Rising demand for skills: evidence from plant-level panel data, 1976-2004*

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Abstract

Large literature has documented a labour demand shift in favor of more skilled workers. Despite extensive research in the area, the existing evidence is rather qualitative and unable to reveal when the skill demand shift actually occurred and which industries were most involved. To address these questions, we estimate the time patterns of the within-plant skill demand shift from a census of manufacturing plants in Finland over the years 1976-2004. The identification of labour price substitution effects is based on geographic variation in skill prices. We find a large increase in the relative demand for skills over the last three decades. The demand shift has been prevalent across industries although its intensity varies substantially. The phase of the demand shift was virtually constant in the 1980s and decelerated during the 1990s.

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1 Introduction

A wealth of literature documents a dramatic shift in manufacturing employment towards nonproduction labour in OECD and other countries during the last three decades. As in many countries the rising share of nonproduction employment has been observed concurrently with rising relative nonproduction wages, the conclusion of the literature is that the main factor behind the shift towards nonproduction employment has been the rising demand for skilled workers.[1] Furthermore, it is widely believed that this skill demand shift was to a great extent a result of skill-biased technical change (SBTC).[2] While the evidence on the existence of the skill demand shift is rather conclusive, little is known about when the demand shift actually happened and how intensive it was.

This study presents new empirical evidence on the evolution of relative demand for skills over the last three decades. Using a unique dataset based on a census of manufacturing plants in Finland over the years 1976-2004 we are able to assess three important questions. First, with our plant level data where each plant has an exact location we are able to exploit regional variation in skill prices to identify the labour demand elasticities for nonproduction and production workers. The correct identification of the effects of labour prices is fundamental in order to account for the contributions of the changes in labour prices on the nonproduction and production labour cost shares. The potential endogeneity of wages in the plant level labour demand equations arises from the concern that firms experiencing a skill-biased productivity shock may simultaneously change wage rates as a response to changes

[1]Berman, Bound and Grilliches (1994), Berman, Bound and Machin (1998), and Berman and Machin (2000) provide evidence on industry level labour demand shifts towards nonproduction workers from developed and developing countries.

[2]Berman, Bound and Grilliches (1994) demonstrate that most of the demand shift cannot be explained by factors unrelated to technology. Berndt, Morrison, and Rosenblum (1992), Berman, Bound and Grilliches (1994), Doms, Dunne, and Troske (1997), Machin and Van Reenen (1998), and Adams (1999) provide evidence that skill-upgrading is positively correlated with high-tech capital, computer investments and research and development expenditures. Chennells and Van Reenen (2002) provide an overview of the literature.

in the productivities of worker groups.[3] Second, our data permits us to identify the freely time-varying patterns of the skill demand shift within industries. This turns out to be important because our results suggest that the intensity of the skill demand shift greatly varies across industries (which invalidates the assumption of equal evolution of the skill demand across industries) and that the rate of the demand shift is not constant over time. Third, as our plant census data covers an exceptionally long time period from 1976 to 2004, we are able to give insight on the evolution of skill demand and tests whether it accelerated or decelerated in a period that witnessed the introduction of important innovations such as personal computers and new communication technologies.

Although an obvious limitation of our study concerning only a small economic area is its generalizability, we believe that our analysis can in an important way improve our understanding about the timing and magnitude of the recent trends in demand for skills across technologically developed economies. Berman, Bound and Machin (1998) provide evidence that within-industry changes in the proportion of nonproduction employment are "very similar" in Denmark, Finland, Sweden, the United Kingdom, and the United States. This suggests that the factors behind the skill demand shift should be relatively similar and simultaneous across countries. For example, consider the effects of two main suspects behind the skill demand shift, skill-biased technical change and international outsourcing. First, we expect the effects of technical change to be similar and rather simultaneous across developed countries as new (skill-biased) technologies become available to businesses in these countries fairly simultaneously. Second, the benefits from outsourcing should have emerged simultaneously across countries as the barriers to trade have been declining

[3]Doms, Dunne and Troske (1997) provide evidence that implementation of new technologies increases wages in all worker groups. Entorf, Gollac and Kramarz (1999) find that firms select high-quality workers when allocating new technologies. Several previous studies acknowledge the endogeneity problem but are unable to find a credible source of exogenous variation in labour prices (see e.g. Berman, Bound, and Grilliches (1994), and Baltagi and Rich (2005)). Our approach is closest to Caroli and Van Reenen (2001) who use regional average wages to control for the effects of skill prices on within-plant skill-upgrading.

all over the world and similar transportation and information technologies are available to all businesses. This suggests that the effects of increased trade openness on the demand for skills should have fairly similar industry patterns across countries.

Our main results are the following. We find a large increase in the relative demand for skills over the last three decades. The demand shift is prevalent across industries although its intensity vary. The demand for skills has been increasing steadily over the late 1970s and through the 1980s. This finding suggests that (1) the skill demand shift did not accelerate in the 1980s but was already intense in the last half of the 1970s and that (2) factors behind the skill demand shift, such as development of microprocessors or increased trade openness, were also at work in the late 1980s rather than only in the turn of the 70s and 80s when personal computers were introduced. Furthermore, we find that R&D is a significant factor behind the demand shift while measures of outsourcing are unable to explain it. This supports the view that the main force behind the skill demand shift has been skill-biased tehcnical change.

The work is organized as follows. In Section 2, we give a brief overview of the general labour composition trends in Finnish manufacturing. In Section 3, we explain our empirical strategy for identifying the skill demand shift and summarize our empirical results. In Section 4, we explore whether R&D and outsourcing are able to explain the skill demand shift. Section 5 concludes.

2 Aggregate trends in the nonproduction wage bill and employment

Figure 1 shows the aggregate evolution of nonproduction wage bill and hours shares for Finland over the years 1976-2004. Most of the increase in the nonproduction wage bill share occurred in the 1980s. Between the years 1980 and 1990 the nonproduction wage bill share increased from 0.307 to 0.373, corresponding to a 0.66 percentage points increase per year. This is in line with the findings of Berman, Bound and Machin (1998) that in Finland and several other countries the nonproduction wage bill share increased sharply during that period. During the recession years 1976-1977 and 1990-1992 the nonproduction share remains generally unchanged, and even decreases after the recovery begins in 1993 although the general trend in the 1990s is positive. The same patterns can be found in the nonproduction hours share series.

In general, changes in the nonproduction wage bill shares are informative about the acceleration or deceleration of the skill demand if (1) the relative prices of inputs are unchanged, and (2) output and capital substitution effects are equal across worker groups or output and capital stock is unchanged. Because these assumptions are often not satisfied, especially when we are looking at a long time period, an econometric approach that will control for the price, output and capital substitution is required in order to net out the skill demand shift.

3 Changes in demand for skills

3.1 Empirical specifications and identification issues

In this section, we explain our empirical strategy for identifying the skill demand shift using plant level panel data. To fix ideas, consider a plant i in year t belonging to industry r that uses materials (M), nonproduction (N) and production labour (P) as variable inputs, and capital (k) as a quasi-fixed input. When the plant is maximizing profits and there is perfect competition in the input markets, we can use Sheppard's lemma to write the variable input cost share of input f , s^f, as a function of the primary input demand factors - the quasi-fixed capital, output, and prices of variable inputs

$$s_{irt}^{f} = s^{f}(p_{it}^{N}, p_{it}^{P}, p_{it}^{M}, k_{it}, y_{it}, \epsilon_{rt}^{f}, \epsilon_{it}^{f}), \quad f \in \{N, P, M\}. \tag{1}$$

Here ϵ_{rt}^{f} and ϵ_{it}^{f} are industry- and firm-specific demand shifters that capture changes in the input cost shares not attributable to primary input demand factors. Traditionally, such changes are thought of being the implication of technical change. Factor-biased technical change increases the relative productivity of some inputs compared with others. In the case of labour inputs, if the implementation of new technologies increases the productivity of skilled workers relatively more than the productivity of unskilled workers, technical change is said to be skill-biased. Also factors that are not related to technical change may affect the input mix within a plant. One such source of factor-augmentation that is not directly related to technical change is international trade and outsourcing. Another concern brought up by many authors is that outsourcing of routine tasks to low-wage countries may be driving down the demand for low-skilled workers. If a plant relocates some of its production to low wage countries, we expect to observe within plant skill-upgrading because routine tasks that are outsourced require less skills.

We use the division to production and nonproduction workers as our measure of within plant skill distribution. Specifically, our measure of the relative share of nonproduction workers is the difference between nonproduction and production worker cost shares, $s^{N} - s^{P}$. The measurement of skill distribution by occupational division has its advantage in labour demand studies as it reflects more directly the tasks within a plant and thus has a stronger link to the within-plant skill requirement than e.g. measures based on education. Berman, Bound and Grilliches (1994) demonstrate that the division to nonproduction and production workers closely resembles the division to occupations requiring more and less skills.

Our aim is to estimate the effect of industry-specific cost share shifters, ϵ_{rt}^{f}, on the relative demand for nonproduction workers. We follow Baltagi and Rich (2005) in defining the relative demand shift as the time-specific residual after controlling for the effects of primary input demand variables. A major advantage of plant level panel data is that we are able to allow for different time patterns of the demand shift across industries. Moreover, we can control for many permanent effects that are possibly correlated with the relative nonproduction demand. We assume translog production technology and define the following relative cost share equation including plant fixed effects (α_i) and industry-year effects (τ_{rt})

$$s_{irt}^N - s_{irt}^P = \sum_{j \in \{P,N,M\}} \beta_j ln(p_{it}^j) + \gamma_k ln(k_{it}) + \gamma_y ln(y_{it}) + \alpha_i + \tau_{rt} + u_{it}. \quad (2)$$

Here plant fixed effects control for any permanent heterogeneity at the plant, industry or region level. Because of the inclusion of plant fixed effects, our identification of βs and γs is based on changes over time in the explanatory variables. Our main parameter of interest is τ_{rt} which is the estimate for the residual demand for skills in industry r.[4] This industry-specific and freely over time varying parameter captures the mutual contribution of the nonproduction and production labour demand shifters on the relative demand described by ϵ_{rt}^N and ϵ_{rt}^P in equation (1). These effects represent the part of the relative nonproduction cost share shift that remains left after controlling for the input price, capital and output substitution, what is our definition of the skill demand shift.

The main challenge in identify τ_{rt} is the following. As it is the time-industry specific residual, it will absorb any biases in βs and γs. In other words, to identify τ_{rt} we need to correctly net out the contribution of changes in the input prices, capital and output on the relative nonproduction share. Our main concern is the

[4] Our industry calssification is based on 2-character NACE classes. See Table 1 for a list of these industries. For a full list of NACE industries see http:// ec.europa.eu/comm/competition/ mergers/cases/index/nace_all.html.

endogeneity of labour prices. For example, a skill-biased productivity shock u_{it} will have a positive effect on the relative skill demand but at the same time it may have an impact on plant level wages across the skill distribution through changes in labour productivities. As an example, consider a case where productivity shock increases the productivity of the workers in the upper part of the skill distribution, and at the same time has no effect on the low-skilled wages but makes obsolete the jobs in the lowest part of the skill distribution, which are also the lowest paid jobs among the low-skilled workers. In this case, we would expect a rise in both the less skilled (production) and more skilled (nonproduction) worker wages.[5] As the skill-biased productivity shock affects the skill demand by rising it, it will be in this example positively correlated with the labour prices p_{it}^N and p_{it}^P what will lead to upward bias in the OLS estimates of β_N and β_P. On the other hand, if the skill-biased productivity shock decreased wages in the lower part of the skill distribution without making these jobs obsolete, we expect to observe lower wages for production workers. In this case, we will have a downward bias in the OLS estimate of β_P. Thus theory predicts that a skill-biased productivity shock should raise the wages of skilled workers while the effect on the low-skilled wages is ambiguous.

In any of the cases presented above, OLS will provide a biased estimate of the labour price substitution effects. The main problem in finding a viable solution for identification is to find any credible source of exogenous variation in skill prices. In our analysis we make use of the characteristic of our plant level data that each plant is by definition located in an exact location. Our identification strategy relies on the idea that there may exists differences in skill prices across regions. The differences may arise if the regional labour markets are (at least partially) isolated in which case the effect of the local skill supply shock on the labour prices will not fully transmit to other regions. There are several potential reasons for region-specific skill

[5] Doms, Dunne, and Troske (1997) provide evidence that technology adaption increases wages for all worker groups.

supply shocks. Demographic factors such as the amount of individuals completing schooling or immigration and emigration flows may affect the local supply of skills. The industry composition may vary across regions and as a result global product demand shocks may have different effects across regions through asymmetric effects on worker flows. Furthermore, the less jobs require industry-specific human capital the more a global product demand shock in one industry induces variation into the price of skills in other industries.

Our plant level panel data enables us to use a much larger set of instruments than region dummies alone, namely the industry-year-region interaction dummies. This instrument will exploit the idea that regional differences in the labour prices may vary across industries and over years. Our identifying assumption is that within an industry there are no region-specific time-varying skill-biased productivity shocks that correlate with labour prices. To consider the validity of our instrument note first that the plant fixed effects, α_i, will absorb the effects of any constant differences in the skill-intensity, managerial practices, or level of technology across plants, regions and industries. The time-specific industry level shocks are absorbed by τ_{rt}, which according to our definition is the relative demand shift. The key identifying assumption is that, within industries, after controlling for primary input demand variables, plant effects, and industry-year effects, the annual changes in the magnitude of skill-biased productivity shocks are similar across regions. In other words, the trends in the within-industry shocks should be common across regions. What are the situations that would invalidate this assumption? For example, the possibility that some regions are lacking behind in the adaption of new technologies is not enough because the plant fixed effects are absorbing the effect of constant differences in the level of technology across regions. What is additionally required to invalidate our assumption is that the effects of different vintages of technologies on skill-intensity differ. We find it unlikely that such regionwide time-varying skill-biased productivity shocks would constitute a major problem for our identification because there are highly advanced manufacturing plants in every region used in our analysis and distances within the country are relatively small.[6] However, we cannot completely rule out the possibility of such shocks. In Section 3.5 we run some robustness tests to further assess the validity of our assumptions.

A second concern in identifying equation (1) is the endogeneity of output. This occurs because the current skill-biased productivity shock may be correlated with current output. To overcome this problem, we use a common approach in the literature and use lagged output as an instrument for current output.

3.2 Data

Our main data source is the Industrial Statistics (IS) database provided by Statistics Finland. The IS database is based on an annual survey and it compiles comprehensive information on the economic activity of plants in manufacturing, mining of quarry, and energy and gas supply. Over our observation period 1976 - 2004, the IS database covers most of the manufacturing plants except the smallest units.[7] The database provides detailed output and input information including the gross value added; the total labour cost of production and nonproduction workers[8] (wage bill plus employer contributions such as compulsory insurance payments); the hours worked by production and nonproduction workers by the accuracy of thou-

[6]For example, a flight from Helsinki in the Southern Finland to Rovaniemi in the Northern Finland takes only about one hour and fifteen minutes.

[7]Prior to the year 1994, plants employing at least 5 persons were sent the questionnaire. From 1995 a plant was included into the sample frame if the firm that owned it had at least 20 employees. This means that from the year 1995 onwards the sample does not include all plants employing 5-19 persons and may include some plants with less than 5 employees. Section 5 shows that our results are robust to the exclution of plants with less than 20 employees.

[8]The category "production workers" is intended to included all persons directly engaged in production or the related activities of the establishment. These include for example packers, service staff, maintenance staff, construction staff, machinists, stokers, and cleaners. Also low level supervisors who take part in the actual production are included in this category. The category "nonproduction workers" refers to all other employees not directly engaged in production. These are typically employees engaged in supervision, sales, technical services, and administration.

sand hours; expenditures on materials and changes in materials inventories; and investments on machinery and equipment. We use the IS to calculate the input cost shares of variable inputs (nonproduction labour, production labour, and materials). From the IS we also calculate the plant level labour prices as the ratio of the total labour costs in a group to the total hours worked in that group.

A major advantage of plant level data is that by definition a plant has unique location. The IS database includes information on the location of the plant at the municipality level. Exact information on the locations of plants essentially enables our identification strategy based on geographic variation in skill prices. We define four labour market regions based on provincial division displayed in Figure 5.[9]

We complement the IS file with the Longitudinal Database on Plants in Finnish Manufacturing (LDPM), which is based on the IS. The LDPM includes only operative units leaving headquarters and other units which are not directly engaged in manufacturing production outside the sample. The LDPM provides plant level information on real output and capital stock. The estimate for the capital stock represents the stock of machinery and equipment. It is calculated using the perpetual inventory method with geometric depreciation pattern.[10] The nominal figures for output and capital stock are deflated to real values with implicit industry price indexes for output and capital acquired from the National Accounts. Finally, data on the prices of material inputs come from the EU-KLEMS database which provides materials price indexes for 2-digit NACE industries.[11] The estimation of the effect of the material price is based on changes over time in the material price within 2-character industries some of which include two or more 2-digit industries.

Because we are essentially estimating parameters for industry-time interaction

[9] The province of Åland constituting of islands in the Baltic sea is excluded from the analysis because of its special location and small size. Northern provinces of Lapland and Oulu are combined.

[10] The depreciation rate used was 0.10. The initial values for the capital stock for plants that have started up prior to 1974 are derived from the fire insurance values.

[11] See http://www.euklems.net.

dummies, we want to eliminate the effects that potentially arises from the fact that some plants are changing the industry code. For this reason we include in our final sample only plants that have the same two-digit industry code over the observation period. We also exclude plants in such industry-region cells that have only 5 or less plants. This is to ensure the validity of the assumption that the plant level input choices are not affecting the prices in the local input markets. The final sample is an unbalanced panel of 8 757 plants and 85 257 plant-years. Table 2 presents the summary statistics for the key variables.

3.3 Estimates of the skill demand shift

In Section 2 we showed the rising aggregate trend in the nonproduction wage bill share. As we pointed out, such descriptive analysis is often unable to capture the exact timing and intensity of the changes in the relative demand for nonproduction labour. Several other factors may be affecting the cost shares as well. Most importantly we have to take into account the supply of highly educated workers which has been increasing in most countries over the last three decades.

In order to capture the patterns of the demand shift, we must net out the contributions of the primary input demand factors - the input prices, output, and capital - for the changes in cost shares. As we discussed in Section 3.1, the fundamental problem in estimating changes in labour demand is the endogeneity of labour prices. It is possible that high productivity firms hire high-skilled workers and pay higher wages. In this section, we demonstrate the importance of assessing this endogeneity problem in estimating labour cost share equations and present our IV estimates for the skill demand shift.

Table 3 presents the OLS and IV estimates for the first-differenced relative nonproduction cost share equation (2). To show the labour demand elasticities underlying our estimates we also display the estimates for the nonproduction and production cost share equations.[12] The OLS estimate of the own price effect in the nonproduction (production) cost share equation is 0.059 (0.099) corresponding to a wage elasticity of -0.449 (-0.370).[13] The IV estimates of the own price effect are lower for nonproduction labour (0.049) and higher for production labour (0.119). The own demand elasticity for nonproduction (production) labour based on IV estimates is -0.516 (-0.312). The differences between the OLS and IV estimates of the labour demand elasticities are realtively large suggesting that there are unobserved productivity shocks correlated with labour prices.

Our labour elasticity estimates indicate that production work is less elastic compared with nonproduction work. One possible explanation for this finding is that nonproduction workers are typically engaged in supervision, sales, technical services, and administration and decreasing this type of work within a plant may decrease the efficiency. On the other hand, production workers are typically part of a production line and a missing, say, packer in the production chain can in the worst case stop the whole production process. The trade-off between monitoring and efficiency on the one hand and the fixed nature of some part of the production labour requirement on the other hand may explain the more elastic demand for nonproduction workers.

We now turn to the estimates for the relative cost share equation. We begin by reporting some test statistics for our IV procedure. The Hausman test indicates endogeneity which provides further evidence on the importance of assessing the endogeneity problem when estimating labour cost share equations. Our main concern is the weak instruments problem as we use 1095 excluded instruments.[14] The over identifying restrictions (OIR) test is not rejecting our specification while the F-test

[12]Note that the relative nonproduction cost share equation (2) can be constructed by subtracting the corresponding nonproduction cost share equation from the production cost share equation.

[13]The own price elasticity of labour category f is calculated as $\hat{\eta}_f = (\hat{\beta}_f^{(f)} + \overline{s}_f^2 - \overline{s}_f)/\overline{s}_f$, where "$(f)$" refer to the relevant cost share equation and the upper bar denotes the sample mean.

[14]There are 17 industries over 29 years and in 4 regions making 1972 industry-year-region cells. Reducing the amount of reference industry-year cells yields $1972 - 29 \cdot 17 = 1479$. Finally, because we require that in each industry-year-region cell there are more than 5 plants, we end up with 1095 excluded instruments where one of the instruments is lagged output and the rest of the 1094 instruments are the remaining industry-year-region interaction dummies.

statistics for the significance of instruments is over the rule of thumb of 10 (Staiger and Stock, 1997) for all endogenous variables.

As explained in Section 3.1, if a skill-biased productivity shock increases wages for all worker groups, the bias in the own price coefficient in the relative nonproduction cost share equation resulting from correlation between skill-intensity and wages will be positive for both labour groups. On the other hand, if the skill-biased productivity shock increases wages for more skilled workers and decreases wages for less skilled workers, we would expect the resulting bias to be negative for the estimates of the production and positive for the estimates of the nonproduction wage coefficients. In the relative nonproduction cost share equation the OLS estimate for the nonproduction labour price is about 40 percent higher than the corresponding IV estimate while for the production labour price the estimate is generally of the same magnitude as the corresponding OLS estimate although slightly smaller. The direction of the bias suggests that skill-biased productivity shocks have increased the nonproduction wages while the production wages have been almost unaffected.[15] The coefficient for output is positive indicating that output expansion is relatively more intensive in nonproduction labour. This may reflect that economies of scale in management and supervision tasks are smaller than in production line tasks. Finally, we find no indication of capital-skill complementarity as the coefficient for capital is almost zero.

Table 4 displays formal tests for the skill demand shift within industries over the period 1976-2004. The first panel represents the shift in relative nonproduction demand ($s_N - s_P$) and the second and third panels represent the shift broken down to nonproduction (s_N) and production shares (s_P). The main observation form Table 4 is that the relative labour demand shift is positive and significant in all industries. Moreover, the shift is driven by the declining input share of production workers

[15]This may reflect the fact that decreasing the wages of already hired production workers in the event of skill-biased productivity shock may be difficult for employees because of binding wage contracts with trade unions. However, the are basically no constraints on increasing wages.

while the share of nonproduction workers is relatively stable. Despite the similarity of general patterns across industries, we find notable differences in the intensity of the skill demand shift. The magnitude of the shift in terms of cost shares ranges from 0.080 (non-metallic mineral products) to 0.259 (electrical and communications equipment). This demonstrates that industries are differently affected by the demand shift factors such as technical change and outsourcing. For example, consider the non-metallic mineral products industry, which includes manufacturing of glass, bricks, tiles, and concrete, and is characterized by mature production technologies, high capital intensity, dependence on large volumes of material inputs, and high transportation costs compared to the value of the final product. In this industry we would not expect a large skill demand shift due to technical change, because the pace of technical change is relatively slow, nor outsourcing, because the benefits are expected to be modest. On the other hand, we would expect a much larger employment shift towards skilled labour within the electrical and communications equipment industry which has experienced rapid changes in available technologies over the last three decades and is expected to have potentially large benefits from outsourcing because products in this industry are typically small and portable.

3.4 The phase of the skill demand shift

To explore the phase of the skill demand shift over the last three decades, we plot in Figure 3 the aggregate skill demand shift which is constructed as the annual wage bill share weighted sum of the industry figures. This figure is striking in three respects. First, the average annual skill demand shift was 0.74 percentage points and almost constant through the 1980s. This contrasts the finding of Baltagi and Rich (2005) from US 4-digit manufacturing data that the skill demand shift occurred mostly before the 1983 and was almost negligible in the period 1984-1996. Moreover, the relative demand for nonproduction workers did not accelerate from late 70s to early

80s but was rather constant. Second, during the early 1990s depression the skill demand shift accelerated. This was due to the rising demand for nonproduction labour and decelerating demand for production labour. In the years 1990-1993 the average annual growth rate of nonproduction share was 0.28 percentage points higher while for production workers it was 0.11 percentage points lower compared to the 1980s. This means that during the recession years the annual growth rate of relative nonproduction demand accelerated by 0.28-(-0.11)=0.39 percentage points in terms of the cost shares. This finding gives support to the general view often made by looking at the evolution of aggregate nonproduction wage bill shares that the demand for nonproduction workers is countercyclical while procyclical for production workers. Third, the skill demand shift seems to have decelerated in the years 1994-2004. During that period the annual growth rate of relative nonproduction demand was 0.46 percentage points, only about 65 percentages compared to the rate in the 1980s and about 42 percentages compared to the rate in the recession years.

To formally tests whether the skill demand shift decelerated we ran regressions of the estimates of the skill demand shift, $\hat{\tau}_{rt}$, on interactions of time trend and relevant subperiod dummies. Table 5 presents the results. In the first column we test the hypothesis whether the skill demand decelerated in the 1990s by testing the difference between the trend coefficient in the periods 1976-1989 and 1990-2004. The row labeled "Trend" shows the average annual increase in the demand for skills for the reference period 1976-1989 while the row labelled "Trend 1990-2004" shows how much the average annual trend in the period 1990-2004 differs from the trend in the period 1976-1989. The average annual growth rate in skill demand is 0.48 percentage points lower in 1990-2004. This estimate is statistically significant suggesting that the skill demand decelerated in the period 1990-2004. The second column displays tests for a larger set of subperiods keeping the period 1981-1989 as a reference. These results show that the difference between the annual growth rates is almost negligible between the periods 1976-1980 and 1981-1989 which is inline with the observations of Berman, Bound and Grilliches (1994) and Berman, Bound and Machin (1998) that the skill demand started to grow already in the 1970s. What is striking in our results is that the shift in the demand for skills did not accelerate from mid-70s to the 80s. We belive that this indicates that the introduction of personal computers in the late 70s and early 80s did not only have an instantaneous effect on the skill demand but rather the adjustment took several years and the effects of the implementation of new computer technologies occurred gradually. The constant phase of the skill demand shift may also reflect the gradual improvement and applicability of computer technologies in manufacturing. The coefficient for the recession years is positive and relatively large although not statistically significant which may be due to small amount of data points in the recession period.

3.5 Robustness tests

In this section we run several robustness tests to validate our chosen specifications and instrumental variable approach. In equation (2) we implicitely assume that the coefficients for continuous varibales and plant fixed effects are constant over the observation period. We are especially concerned about the effects of the early 1990s recession which caused an especially severe economic crisis in Finland.[16] To test whether our specification is robust over time we split the sample to periods 1976-1989 and 1990-2004. Column 1 of Table 5 replicates the IV estimates from Table 3 and columns 2 to 3 present the IV estimates for the periods 1976-1989 and 1990-2004. Both labour price coefficients are in general similar and of the magnitude in all periods. The differences are largest for the material price coefficient but because the presicion of this estimate is low this may be solely due to sample bias. The coefficients for output and capital are not changing significantly through the

[16]An overview of the 1990s recession in Finland is provided in Honkapohja and Koskela (1999) and Koskela and Uusitalo (2006).

samples.

To see the effect of dividing our sample to two periods we plot in Figure 5 our estimates of the skill demand shift for the full sample and combined series for subperiod samples where we the full sample estimate is imputed for the change between the cutoff years 1989 and 1990. The patterns in these two series are in general very similar. Figure 5 also plots the skill demand series based on the OLS estimates. The difference between the IV and OLS estimates are striking and show that in our data the OLS underestimate the skill demand shift substantially.

4 Technology, outsourcing and changes in demand for skills

In the previous section we found that the demand for skills has increased substantially over the last three decades. In this section we explore the factors explaining the skill demand shift. In previous literature, the main suspects for increased inequality between low- and high-skilled workers are skill-biased technical change and international outsourcing. To test these competing hypotheses we construct an industry level panel data by linking proxy variables for these potential sources of the skill demand trends to our estimates of industry-specific skill demand from the previous section. With this industry level panel data we are able to simultaneously assess the importance of technology and trade based explanations of the skill demand shift. The advantage of our approach is that our estimates for the skill demand shift are clean from the input price, capital and output substitution effects and as a result the potential omitted variable bias from excluding labour prices is not invalidating our estimates. This may be important because R&D is highly skill-intensive activity and a large share of R&D costs are labour costs. Changes in the price of high-skilled labour will affect both the R&D desicion and the relative demand for nonproduction labour. Thus regressions of relative nonproduction cost share on R&D expenditure may suffer from severe ommited variable bias and overestimate the effect of R&D on skill distribution if the effect of labour prices are ignored.

In order to test the skill-biased technical change and trade based explanations of the skill demand shift we estimate the following equation

$$\hat{\tau}_{rt} = \beta_1 R\&D_{rt} + \beta_2 R\&D_{r,t-2} + \beta_3 OUTS_{rt} + d_r + d_t + u_{rt}. \tag{3}$$

Here $\hat{\tau}_{rt}$ is our estimate of the skill demand shift in industry r and year t; $R\&D_{rt}$ is the log of R&D expenditure; $OUTS_{rt}$ is the log of the relevant measure of outsourcing. To control for industry-specific and common time-specific shocks we include industry dummies d_r and year dummies d_t. As our dependent variables are in logs the time dummies will absorb general increases in prices. Positive estimates of β_1 and β_2 indicate that technical change has been skill-biased. On the other hand, a positive estimate of β_3 provides support for the trade based explanation of increasing demand for skills.

Our R&D expenditure variable comes from the OECD STAN database.[17] The figure represents nominal values by industry. The R&D expenditure figures in STAN are based on the R&D survey by Statistics Finland in the years 1989, 1991, and 1993-2004. For the years 1976-1988, 1990 and 1992 the values are estimated. To construct our outsourcing variable we use the input usage tables for imports provided by Statistics Finland for the years 1995-2004. The availability of specific imports usage data restricts our analysis including outsourcing to the last ten years of our observation period. During this period the world economy experienced dramatic changes in trade openness led by the opening up of China to foreign companies. Thus if outsourcing has had an effect on within plant changes in skill demand we would expect to find it especially in this period.

[17]See http://www.sourceoecd.org.

We approximate technological change by R&D expenditure which is likely to correlate with the level of technical progress within an industry. One of the main problems in the standard regressions of a measure of skill distribution on R&D is that in industries with more skilled workers more R&D intensive business strategies may be introduced. In this case we are unable to identify whether it is the increased R&D effort (that implemented new technologies) that affect the skill demand, or whether because of the rising share of skilled workers more R&D is conducted. This problem can be especially severe if the supply of skilled workers is rising strongly as has been the case in most countries during the last three decades. Furthermore, increasing R&D effort is likely to take effect with delay because the commercialization of products and implementation of new production methods require time. Because of these considerations we also include two years lagged R&D expenditure into our empirical model. This will mitigate problems mentioned above because the effect of the lagged R&D should realize within two years. Furthermore, increased R&D effort in year $t-2$ is unlikely to be a result of recruiting skilled workers in year t. Thus if we find, say, a positive effect of lagged R&D on the skill demand, we are more confident that the effect is due to innovations that have already realized. Following Feenstra and Hanson (1996, 1999), we also include a measure of international outsourcing. The narrow outsourcing is defined as industry's imports of intermediate inputs from its own industry while the broad outsourcing is defined as the industry's total imports of intermediate inputs.

Table 5 displays our results for the full panel and subsamples covering the years 1989, 1991, and 1993-2004, and the years 1995-2004. The current R&D has a strong positive correlation with skill demand through out the samples and specifications. As explained above, there is a concern that rather than being a causal effect of R&D on skill demand, the coefficient for current R&D may reflect the effect of skill intensity on R&D. A more reliable measure of technical change is the lagged R&D

expenditure. For this variable the coefficient is positive and significant while lower than for the current R&D through out the samples and specifications. This finding provides us with strong evidence that the recent labour demand shift towards skilled workers has been driven by technical change.

Now turning to the effects of outsourcing, column 3 (column 4) in the third panel of Table 5 present results for regressions where only narrow (broad) outsourcing is included as an explanatory variable. Somewhat surprisingly the effect of narrow outsourcing is significantly negative while the coefficient of broad outsourcing is insignificant. When we include current R&D and two years lagged R&D the effect of narrow outsourcing disappears. It is important to note that in our plant level approach, $\hat{\tau}_{rt}$ captures only the contribution of within-plant changes in relative nonproduction worker demand. For example, it will not capture the effects of outsourcing in the case when a whole plant is relocated. As the relocation of plants is one of the main channels through which outsourcing may affect, our within plant skill demand shift may not capture the effects through exits of outsourced establishments. However, we do not have a clear explanation for the negative effect of outsourcing in some cases.

5 Conclusions

This paper has provided evidence on the magnitude and timing of the recent skill demand shift. Our plant level manufacturing data allows us to contribute to the literature in two important ways. First, we allow the patterns of the skill demand shift to vary across industries. This proves to be essential as the evolution of the skill demand varies substantially across industries. Second, we use regional variation in skill prices to account for the endogeneity of wages in the within-plant relative nonproduction labour demand equations. We verify that plant level wages are endogenous and that ignoring the endogeneity bias will lead to large errors in the estimates of labour demand elasticities. Furthermore, as the main challenge in estimating the labour demand shift is to correctly control for relative labour price movements, the biases in the coefficients for wages will lead to biases in the estimates of the skill demand shift. In our data the bias will lead to sizeable underestimation of the skill demand shift.

In summary, we find that the demand for skills has increased considerably over the period 1976-2004. This is almost solely attributable to the declining share of production workers in total variable costs while the share of nonproduction workers has been stable. The skill demand shift is prevalent across industries but its intensity varies substantially. The skill demand shift has been persistently intense in the late 1970s and through out the 1980s and decelerated to about two thirds of the average annual rate of the 1980s during the 1990s.

Our industry level analysis shows strong positive correlation between skill demand and R&D expenditures. This result is consistent with the view that the recent technological change has been biased in favor of highly skilled workers.

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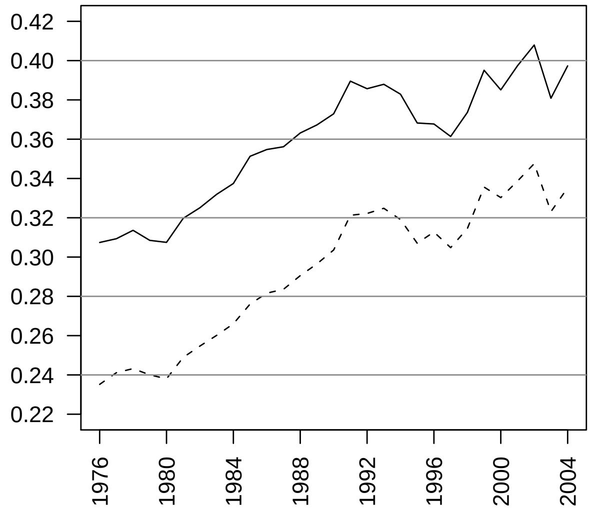

Figure 1: Trends in nonproduction worker wage bill and employment share, Finland 1976-2004.

Table 1: Industry key

	NACE industry classes	
Industry	2-character	2-digit
Mining and quarrying of energy producing materials	CA	10, 11, 12
Mining and quarrying, exept of energy materials	CB	13, 14
Food products and beverages	DA	15, 16
Textiles	DB	17, 18
Leather and leather products	DC	19
Wood and wood products	DD	20
Pulp and paper products	DE	21, 22
Coke, refined petroleum products and nuclear fuel	DF	23
Chemicals	DG	24
Plastic products	DH	25
Non-metallic mineral products	DI	26
Metals	DJ	27, 28
Machinery and equipment	DK	29
Electrical and communication equipment	DL	30, 31, 32, 33
Transportation equipment	DM	34, 35
N.e.c.	DN	36, 37
Electricity, gas and water supply	EE	40, 41

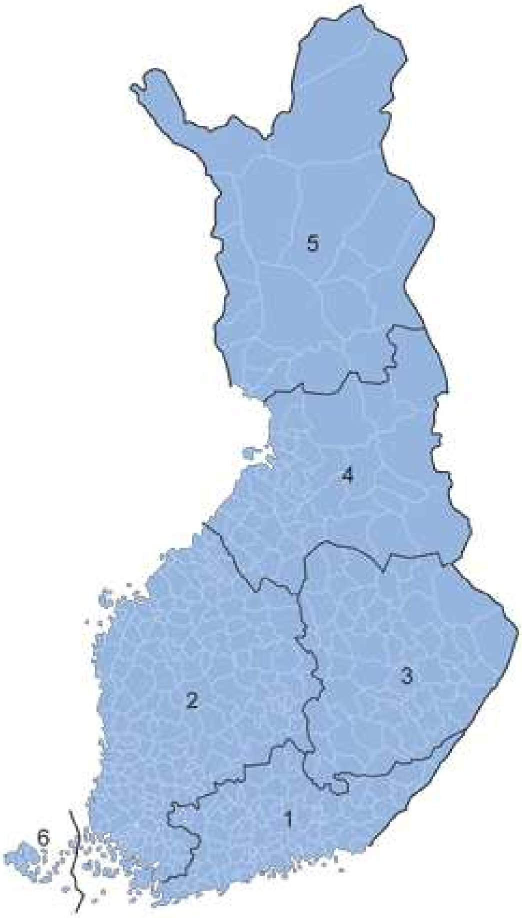

Figure 2: Provincial division in Finland (1 - Southern Finland; 2 - Western Finland; 3 - Eastern Finland; 4 - Oulu; 5 - Lapland; 6 - Åland). The regional classification used in our analyses excludes Åland constituting of islands in the Baltic sea and combines Lapland and Oulu.

Table 2: Summary statistics

	Mean	Std. dev.
Production worker cost share	0.330	0.188
Nonproduction worker cost share	0.147	0.132
log(Production worker price)	2.03	0.61
log(Nonproduction worker price)	2.35	0.62
log(Material price)	4.27	0.34
log(Real output)	8.12	1.62
log(Real capital stock)	6.86	2.09
Production worker price	9.10	5.52
Nonproduction worker price	12.60	7.74
Material price	75.43	23.36
Real output	15 230	69 730
Real capital stock	7 146	30 263
N	85 257	

Labour prices represent the hourly cost.

Material price is the material price index.

Output and capital stock in thousands of 2000 euros.

Table 3: First-differenced panel-IV estimates

	OLS		IV	
Nonproduction worker cost share (s_N)				
$\log(p^N)$	0.059	(0.001)	0.049	(0.006)
$\log(p^P)$	-0.035	(0.001)	-0.013	(0.008)
$\log(p^M)$	-0.001	(0.006)	-0.001	(0.006)
$\log(y)$	-0.03	(0.001)	-0.026	(0.004)
$\log(k)$	0.002	(0.001)	0.001	(0.001)
Production worker cost share (s_P)				
$\log(p^N)$	-0.031	(0.001)	-0.015	(0.008)
$\log(p^P)$	0.099	(0.002)	0.118	(0.011)
$\log(p^M)$	-0.024	(0.007)	-0.025	(0.007)
$\log(y)$	-0.041	(0.002)	-0.043	(0.006)
$\log(k)$	0.003	(0.001)	0.003	(0.001)
Relative cost share (s_N-s_P)				
$\log(p^N)$	0.090	(0.002)	0.064	(0.010)
$\log(p^P)$	-0.134	(0.003)	-0.131	(0.014)
$\log(p^M)$	0.023	(0.009)	0.025	(0.009)
$\log(y)$	0.011	(0.002)	0.016	(0.006)
$\log(k)$	-0.001	(0.001)	-0.002	(0.001)
R^2	0.146		0.113	
N	85 257		85 257	

Tests for relative cost share equation		
OIR-statistic (1057 excluded instruments)	1 050	[0.554]
F-statistic for Hausman tests of no endogeneity	789	[0.000]
Joint significance of instruments in 1^{st} stage regressions on		
$\log(p^N)$	83.8	[0.000]
$\log(p^P)$	86.2	[0.000]
$\log(y)$	23.9	[0.000]
# endogenous variables	3	
# instruments	1488	
# excluded instruments	1095	

Notes: Heteroskedasticity-robust standard errors in parentheses. P-values in brackets. Plant and industry-year interaction dummies are included but estimates are not shown.

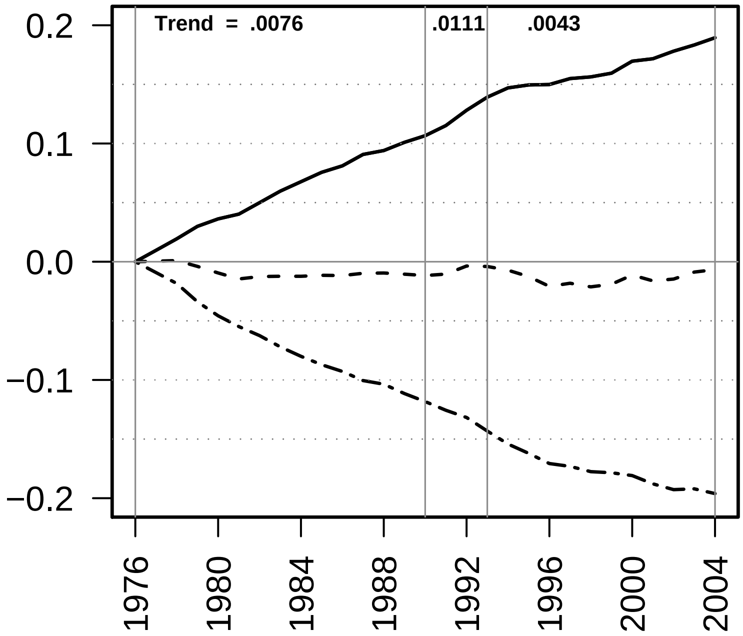

Figure 3: Aggregate skill demand shift, 1974-2004 (relative - solid black; nonproduction - dashed; production - dot-dashed)

Table 4: Skill demand shift by industry, 1976-2004 (IV estimates)

	Relative		Nonproduction		Production	
Industry	Demand shift	P-value	Demand shift	P-value	Demand shift	P-value
Food products and beverages	0.080	0.030	-0.022	0.288	-0.102	0.001
Textiles	0.235	0.000	0.026	0.332	-0.210	0.000
Leather and leather products	0.219	0.000	0.019	0.652	-0.200	0.002
Wood and wood products	0.146	0.000	-0.042	0.039	-0.188	0.000
Pulp and paper products	0.191	0.000	-0.012	0.569	-0.203	0.000
Chemicals	0.141	0.013	0.003	0.936	-0.138	0.000
Plastic products	0.173	0.000	-0.020	0.425	-0.193	0.000
Non-metallic mineral products	0.095	0.026	-0.039	0.102	-0.135	0.000
Metals	0.200	0.000	-0.023	0.285	-0.223	0.000
Machinery and equipment	0.172	0.000	-0.028	0.292	-0.199	0.000
Electrical and communication equipment	0.259	0.000	0.043	0.210	-0.216	0.000
Transportation equipment	0.187	0.002	-0.022	0.597	-0.209	0.000
N.e.c.	0.208	0.000	-0.003	0.918	-0.210	0.000

Table 5: Trends in skill demand shift

	(1)		(2)	
Trend	0.0082	(16.1)	0.0089	(8.89)
Trend*Dummy(Year=1990-2004)	-0.0048	(6.75)		
Trend*Dummy(Year=1976-1980)			-0.0009	(0.355)
Trend*Dummy(Year=1990-1993)			0.0025	(0.683)
Trend*Dummy(Year=1994-2004)			-0.0052	(4.05)
Constant	-16.032	(15.9)	-16.032	(15.9)
N	439		439	
R^2	0.828		0.831	
$\hat{\sigma}$	0.031		0.031	

Notes: Absolute t-values in parentheses. The reference period is 1981-1989. All models include industry dummies and period dummies for non-reference periods but estimates are not shown.

Table 6: Alternative IV estimates for the relative nonproduction cost share equation

Period	1976-2004		1976-1989		1990-2004	
$\log(p^N)$	0.064	(0.010)	0.077	(0.014)	0.053	(0.015)
$\log(p^P)$	-0.131	(0.014)	-0.150	(0.019)	-0.120	(0.023)
$\log(p^M)$	0.025	(0.009)	0.029	(0.010)	0.008	(0.016)
$\log(y)$	0.016	(0.006)	0.011	(0.007)	0.017	(0.012)
$\log(k)$	-0.002	(0.001)	-0.001	(0.001)	-0.004	(0.002)
R^2	0.113		0.149		0.088	
N	85 257		57 306		26 393	

Notes: Standard errors in parentheses.

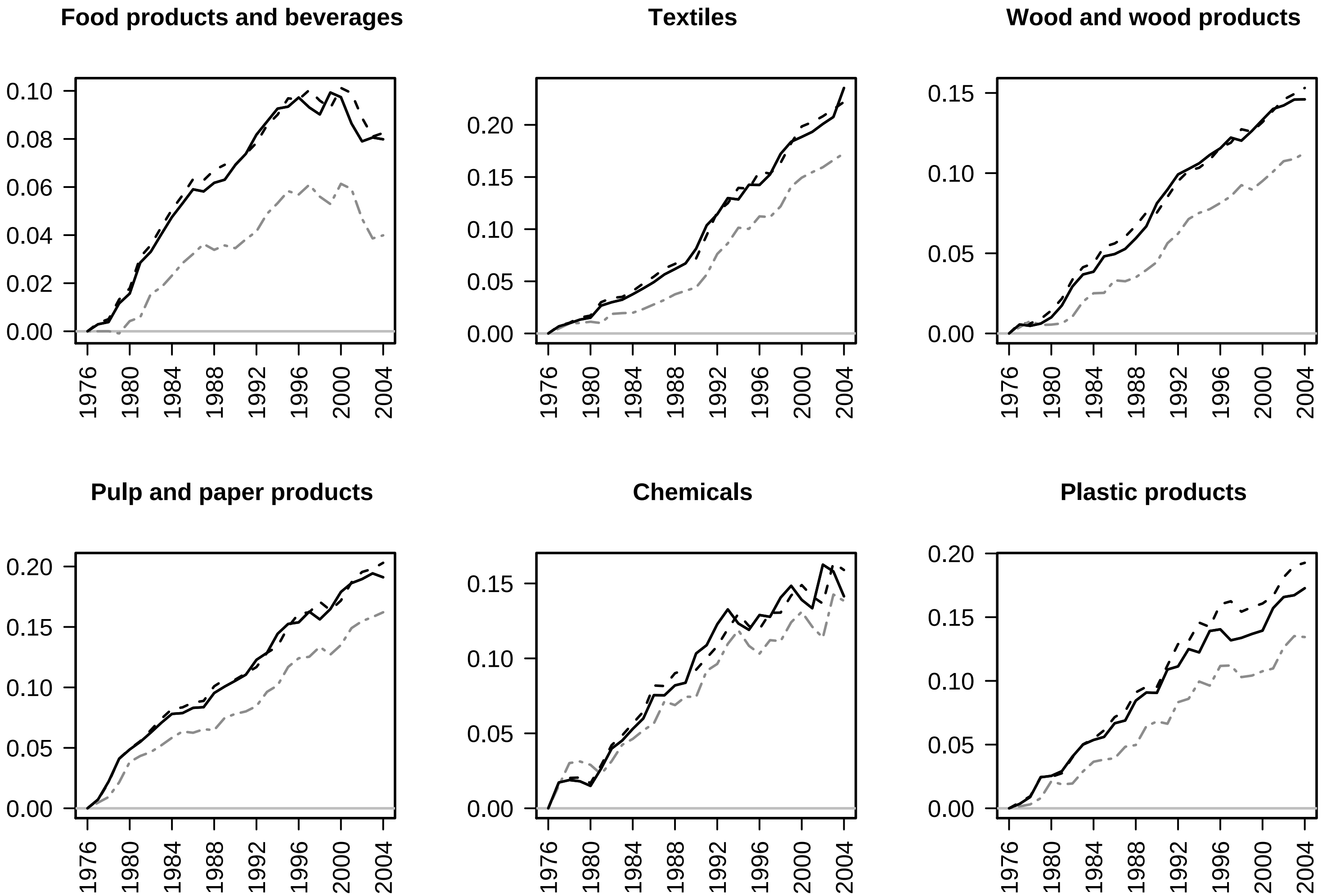

Figure 4: Alternative estimates for industry patterns of the skill demand shift: OLS (dash-dotted gray), IV (solid black), and subperiod IV (dashed black) estimates

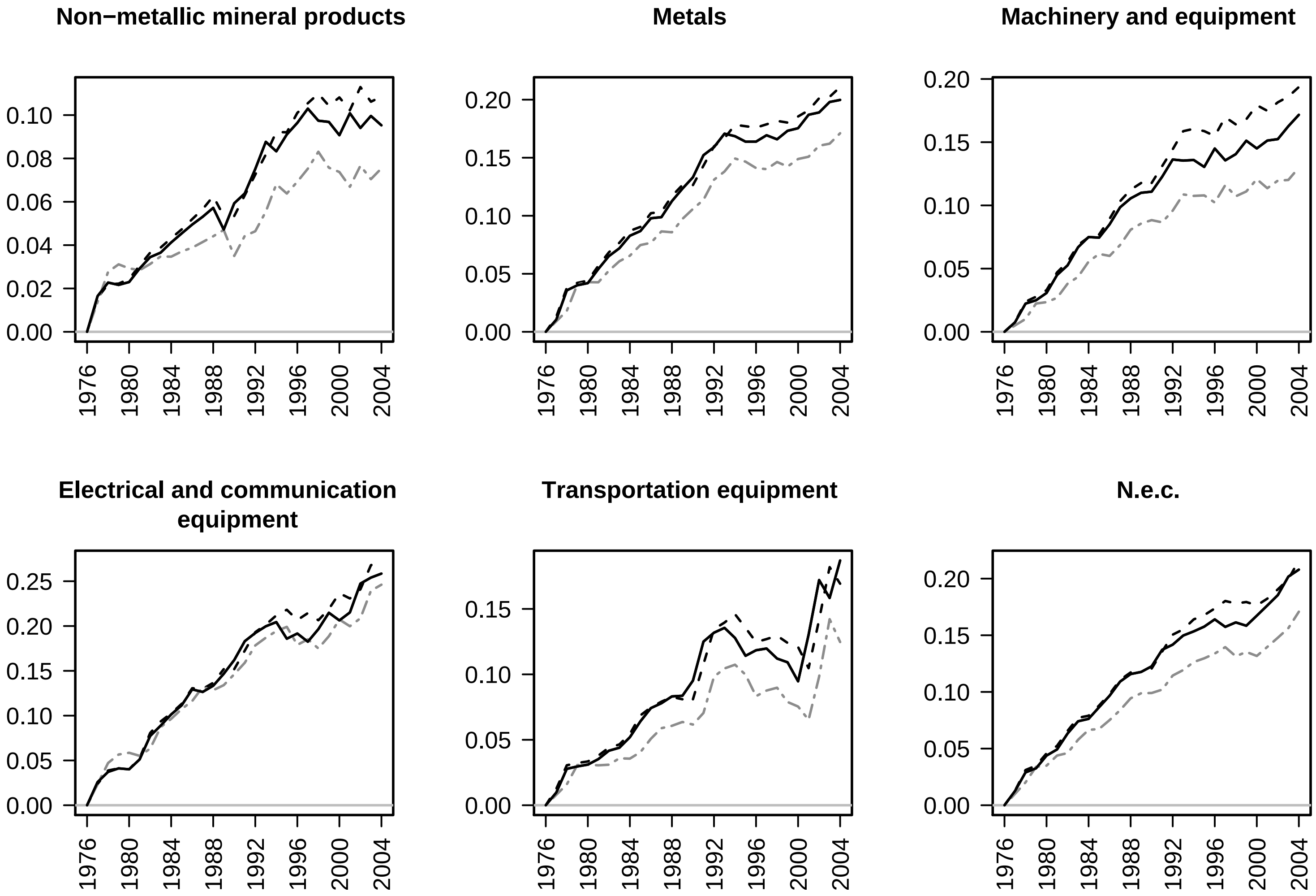

Figure 4: *(continued)*

Table 7: Research and development, outsourcing, and skill demand

Years	1976-2004[a]		1989,1991,1993-2004		1995-2004							
	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D$_t$	0.016	0.012	0.011	0.007	0.017	0.013			0.017	0.016	0.014	0.013
	(6.263)	(3.867)	(3.563)	(2.015)	(3.296)	(2.467)			(3.412)	(3.165)	(2.645)	(2.432)
R&D$_{t-2}$		0.006		0.006		0.010					0.009	0.010
		(1.916)		(1.658)		(2.294)					(2.122)	(2.231)
Outsourcing (narrow)							-0.009		-0.010		-0.008	
							(1.714)		(1.932)		(1.569)	
Outsourcing (broad)								-0.008		-0.006		-0.006
								(1.169)		(0.820)		(0.911)
Obs.	344	316	174		130	126	130	130	130	130	126	126
R^2	0.946	0.956	0.933		0.925	0.936	0.919	0.918	0.927	0.925	0.937	0.936
$\hat{\sigma}$	0.015	0.013	0.012		0.012	0.011	0.012	0.012	0.012	0.012	0.011	0.011

Notes: Absolute t-values in parenthesis. All explanatory variables are in logarithms. Industry and year dummies are included in all models but coefficients are not shown. a - An OECD estimate for R&D expenditure is used for the years 1976-1988, 1990, and 1992. Narrow outsourcing is the industry's intermediate input imports from the same industry. Broad outsourcing is the total of industry's intermediate input imports.