with the trade hypothesis, according to which low-skilled workers and such imports are substitutes.[35]

In order to ascertain that the own-price elasticity of demand for intermediate goods is negative, as required by the regularity conditions, it has been necessary to impose constraints on α_{L_1M}, α_{L_3M}, and α_{EM}; cf. Table 6. A LR test of these constraints is rejected at the 5 % level of significance, implying that, taken together, the restrictions are not supported by the data. Fortunately, they do not affect individual estimates very much, however. Of all the estimates in Table 5 only one, that of α_{EM}, is significantly different from the unrestricted estimates.[36]

To be well-behaved, the cost function should also be decreasing and convex in the quasi-fixed factor, i.e. in S. The necessary conditions for these properties are that $\gamma_{SS} > 0$ and at least one of the $\delta-$parameters are negative, indicating that the corresponding variable input and structures are long-run substitutes. From Table 6 it is clear that these conditions are satisfied and closer examination of the results show that cost function is indeed decreasing and convex in S.[37] The estimates of the δ_{L_iS} provide support for the capital/skill-complementarity hypothesis; level 1 workers and structures are substitutes, at level 2 they are neither substitutes nor complements, and at levels 3 and 4 they are complements.

[35] Unfortunately, there is no information about the import content of intermediate goods.

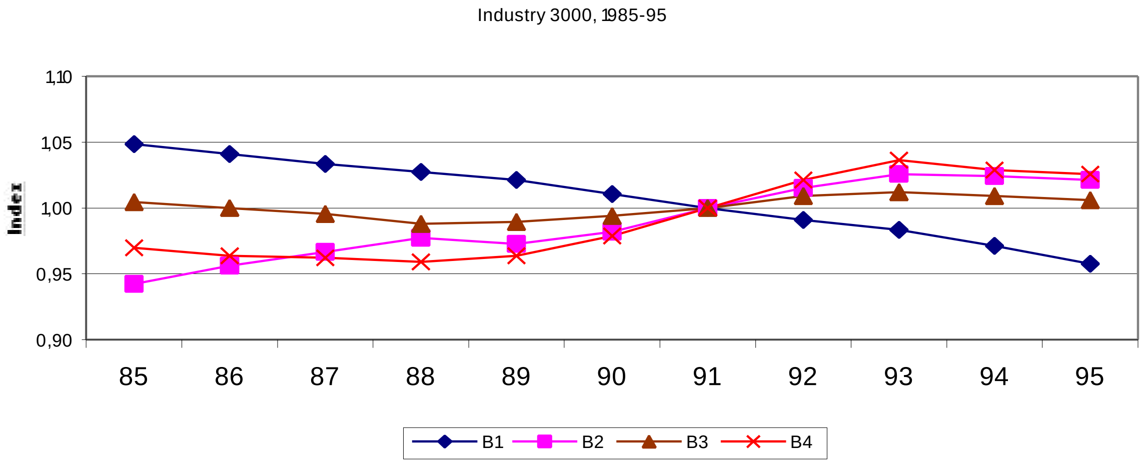
[36] The unrestricted estimates are not reported here but are available on request.

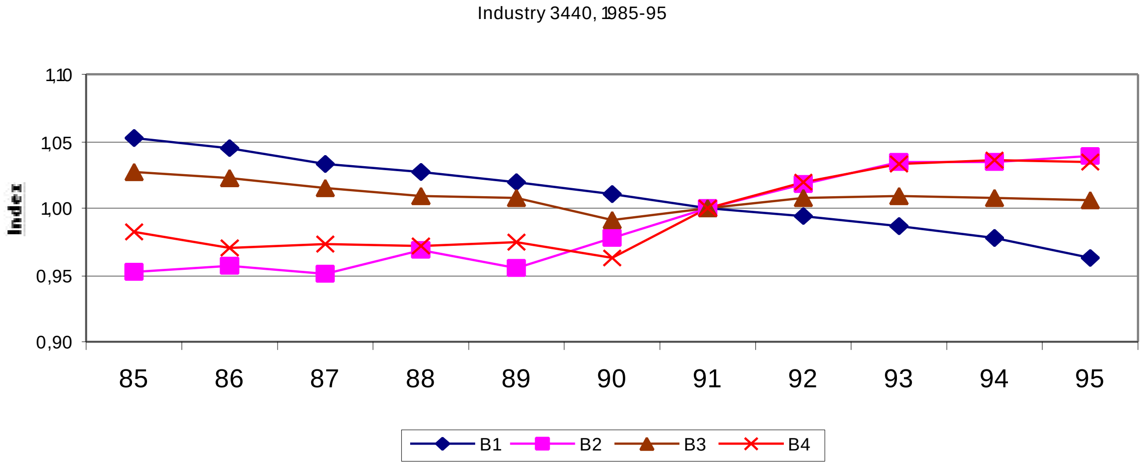
[37] The closer examination involves evaluating the estimated shadow prices for structures and the second order derivatives of the variable cost function at all points in time, for all industries.

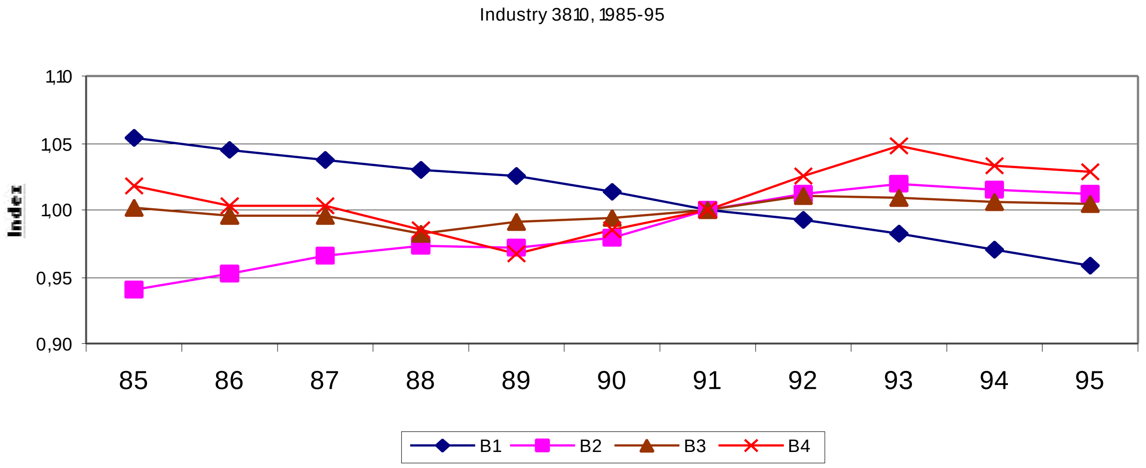
6.2. Efects of labor quality characteristics and relative prices

The estimated quality indexes are plotted in Diagram 4.

Diagram 4: Labor efficiency indexes by educational level, for the whole manufacturing sector and two selected industries.







For the manufacturing sector as a whole, the index for level 1 workers deteriorates steadily from 1.05 in 1985 to 0.95 in 1995, i.e. with 1 percentage point per year. This development is due to the fact that the workers under 50, which contribute more than proportionally to effective labor, have decreased their share while the opposite is true for the oldest employees, the 50–74 year olds, which contribute less than proportionally to effective labor; cf. Table 4b and Table 3.

For level 2 workers the quality index has instead increased, from about 0.94 to around 1.02. Tables 4b and 3 show that in this category, changes in the age distribution have had the effect of increasing effective labor input. For workers with upper secondary school (level 3), the index fluctuates around 1, implying that effective labor has been roughly constant compared to the base-year, 1991, level. The quality index for employees with some university education, finally, has increased slightly over the period, from around 0.97 to 1.02, i.e. by 0.5 percentage points per year. Here, favorable changes in the age distribution have been reinforced by shifts in the fields-of-study distribution.

The importance of the quality indexes can be tested by means of a likelihood ratio (LR) test of the constraint $B_i = 1 \; \forall \, i$, imposed on the system (5.2). This constraint is strongly rejected; the LR statistic is 24.3 and the number of degrees of freedom is equal to 27, implying a significance level below 0.5 %.

To illustrate the demand effects of changes in labor quality characteristics, assume that measures are taken to counteract the decreasing shares of 16-29 year olds and the increasing shares of 50-74 year olds in the manufacturing sector as a whole. Specifically, assume that in the base-year 1991 the number of individuals in the former age interval is increased by 2000 and that the latter group is reduced by the same number. In relative terms, these changes correspond to approximately a 1 % increase and a 1 % decrease, respectively. Assume, further, that these changes are evenly spread across educational levels; at each level the number of 16-29 year olds is increased by 500 and the number of 50-74 year olds reduced by 500. Application of (4.25), (4.28), and Appendix B yields the following results.

Table 6: Labor demand effects in 1991 of replacing 500 individuals aged 50-74 by 16-29 year olds, in the manufacturing sector as a whole.

a: Short run effects

Industry 3000	N1	N2	N3	N4	Total
%	-0.61	+0.56	+0.07	+0.45	+0.06
#	-1046	+760	+276	+495	+485

b: Long run effects

Industry 3000	N1	N2	N3	N4	Total
%	-0.54	+0.59	+0.09	+0.57	+0.05
#	-1256	+774	+306	+540	+364

The intuition is provided by the estimates in Table 4b. For Level 1, the change means reducing a category of workers which contributes less than proportionally to effective labor and increasing a category contributing more than proportionally. It seems reasonable that this should decrease the total demand for level 1 workers, which is just what happens. For levels 2, 3, and 4 the parameters have the opposite signs, which leads to demand increases. Summation across educational levels shows that the effect on *total* labor demand is positive, too.

Short-run and long-run price elasticities of demand for 1986, 1991 and 1995 are reported in Tables 7, 8, and 9, respectively, for the whole manufacturing sector (3000), Printing and Publishing (3440), and Metal Products (3810).[38]

[38] Elasticities for all 24 industries during 1986-95 are available on request.

Table 7: Price elasticities of demand in 1986 for the whole manufacturing sector and two selected industries.

a: Short run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-1.18	0.61	1.21	-0.71	0.06	0.00
N2	0.99	-0.82	-0.23	0.16	0.11	-0.21
N3	0.72	-0.08	-0.95	0.22	0.09	0.00
N4	-1.33	0.19	0.69	-0.43	0.01	0.88
E	0.05	0.06	0.13	0.00	-0.11	-0.13
M	0.00	-0.01	0.00	0.04	-0.01	-0.02

Industry 3440	N1	N2	N3	N4	E	M
N1	-1.15	0.59	1.18	-0.69	0.07	0.00
N2	0.67	-0.57	-0.15	0.11	0.08	-0.14
N3	0.53	-0.06	-0.7	0.16	0.07	0.00
N4	-0.85	0.12	0.45	-0.26	0.00	0.54
E	0.06	0.06	0.14	0.00	-0.12	-0.14
M	0.00	-0.01	0.00	0.05	-0.02	-0.02

Industry 3810	N1	N2	N3	N4	E	M
N1	-0.85	0.44	0.87	-0.51	0.05	0.00
N2	0.71	-0.60	-0.16	0.12	0.09	-0.15
N3	0.50	-0.06	-0.66	0.15	0.07	0.00
N4	-1.77	0.25	0.92	-0.57	0.01	1.15
E	0.06	0.06	0.14	0.00	-0.12	-0.14
M	0.00	-0.01	0.00	0.05	-0.02	-0.02

b: Long run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-1.69	0.65	1.75	-0.49	0.13	-0.47
N2	1.06	-0.83	-0.3	0.13	0.1	-0.15
N3	1.12	-0.11	-1.37	0.05	0.04	0.37
N4	-0.8	0.15	0.13	-0.67	-0.07	1.38
E	0.12	0.05	0.06	-0.03	-0.12	-0.07
M	-0.05	-0.01	0.05	0.06	-0.01	-0.06

Industry 3440	N1	N2	N3	N4	E	M
N1	-1.66	0.62	1.72	-0.47	0.15	-0.45
N2	0.71	-0.57	-0.20	0.09	0.08	-0.10
N3	0.82	-0.08	-1.01	0.04	0.03	0.26
N4	-0.52	0.10	0.10	-0.41	-0.05	0.83
E	0.14	0.06	0.06	-0.03	-0.14	-0.07
M	-0.05	-0.01	0.06	0.07	-0.01	-0.06

Industry 3810	N1	N2	N3	N4	E	M
N1	-1.26	0.47	1.30	-0.33	0.12	-0.37
N2	0.75	-0.60	-0.21	0.09	0.08	-0.11
N3	0.78	-0.08	-0.96	0.03	0.02	0.26
N4	-0.97	0.20	0.07	-0.92	-0.12	1.89
E	0.15	0.06	0.05	-0.04	-0.14	-0.07
M	-0.06	-0.01	0.06	0.08	-0.01	-0.07

Table 8: Price elasticities of demand in 1991 for the whole manufacturing sector and two selected industries.

a: Short run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-2.04	1.04	2.06	-1.16	0.09	0.00
N2	1.37	-1.14	-0.30	0.21	0.13	-0.27
N3	0.83	-0.09	-1.06	0.24	0.09	0.00
N4	-1.17	0.16	0.59	-0.28	0.00	0.69
E	0.06	0.06	0.00	0.00	-0.14	-0.14
M	0.00	-0.01	0.00	0.05	-0.01	-0.02

Industry 3440	N1	N2	N3	N4	E	M
N1	-2.07	1.06	2.1	-1.19	0.1	0.00
N2	0.86	-0.72	-0.19	0.13	0.08	-0.17
N3	0.60	-0.07	-0.76	0.17	0.06	0.00
N4	-0.78	0.11	0.40	-0.19	0.00	0.46
E	0.07	0.07	0.16	0.00	-0.16	-0.15
M	0.00	-0.02	0.00	0.05	-0.02	-0.02

Industry 3810	N1	N2	N3	N4	E	M
N1	-1.23	0.63	1.24	-0.7	0.06	0.00
N2	0.92	-0.76	-0.20	0.14	0.08	-0.18
N3	0.56	-0.06	-0.72	0.16	0.06	0.00
N4	-1.47	0.21	0.75	-0.35	0.01	0.86
E	0.07	0.08	0.17	0.00	-0.16	-0.16
M	0.00	-0.02	0.00	0.05	-0.02	-0.02

b: Long run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-2.63	1.08	2.64	-0.94	0.14	-0.44
N2	1.44	-1.15	-0.37	0.19	0.12	-0.22
N3	1.20	-0.11	-1.42	0.10	0.05	0.28
N4	-0.82	0.14	0.25	-0.41	-0.03	0.95
E	0.11	0.06	0.10	-0.02	-0.14	-0.10
M	-0.04	-0.01	0.04	0.06	-0.01	-0.05

Industry 3440	N1	N2	N3	N4	E	M
N1	-2.72	1.10	2.75	-0.94	0.15	-0.48
N2	0.91	-0.72	-0.23	0.12	0.08	-0.14
N3	0.86	-0.08	-1.02	0.07	0.04	0.19
N4	-0.55	0.09	0.17	-0.27	-0.02	0.63
E	0.13	0.07	0.11	-0.02	-0.16	-0.11
M	-0.05	-0.01	0.05	0.07	-0.01	-0.06

Industry 3810	N1	N2	N3	N4	E	M
N1	-1.62	0.65	1.63	-0.55	0.09	-0.29
N2	0.96	-0.77	-0.25	0.13	0.08	-0.15
N3	0.80	-0.08	-0.96	0.07	0.04	0.18
N4	-1.01	0.18	0.29	-0.52	-0.03	1.20
E	0.13	0.07	0.11	-0.02	-0.17	-0.12
M	-0.05	-0.01	0.05	0.07	-0.01	-0.06

Table 9: Price elasticities of demand in 1995 for the whole manufacturing sector and two selected industries.

a: Short run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-3.60	1.83	3.57	-1.95	0.15	0.00
N2	1.77	-1.47	-0.38	0.26	0.15	-0.33
N3	0.97	-0.11	-1.22	0.26	0.09	0.00
N4	-1.17	0.16	0.58	-0.23	0.00	0.66
E	0.06	0.07	0.14	0.00	-0.14	-0.14
M	0.00	-0.01	0.00	0.05	-0.01	-0.02

Industry 3440	N1	N2	N3	N4	E	M
N1	-4.05	2.07	4.06	-2.24	0.16	0.00
N2	1.01	-0.83	-0.22	0.15	0.08	-0.19
N3	0.65	-0.07	-0.81	0.18	0.06	0.00
N4	-0.74	0.1	0.37	-0.17	0.00	0.43
E	0.08	0.08	0.18	0.00	-0.18	-0.17
M	0.00	-0.02	0.00	0.05	-0.01	-0.02

Industry 3810	N1	N2	N3	N4	E	M
N1	-1.7	0.86	1.69	-0.93	0.07	0.00
N2	1.06	-0.87	-0.23	0.15	0.09	-0.2
N3	0.61	-0.07	-0.77	0.17	0.06	0.00
N4	-1.48	0.2	0.73	-0.3	0.01	0.84
E	0.08	0.08	0.18	0.00	-0.18	-0.17
M	0.00	-0.02	0.00	0.06	-0.02	-0.02

b: Long run elasticities

Industry 3000	N1	N2	N3	N4	E	M
N1	-6.01	2.01	5.88	-1.11	0.36	-1.65
N2	1.95	-1.48	-0.55	0.20	0.13	-0.21
N3	1.63	-0.16	-1.85	0.03	0.04	0.45
N4	-0.64	0.12	0.06	-0.42	-0.04	1.03
E	0.17	0.06	0.06	-0.03	-0.15	-0.07
M	-0.07	-0.01	0.07	0.07	-0.01	-0.07

Industry 3440	N1	N2	N3	N4	E	M
N1	-6.34	2.23	6.35	-1.38	0.33	-1.68
N2	1.11	-0.84	-0.32	0.11	0.07	-0.12
N3	1.11	-0.11	-1.27	0.01	0.02	0.34
N4	-0.39	0.08	0.02	-0.30	-0.02	0.69
E	0.19	0.07	0.08	-0.04	-0.18	-0.10
M	-0.08	-0.01	-0.01	0.08	-0.01	-0.08

Industry 3810	N1	N2	N3	N4	E	M
N1	-2.86	0.95	2.81	-0.51	0.16	-0.82
N2	1.17	-0.88	-0.33	0.12	0.08	-0.12
N3	1.04	-0.10	-1.17	0.02	0.02	0.30
N4	-0.79	0.15	0.07	-0.54	-0.05	1.32
E	0.20	0.08	0.07	-0.04	-0.19	-0.09
M	-0.09	-0.01	0.08	0.09	-0.01	-0.09

The own-price elasticities are on the main diagonal of the tables. The lower the levels of education, the higher are the own-price elasticities, which is what one would expect.[39] While there are considerable differences across industries, a common feature is that there are time trends in the elasticities; with respect to N_1, N_2, and N_3 they increase in magnitude over time whereas the opposite is true for N_4. At the end of the period, for the manufacturing sector as a whole, demand is elastic for labor with at most upper secondary school, i.e. the own-price elasticities are below -1 for these categories. Except for level 2 labor, the long-run own-price elasticities are distinctly larger in magnitude than the short-run elasticities. Note that the own-price elasticities for equipment (E) and intermediate goods (M) are much smaller than for all categories of labor.

The off-diagonal elements are the cross-price elasticities. These are not symmetric. Consider, e.g., the short-run cross-price elasticities between labor with educational levels 1 and 3 in 1995, for the manufacturing sector as a whole. The element in column 1, row 3, of Table 9a says that a 1 % increase in the wage of level 1 labor increases demand for level 3 labor by 0.97 %. The row 1, column 3, element, on the other hand, says that a 1 % increase in the wage of level 3 labor increases demand for level 1 labor by 3.57 %. These elasticities seem very different, but to a large extent they reflect differences in employment levels.[40]

Most pairs of labor are found to be substitutes. This is especially true for level 1 and level 2 labor; for the manufacturing sector as a whole both the short-run and the long-run cross-price elasticities are larger than 1 in 1991 and in 1995. The cross-price elasticities for level 1 and level 3 labor are also quite high. In contrast, labor with educational levels 1 and 4 are found to be complements. Possibly, this

[39] With respect to the long-run elasticities the relationship is not completely monotonic, however. The elasticities for level 2 labor are somewhat larger in magnitude than for level 3 labor.

[40] The predicted employment is 115,208 for level 1 labor and 394,193 for level 3 labor. Accordingly, a 1 % increase in the wage of level 3 labor increases demand for level 1 labor by $0.037 \times 115,208 = 4,113$ individuals, while a 1 % increase in the level 1 wage increases demand for level 3 labor by $0.0097 \times 394,193 = 3,824$ individuals.

has to do with restructuring. It might be that when introducing new equipment, the predominantly young level 4 workers need the experience that the mostly older level 1 workers have with the obsolete systems to be replaced.[41]

The high own-price and cross-price elasticities of demand for low-skilled labor indicate that small wage changes for these groups will have substantial effects on demand. To illustrate, consider the following experiments. The labor cost of either level 1 or level 2 labor can be cut by 1 %, in 1995. With respect to the manufacturing sector as a whole, which of these measures has the most favorable effect on the total demand for these two categories of labor? The total demand effect on level 1 and level 2 workers from a 1 % decrease in the wage of level i is

$$e^{\Phi R}_{N_i N_i} \times N_i^{\Phi R} - e^{\Phi R}_{N_h N_i} \times N_h^{\Phi R}, \qquad i, h = 1, 2, \qquad \Phi = S, R.$$

The short run predicted employment for level 1 and level 2 workers are $115,208$ and $119,872$, respectively. Thus, by Table 9a the short run demand effect of a 1 percent wage cut for level 1 workers is $0.0360 \times 115,208 - 0.0177 \times 119,872 = 2,026$ workers. The effect of cutting the wage for level two workers is $0.0147 \times 119,872 - 0.0183 \times 115,208 = -346$! The positive effect on the demand for level 2 workers is more than offset by a reduced demand for level 1 labor. Thus, two very similar measures to increase the demand for low-skilled labor can yield very different results. The difference between the long run effects is even more dramatic: $0.0601 \times 120,095 - 0.0195 \times 119,460 = 4888$ as opposed to $0.0148 \times 119,460 - 2.01 \times 120,095 = -646$.

Concerning the capital/skill – complementarity hypothesis it has already been noted that the estimates of the $\delta_{L_i S}$ – parameters support the hypothesis with respect to structure capital. For equipment capital, the cross-price elasticities provide an example of the possibility that the short-run and long-run elasticities

[41] Of course, this is just a transitional effect. Future increases in the demand for level 4 workers thus cannot be expected to be accompanied by increased demands for level 1 workers.

classify the relationship between two factors differently. This can be seen by comparing the E(quipment) columns in the a and b charts of Tables 7, 8, and 9. The short-run cross-price elasticities between level 4 labor and equipment, given in the a charts, are very small but non-negative, indicating that these two factors are short-run weak substitutes. The corresponding long-run cross-price elasticities, given in the b charts, are negative, indicating long-run complementarity. On the whole, the long-run cross-price elasticities look just like predicted by the capital/skill – complementarity hypothesis: the elasticities are highest for level 1 labor, lower for level 2 and level 3 labor and negative for level 4 labor. It should be emphasized, however, that these elasticities are not very precisely estimated.

6.3. Effects of technical change

Table 10 clearly shows that technical change hurts the demand for low-skilled labor, and that it hurts harder the lower the level of education. Positive demand effects are found only for workers with (some) university education. Moreover, in percentage terms, the detrimental effects on the demand for workers with educational levels 1, 2, and 3 increase in magnitude over time. The positive demand effects for level 4 workers fall over time, but very slightly.. As a consequence, the gap between the high-skilled and the low-skilled increase over time.

While the short-run and the long-run effects are very close, there are large differences across industries. For example, in the comparatively "high-tech" Printing and Publishing industry (3440) technical changes reduces the demand for level 1 workers at a much faster rate than in the Metal Products industry (3810). With respect to high-skilled (level 4) labor, on the other hand, the rate of demand increase in Metal Products is about twice as high as in Printing and Publishing.[42]

[42] Partly, these differences are explained by differences in employment levels in these two industries. As seen in Diagram 1, the number of individuals with educational level 1 is much smaller in 3440 than in 3810. Hence a reduction of demand by, say, 1,000 level 1 individuals will amount to a much larger relative decrease in 3440 than in 3810. Similarly, a demand increase of 1,000 level 4 workers will be much larger in relative terms in 3810 than in 3440.

Table 10: Relative changes in input demands and costs, induced by technical change in 1986, 1991, and 1995, for the whole manufacturing sector and two selected industries.

a: Short run, %

Industry 3000	N1	N2	N3	N4	E	M	VC
1986	-5.8	-3.7	-2.4	3.1	-0.4	-1.1	-1.4
1991	-10.2	-5.0	-2.6	2.5	-0.3	-1.1	-1.7
1995	-18.2	-6.3	-3.0	2.4	-0.3	-1.2	-1.8

Industry 3440	N1	N2	N3	N4	E	M	VC
1986	-5.7	-2.5	-1.7	2.0	-0.4	-1.2	-1.4
1991	-10.4	-3.1	-1.9	1.7	-0.4	-1.3	-1.6
1995	-20.2	-3.7	-2.0	1.6	-0.4	-1.3	-1.8

Industry 3810	N1	N2	N3	N4	E	M	VC
1986	-4.2	-2.6	-1.6	4.1	-0.4	-1.3	-1.5
1991	-6.1	-3.3	-1.8	3.2	-0.4	-1.4	-1.7
1995	-8.6	-3.8	-1.9	3.0	-0.4	-1.4	-1.9

b: Long run, %

Industry 3000	N1	N2	N3	N4	E	M	TC
1986	-5.0	-3.7	-2.5	3.5	-0.4	-1.1	-1.4
1991	-7.5	-5.1	-3.1	3.0	-0.4	-1.1	-1.6
1995	-17.5	-6.4	-3.0	2.4	-0.3	-1.2	-1.8

Industry 3440	N1	N2	N3	N4	E	M	TC
1986	-5.0	-2.5	-1.9	2.1	-0.4	-1.2	-1.4
1991	-8.0	-3.2	-2.1	1.9	-0.4	-1.2	-1.6
1995	-16.6	-3.7	-2.1	1.6	-0.4	-1.3	-1.8

Industry 3810	N1	N2	N3	N4	E	M	TC
1986	-3.8	-2.7	-1.7	4.9	-0.5	-1.3	-1.5
1991	-5.0	-3.4	-2.0	3.9	-0.4	-1.3	-1.7
1995	-8.4	-3.8	-1.9	3.1	-0.4	-1.4	-1.9

An interesting feature of the technical change effects are their time patterns. These can be most clearly seen by considering the absolute effects, i.e. $\partial N_i/\partial t$, rather than the relative effects provided in Table 10. Since

$$\frac{\partial N_i}{\partial t} = \lambda_{L_i} \cdot \frac{Y}{B_i}, \qquad i = 1, 2, 3, 4. \tag{6.1}$$

total differentiation yields

$$d\left(\frac{\partial N_i}{\partial t}\right) = \lambda_{L_i} \cdot \left(\frac{1}{B_i} \cdot dY - \frac{Y}{B_i^2} \cdot dB_i\right), \qquad i = 1, 2, 3, 4. \tag{6.2}$$

From (6.2) it is evident why, e.g., the negative effect of technical change on the demand for level 1 workers increases much more rapidly than the negative effect level 2 workers. While λ_{L_1} and λ_{L_2} are both negative the B_1 decrease over time, making the negative effect of technical change larger in magnitude, whereas the opposite is true for the B_2. Similarly, the result that the positive effect of technical change on the demand for university educated (level 4) workers diminishes over time comes from λ_{L_4} being positive and B_4 developing along a positive trend.[43]

The intuition for the time profiles can be gained from (6.1), noting that the effect of technical change can be expressed as the effect on effective labor input, $\lambda_{L_i} \cdot Y$, divided by labor quality, B_i. If labor quality deteriorates (improves) relative to the base-year, i.e. if B_i becomes smaller (larger) than one, the effect of technical change on labor demand must exceed (fall short of) the effect on effective labor; it takes more (less) than one worker to produce one unit of effective labor.

The results on technical change compare well with the results for the U.S.

[43] Empirically, it might seem difficult to separate the effects of technical change, as measured by a time index, and changes in the quality indexes, which to a large extent are driven by demographic developments that also take place smoothly over time. The estimation procedure used here takes care of this problem, however; the effects of the demographic changes are captured in the first stage regressions of the instruments and the B_i indexes, while the effects of technical change are estimated in second stage regressions of the cost function parameters.

obtained by Morrison and Siegel (1997).[44] They also find that technical change reduces the demand for workers with at most upper secondary school (high school) and increases the demand for workers with at least some university education (college). Also, the demand-decreasing effect for workers with at most high school is found to increase over time.

Two differences relative to Morrison and Siegel (op.cit.) are worth noting. First, their results do not indicate that the rate of increase in the demand for high-skilled (at least some college) falls over time.[45] Secondly, surprisingly, they find that technical change reduces the demand for those with a high-school diploma more than it decreases the demand for those with no high school diploma.

These differences do not seem very important, however. On the contrary, taking into account that this study i) is based on data for another country, and ii) controls for the workers' age, sex, immigrant status, work hours and fields-of-study, the similarity must be considered quite remarkable, providing strong additional support for the skill-biased technical change hypothesis.

The biases in technical change are given in Table 11. Relative to Table 10 two qualitative differences can be noted: unlike the demand effects the biases for equipment capital (E) and intermediate goods (M) are positive. Thus, compared to a cost-share weighted average of the effects of technical change on all input demands the effects on demands for equipment and intermediate goods are positive. This means that in addition to a skill-bias in technical change there is also a "non-labor bias" which further aggravates the situation for the low-skilled, by partly directing input demand away from low-skilled labor and towards equipment and intermediate goods.[46] Apart from Morrison and Siegel (1997) earlier studies

[44] Machin, Ryan and Van Reenan (1996) report results for the U.S. and the U.K. The former are in line with Morrison and Siegel (1997). The U.K. results are slightly different but not directly comparable.

[45] Possibly, this can be partly explained by the fact that their data end already in 1989.

[46] It should be noted that the fact that the estimate of λ_{Et} is insignificant and, hence, can be replaced by 0 *strengthens* this conclusion, because such a substitution would yield a positive bias *larger* than the one in Table 11.

Table 11: Biases in technical change in 1986, 1991, and 1995, for the whole manufacturing sector and two selected industries.

a: Short run, %

Industry 3000	N1	N2	N3	N4	E	M
1986	-4.4	-2.3	-0.9	4.6	1.0	0.3
1991	-8.5	-3.3	-1.0	4.2	1.3	0.5
1995	-16.4	-4.5	-1.2	4.3	1.4	0.6

Industry 3440	N1	N2	N3	N4	E	M
1986	-4.3	-1.1	-0.3	3.4	1.0	0.2
1991	-8.7	-1.5	-0.3	3.3	1.2	0.4
1995	-18.5	-1.9	-0.3	3.4	1.4	0.4

Industry 3810	N1	N2	N3	N4	E	M
1986	-2.7	-1.2	-0.2	5.6	1.0	0.2
1991	-4.4	-1.6	-0.1	4.9	1.3	0.3
1995	-6.8	-1.9	0.0	4.9	1.5	0.4

b: Long run, %

Industry 3000	N1	N2	N3	N4	E	M
1986	-3.7	-2.3	-1.1	4.9	1.0	0.3
1991	-5.9	-3.5	-1.4	4.6	1.3	0.5
1995	-15.7	-4.5	-1.2	4.3	1.4	0.6

Industry 3440	N1	N2	N3	N4	E	M
1986	-3.6	-1.1	-0.5	3.5	1.0	0.2
1991	-6.4	-1.6	-0.5	3.5	1.2	0.4
1995	-14.8	-1.9	-0.3	3.4	1.4	0.4

Industry 3810	N1	N2	N3	N4	E	M
1986	-2.3	-1.2	-0.3	6.4	1.0	0.2
1991	-3.4	-1.7	-0.3	5.6	1.3	0.4
1995	-6.6	-1.9	0.0	5.0	1.5	0.4

have only considered the demand for different categories of labor and so have not been able to capture this "non-labor bias" in technical change.

7. Conclusions

Five results emerge from the analysis in this paper.

The first result is that *the skill-biased technical change hypothesis*, which has received strong support in earlier analyses, *is further corroborated.* The robustness exercise carried out in this study addresses the possibility that, by focusing on educational (skill) levels only, previous estimates of skill-biases might be more or less spurious in the sense of confusing the influence of technological developments with effects of changes in other characteristics of labor. However, the conditioning of labor demands on age, sex, immigrant status, work hours, and fields-of-study, as well as level of education, does not qualitatively change the earlier conclusions. The effects of technical change on labor demand are still significantly different across groups. And, in accordance with *a priori* expectations, technical change hurts demand harder the lower the worker's level of education. Positive effects on demand are found only for workers with university education.

In 1995, the aggregate, employment-weighted, long run rates of demand changes induced by technical change are –17.5 %, –6.4 %, –3.0 %, and +2.4 % per year, for workers with elementary school, 9 year compulsory school, upper secondary school, and at least some university, respectively. The corresponding (predicted) levels of employment are, in thousands, 120,000, 119,000, 389,000, and 127,000, implying demand changes of –21,000, -8,000, -12,000 and +3,000, respectively. Together, these effects reduce labor demand by 44,000, from 755,000 to 711,000.

In addition to the skill bias, there is also a "non-labor bias" in technical change, which has not been recognized in earlier studies. By saving more on low-skilled labor than on equipment and intermediate goods, technical change directs input demand away from low-skilled labor towards these non-labor inputs.

The second result is that there is a *substantial difference between measuring labor in purely quantitative terms and by means of the "quality–adjusted" specification of effective labor.* Disregarding, e.g., the workers' age distribution is justified only if the contributions to labor input from workers in different age categories match their frequencies in the age distribution. With respect to the distributions over age, sex, immigrant status, and fields-of-study this is not the case.

For workers with a given level of education, the estimated "quality" indexes summarize the effects of the other characteristics on effective labor input. The indexes are normalized to unity in 1991 and thus measure labor "quality" relative to that year. The aggregate, employment-weighted, index for workers with elementary school decreases steadily from 1.05 in 1985 to 0.95 in 1995. For workers with 9 year compulsory school the aggregate index instead increases almost monotonically from 0.94 to 1.025. The index for upper secondary school fluctuates around 1.0. For workers with at least some university education, the aggregate index is 0.97 in 1985 and rises to 1.03 in 1995. Thus, in 1995 effective labor inputs, measured relative to labor "quality" in 1991, were 5 % lower, 2.5 % higher, about the same, and 3 % higher than actual employment for the four levels of education.

There is an important connection between the developments of the quality indexes and the effects of skill-biased technical change. If labor quality deteriorates (improves) this increases (decreases) the magnitude of the effect of technical change on labor demand. The indexes are also useful for policy analyses of labor demand effects from, e.g., demographic changes or changes in educational priorities with respect to subjects of study.

The third result is that there are *large differences between the two categories with the lowest levels of education*, implying that the treatment in earlier studies of low-skilled workers as a homogenous group can be seriously questioned. From the above discussion it is clear that there are large differences with respect to the effects of technical change and in terms of effective labor input. The differences extend to price elasticities as well. In 1995, the estimated aggregate own-price elasticities are –3.60 (–6.01) for workers with elementary school in the short (long) run. Thus, the demand for these workers is extremely elastic; a 1 % increase in labor costs reduce demand by 3.6 % in the short run and 6 % in the long run. For workers with 9 year compulsory school the corresponding elasticities are –1.47 (–1.48), i.e. aggregate demand is elastic for this category, too, but much less so.

To further illustrate the differences between the two low-skilled groups the following thought experiment can be conducted. Assume that labor costs in 1995 are cut by 1 % either for workers with elementary education (level 1) or for workers with 9 year compulsory school (level 2). Which of these measures are more efficient in increasing demand for the two low-skilled groups together? The answer, which requires accounting for cross-price elasticities as well as own-price elasticities, shows that a 1 percent cut in the wage cost of level 1 workers increases the total demand for level 1 and level 2 workers by approximately 2,000 (4900) individuals in the short (long) run. In contrast, a 1 percent wage decrease for level 2 workers results in short (long) run demand *reduction* of 300 (600) individuals! In the latter case, the positive direct effect is more than offset by a cross-price effect.

The fourth result is that *the capital-skill complementarity hypothesis is supported*, which further adds to the gloomy prospects for the low-skilled. For the whole manufacturing sector in 1995, the long run cross-price elasticities between equipment capital and the most highly educated workers (those with at least some university education), are slightly negative, indicating complementarity. For workers with at most upper secondary school the elasticities are positive, indicating substitutes. The results are similar with respect to structures; the main difference is that in addition to university educated workers, individuals with upper secondary education and structures are also complements.

The fifth result is that there is *no evidence, at the industry level, of substitution of intermediate goods for low-skilled labor*; both the short run and the long run elasticities are either negative, indicating complementarity, or zero. In addition to being an important result in itself, it might have bearing on the hypothesis that competition from the Third World reduces the demand for the low-skilled. If imports from the Third World make up a significant part of intermediate goods, then the result is not consistent with the hypothesis' implication that low-skilled labor and imports from low-wage countries are substitutes. In that case the result here instead extends earlier results showing weak effects from trade and outsourcing at high levels of aggregation on labor demand at lower aggregation levels.

References

[1] Bartel, A.P. and F.R. Lichtenberg (1987) "The Comparative Advantage of Educated Workers in Implementing New Technology", *Review of Economics and Statistics*, Vol. LXIX, pp. 1-11.

[2] Berger, M. (1983) "Changes in Labor Force Competition and Male Earnings: A Production Approach", *Journal of Human Resources*, Vol. 1, pp. 177-196.

[3] Berman, E., J. Bound, and Z. Griliches (1994) "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures", *Quarterly Journal of Economics*, Vol. 109, pp. 367-397.

[4] Berman, E., J. Bound, and S. Machin (1998) "Implications of Skill-Biased Technological Change: International Evidence, *Quarterly Journal of Economics*, Vol. 113, pp. 1245-1280.

[5] Blackorby, C., D. Primont, and R.R. Russell (1978) *Duality, Separability, and Functional Structure: Theory and Economic Applications*, North-Holland, New York.

[6] Dinopoulos, E. and P. Segerstrom (1999), "A Schumpeterian Model of Protection and Relative Wages", *American Economic Review*, Vol. 89, pp. 450–473.

[7] Fallon, J, and P. Layard (1975) "Capital–Skill Complementarity, Income Distribution, and Output Accounting, *Journal of Political Economy*, Vol. 83, pp. 279–302.

[8] Griliches, Z. (1969) "Capital-Skill Complementarity", *Review of Economics and Statistics*, Vol. LI, pp. 465-468.

[9] Gyapong, A.G. and K.Gyimah-Brempong (1988) "Factor Substitution, Price Elasticity of Factor Demand and Returns to Scale in Police Production: Evidence from Michigan", *Southern Economic Journal*, Vol. 54, pp. 863-878.

[10] Haessel, W. (1978), "Measuring Goodness of Fit in Linear and Nonlinear Models", *Southern Economic Journal*, Vol. 44, pp. 648-652.

[11] Hamermesh, D.S. (1993) *Labor Demand*, Princeton University Press, Princeton.

[12] Hansson, P. (1996) "Trade, Technology and Changes in Employment of Skilled Labour in Swedish Manufacturing", Working Paper No. 131, Trade Union Institute for Economic Research, Stockholm.

[13] Hansson, P. (1999) "Relative Demand for Skills in Swedish Manufacturing: Technology or Trade", Working Paper No. 152, Trade Union Institute for Economic Research, Stockholm.

[14] Harper, M.J., E.R. Berndt and D.O. Wood (1989) "Rates of Return and Capital Aggregation Using Alternative Rental Prices", in D.W. Jorgenson and R. Landau (eds.) *Technology and Capital Formation*, MIT Press, Cambridge, Mass.

[15] Kazamaki Ottersten, E., T. Lindh and E. Mellander (1998) "Evaluating Firm Training, Effects on Performance and Labour Demand", *Applied Economics Letters*, Vol. 6, pp. 431–437.

[16] Lindbeck, A. and D.J. Snower (1999), "Multi-Task Learning and the Reorganization of Work – From Tayloristic to Holistic Organizations", *Journal of Labor Economics*, forthcoming.

[17] Machin, S. (1996) "Changes in the relative demand for skills", in A.L. Booth and D.J. Snower (eds.) *Acquiring skills: Market Failures, Their Symptoms and Policy Responses*, Cambridge University Press, Cambridge.

[18] Machin, S., A. Ryan, and J. van Reenan (1996) "Technology and Changes in Skill Structure: Evidence from an International Panel of Industries", Dis-

cussion Paper No 297, Center for Economic Performance, London School of Economics and Political Science.

[19] Machin, S. and J Van Reenan (1998), "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries", *Quarterly Journal of Economics*, Vol. CXIII, pp. 1215–1244.

[20] Morrison, C.J. (1988) "Quasi-Fixed Inputs in U.S. and Japanese Manufacturing: A Generalized Leontief Restricted Cost Function Approach", *Review of Economics and Statistics*, Vol. LXXIV, pp. 275-287.

[21] Morrison, C.J. and E.R. Berndt (1981) "Short–Run Labor Productivity in a Dynamic Model", *Journal of Econometrics*, Vol. 16, pp. 339–365.

[22] Morrison, C.J. and D. Siegel (1997) "The Impacts of Technology, Trade and Outsourcing on Employment and Labor Composition", manuscript.

[23] Nickell, S. and B. Bell (1995) "The Collapse in Demand for the Unskilled and Unemployment Across the OECD", *Oxford Review of Economic Policy*, Vol. 11, pp. 40-62.

[24] Ohta, M. (1975), "A Note on the Duality between Production and Cost Functions: Rate of Return to Scale and Rate of Technical Progress", *Economic Studies Quarterly*, Vol. 25, pp. 63-65.

[25] van Ours, J.C. and G. Ridder (1995) "Job Matching and Job Competition: Are Lower Educated Workers at the Back of Job Queues?", *European Economic Review*, Vol. 39, pp. 1717-1731.

[26] Parks, R.W. (1971) "Price Responsiveness of Factor Utilization in Swedish Manufacturing, 1870-1950", *Review of Economics and Statistics*, Vol. LIII, pp. 129-139.

A. Decomposition of changes in employment shares into between- and within-industry changes

Using the notation in Berman et al. (1994), the aggregate employment share for category j labor, $P^E_{\bullet j}$, equals the sum of the corresponding 24 industry shares, S_i, weighted by their shares in total employment:

$$P^E_{\bullet j} = \sum_{i=1}^{24} P^E_{ij} S_i \,; \qquad \text{where} \quad P^E_{ij} = \frac{E_{ij}}{\sum_{j=1}^{4} E_{ij}} \quad \text{and} \quad S_i = \frac{\sum_{j=1}^{4} E_{ij}}{\sum_{i=1}^{24}\sum_{j=1}^{4} E_{ij}} \,, \tag{A.1}$$

for $j = 1, 2, 3, 4$. A discrete approximation of the (annualized) change in $P^E_{\bullet j}$ between two points in time, t and $t+v$ say, is given by

$$\Delta P^E_{\bullet j} = \underbrace{\sum_{i=1}^{24} \Delta S_i \overline{P}^E_{ij}}_{\text{between industry changes}} + \underbrace{\sum_{i=1}^{24} \Delta P^E_{ij} \overline{S}_i}_{\text{within industry changes}} \tag{A.2}$$

where the Δ denote average annual changes, defined according to

$$\Delta Z_{t,t+v} \equiv \frac{Z_{t+v} - Z_t}{v} \,, \qquad Z = P^E_{\bullet j} \,,\, S_i \,,\, P^E_{ij}$$

and the "constants" are computed as simple arithmetic averages, i.e.

$$\overline{C} \equiv \frac{C_t + C_{t+v}}{2} \,, \qquad C = P^E_{ij} \,,\, S_i \,.$$

The results of applying the decomposition to the two business cycle peaks, $t = 1988$ and $t + v = 1994$, and to the endpoints of the period are given in Table A1.The changes in the employment shares are completely dominated by within industry changes; cf. the last column.

Table A1: Decomposition of changes in employment shares, % per annum.

Period	Labor category	Total change, % per annum	Between industry	Within industry	Contrib. of within, %
1988-94	1	-1.314	-0.063	-1.251	95
	2	-0.464	-0.006	-0.458	99
	3	+0.826	+0.004	+0.822	99
	4	+0.953	+0.065	+0.888	93
1985-95	1	-1.405	-0.054	-1.352	96
	2	-0.291	-0.002	-0.289	99
	3	+0.978	+0.018	+0.960	98
	4	+0.718	+0.037	+0.680	95

B. The effect on the quality index from a change in the distribution over a given characteristic

To evaluate the effect on the quality index B_i from a change in the distribution over the jth characteristic, first consider the effect from a change in the jth characteristic at given shares. Defining:

$$D_{ij} \equiv \sum_{k=1}^{K_i} \left(1+\theta_{ijk}\right) H_{ijk}\,, \tag{B.1}$$

(4.8) implies

$$\frac{\partial B_i}{\partial D_{ij}} = \nu_{ij} \left(\frac{B_i}{D_{ij}}\right)^{1+\rho_i} \tag{B.2}$$

The next step is to evaluate

$$\left(\frac{\partial D_{ij}}{\partial \mathbf{H}_{\overline{ij}k}}\bigg|_{\overline{N_i^{\Phi R}}}\right), \qquad \Phi = S, L, \tag{B.3}$$

which denotes the change in D_{ij}, represented by changes in the K_{j_i} shares H_{ijk} at a given labor demand, $\overline{N_i^{\Phi R}}$, $\Phi = S, L$. Define

$$N_i^{\Phi R} \equiv N_{ij1}^{\Phi R} + N_{ij2}^{\Phi R} + ... + N_{ijK_{j_i}}^{\Phi R} \tag{B.4}$$

and

$$H_{ijk}^{\Phi R} \equiv \frac{N_{ijk}^{\Phi R}}{N_i^{\Phi R}}. \tag{B.5}$$

Assume that the K_{j_i} subgroups change by $dN_{ijk}^{\Phi R}$, $k = 1, ..., K_{j_i}$. Each one of the changes involve a change in labor demand by the same magnitude, as well as a change in the distribution over the jth characteristic. To isolate the latter effect, define a scale factor, η, such that

$$\eta \equiv \frac{\sum_{k=1}^{K_{j_i}} N_{ijk}^{\Phi R}}{\sum_{k=1}^{K_{j_i}} \left(N_{ijk}^{\Phi R} + dN_{ijk}^{\Phi R}\right)}. \tag{B.6}$$

Next, define

$$\left(N^{\Phi R}_{ijk}\right)^{*} \equiv \eta \cdot \left(N^{\Phi R}_{ijk} + dN^{\Phi R}_{ijk}\right), \quad k = 1, ..., K_{j_i}. \tag{B.7}$$

The $\left(N^{\Phi R}_{ijk}\right)^{*}$ have two properties which make them appropriate for the evaluation of changes in the subgroups. First, from (B.6) it is clear that $\sum_{k=1}^{K_{j_i}} \left(N^{\Phi R}_{ijk}\right)^{*} = \sum_{k=1}^{K_{j_i}} \left(N^{\Phi R}_{ijk}\right)$, i.e. the scaling by η makes the sum over the new subgroups equal to the sum over the original subgroups. Thus, the $\left(N^{\Phi R}_{ijk}\right)^{*}$ correspond to the same level of labor demand as the $N^{\Phi R}_{ijk}$. Moreover,

$$\frac{\left(N^{\Phi R}_{ijk}\right)^{*}}{\left(N^{\Phi R}_{ij\ell}\right)^{*}} = \frac{N^{\Phi R}_{ijk} + dN^{\Phi R}_{ijk}}{N^{\Phi R}_{ij\ell} + dN^{\Phi R}_{ij\ell}}, \quad k \neq \ell, \tag{B.8}$$

i.e. the scaling preserves the relations between the new subgroups.

To move to changes in subgroup shares, define

$$\left(dN^{\Phi R}\right)^{*}_{ijk} \equiv \left(N^{\Phi R}_{ijk}\right)^{*} - N^{\Phi R}_{ijk}, \quad k = 1, \ldots, K_{j_i}. \tag{B.9}$$

Obviously, $\sum_{k=1}^{K_{j_i}} \left(dN^{\Phi R}\right)^{*}_{ijk} = 0$, as required. Next, totally differentiate the population shares to obtain the general relation between changes in the shares and changes in the sizes of the subpopulations:

$$\begin{aligned} dH^{\Phi R}_{ijk} &= \tfrac{\partial H^{\Phi R}_{ijk}}{\partial N^{\Phi R}_{ij1}} dN^{\Phi R}_{ij1} + \cdots + \tfrac{\partial H^{\Phi R}_{ijk}}{\partial N^{\Phi R}_{ijk}} dN^{\Phi R}_{ijk} + \cdots + \tfrac{\partial H^{\Phi R}_{ijk}}{\partial N^{\Phi R}_{ijK_{j_i}}} dN^{\Phi R}_{ijK_{j_i}} \\ &= \tfrac{N^{\Phi R}_{i} - N^{\Phi R}_{ijk}}{\left(N^{\Phi R}_{i}\right)^2} dN^{\Phi R}_{ijk} - \tfrac{N^{\Phi R}_{ijk}}{\left(N^{\Phi R}_{i}\right)^2} \Big(dN^{\Phi R}_{ij1} + ... + dN^{\Phi R}_{ijk-1} \\ &\quad + dN^{\Phi R}_{ijk+1} + ... + dN^{\Phi R}_{ijK_{j_i}} \Big). \end{aligned} \tag{B.10}$$

In analogy with (B.10), next define share changes corresponding to (B.9), i.e.

share changes that do not involve any change in the size of the total population:

$$\left(dH^{\Phi R}\right)^*_{ijk} = \frac{N_i^{\Phi R}-N_{ijk}^{\Phi R}}{\left(N_i^{\Phi R}\right)^2}\left(dN^{\Phi R}\right)^*_{ijk} - \frac{N_{ijk}^{\Phi R}}{\left(N_i^{\Phi R}\right)^2}\left[\left(dN^{\Phi R}\right)^*_{ij1} + ... + \left(dN^{\Phi R}\right)^*_{ijk-1} + \left(dN^{\Phi R}\right)^*_{ijk+1} + ... + \left(dN^{\Phi R}\right)^*_{ijK_{j_i}}\right]. \tag{B.11}$$

Since the $\left(dN^{\Phi R}\right)^*_{ijk}$ sum to zero

$$\left(dN^{\Phi R}\right)^*_{ij1} + \cdots + \left(dN^{\Phi R}\right)^*_{ijk-1} + \left(dN^{\Phi R}\right)^*_{ijk+1} + \cdots + \left(dN^{\Phi R}\right)^*_{ijK_{j_i}} = -\left(dN^{\Phi R}\right)^*_{ijk}$$

which implies that (B.11) can be simplified to

$$\left(dH^{\Phi R}\right)^*_{ijk} = \frac{1}{N_i^{\Phi R}}\left(dN^{\Phi R}\right)^*_{ijk}, \quad k = 1, ..., K_{j_i}\,. \tag{B.12}$$

Collecting results and simplifying we obtain

$$\left(\left.\frac{\partial B_i}{\partial \mathbf{H}_{\overline{ijk}}}\right|_{\overline{N_i^{\Phi R}}}\right) = \nu_{ij}\frac{B_i}{\sum_{k=1}^{K_{j_i}}\left(1+\theta_{ijk}\right)H_{ijk}}\sum_{k=1}^{K_{j_i}}\left(1+\theta_{ijk}\right)\frac{\left(\eta-1\right)N_{ijk}^{\Phi R}+\eta dN_{ijk}^{\Phi R}}{N_i^{\Phi R}}$$

where η is defined by (B.6). Note that if the assumed changes do not imply a change in the level of labor demand then $\eta = 1$ and the last ratio simplifies to $dN_{ijk}^{\Phi R}/N_i^{\Phi R}$.