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The Role of Technical Progress and Trade in Explaining Wage Differentials in Italian Firms

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Working on the Train? The Role of Technical Progress and Trade in Explaining Wage Differentials in Italian Firms*

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Abstract

This paper presents firm-level evidence on the dynamics of the relative demand for non-manual workers in Italian manufacturing during the 1990s. The analysis provides a number of interesting results. First, *within-firm* skill upgrading is the main determinant of the increase in the non-manual wage bill share. By contrast, demand changes associated to trade have shifted employment *away* from skill-intensive firms. Second, while the relative number of *hours* worked by skilled workers *within firms* has risen, the hourly wage premium has fallen. Third, *within-firm* skill upgrading is strongly and significantly related to investment in computers and R&D, suggesting skill-biased technical progress as the main explanation for the increase in the relative demand for non-manual workers. Finally, the paper shows that failing to disaggregate annual wages into the number of hours worked and hourly wages, leads to underestimate the skill-*bias* of technical progress.

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1 Introduction

Once upon a time, before the era of portable computers and cellular phones, commuters on the Milan-Rome train route broadly fell into two categories: first class travellers, mainly business people and academics, usually spending their time reading the financial and general press, or taking naps (the latter); economy class travellers, mainly families, young people and tourists, often involved in animated conversations with fellow travellers, typically about soccer or politics. Nowadays, first-class travellers can be seen silently hunched over their laptops, or heard noisily talking business over their cellular phones. Most second-class travellers still chat their way to their destination, although now over cellular phones, and some watch DVD's on their lap-tops. Academics, now travelling in economy class, either read newspapers or work on their laptops (or take naps).[1]

This anecdotal evidence suggests three working hypotheses: 1. technical progress in Italy, as in many other countries, has been *skill-biased*, that is, it has raised the relative *productivity* of more educated workers (first-class travellers presumably make a more productive use of personal computers) as well as the relative number of *hours* worked by skilled workers (first class travellers now work instead of relaxing); 2. relative *wages* in Italy have not (fully) adjusted to the change in relative productivity and hours (as a consequence, academics no longer can afford to travel – and take naps – in first class); 3. possibly as a result, firms have considerably raised the proportion of non-manual workers in *employment*.

This paper explores these conjectures by investigating the dynamics of manual and non-manual employment and wages in Italian manufacturing during the 1990s. We present firm-level evidence on the sources and determinants of the increase in the demand for non-manual workers, based on a new data set, previously unavailable for research, that covers a large panel of manufacturing firms between 1989 and 1995. The analysis provides a number of results supporting these conjectures.

[1]We are grateful to Giorgio Basevi for this example.

First, Italian firms have substituted unskilled for skilled workers at a rate comparable to those experienced in other industrialized countries (with high-tech firms playing a leading role in this process): *within-firm* skill upgrading is the main determinant of the shift in relative labor demand in the nineties. By contrast, demand changes associated to trade have moved employment *away* from skill-intensive firms, contributing to *moderate* the change in relative factor prices: *between-firm* employment shifts have reduced the relative demand for skills. Thus the evidence supports the idea of an Italian "anomaly", in that trade lowers wage inequality (cf Manasse et al. (2003)). Second, and most important, we add a second anomaly for the Italian case: the relative stability of wage differentials within firms hides an important *composition effect.* At firm level the relative number of *hours* worked by skilled workers has risen, due to skilled biased technical change, whereas relative wages have *not* adjusted. As a result, non-manual *hourly wages* have fallen in relative terms. Third, *within-firm* skill upgrading, measured by changes in both relative employment and number of hours, is strongly and significantly related to investment in computers and R&D. Finally, we show that the conventional approach that measures annual, rather than *hourly* relative wages, produces a downward bias in the estimate of the skill-*bias* of technical progress. The reason is that changes in relative *hours* worked are incorrectly attributed to changes in factor *prices* rather than *quantities.* When properly measured, technical progress is estimated to raise the relative productivity of non-manual workers by roughly half a percentage point per year.

The paper is structured as follows. Section 2 briefly discusses the theoretical background of the analysis and relates the present work to the literature. Section 3 provides a description of the data set and presents some stylized facts of relative wage and employment dynamics in Italy in the last decade. In section 4 we present a decomposition of the aggregate changes in the relative wage bill, employment and wages, into their respective *within-firm* and *between-firm* components. Section 5 takes a closer look at the behavior of wages, and shows the implications of disaggregating annual wages into the number of hours worked and hourly wages. In section 6 we present evidence from firm-level regressions to provide an interpretation of the observed wage and employment dynamics, and section 7 focuses on the bias of skill-biased technical change. Section 8 concludes with a discussion of the main results.

2 Technology, trade and wages

In the last two decades labor markets in OECD countries have witnessed a significant change in the structure of employment and wages for skilled and unskilled workers. Since the early 1980s, both the share of non-manual employment and the wage differential between manual and non-manual workers have grown considerably in the US and the UK.[2] In continental Europe, wage differentials have been stable, and most of the adjustment has taken place on the quantity side, with rising non-manual workers' employment rates and manual workers' unemployment rates.[3] The conventional wisdom for Europe is that the lack of adjustment in relative wages is due to more rigid labor market institutions (minimum wages, hiring and firing costs, centralized bargaining and union power, etc.), with unemployment rates adjusting to the falling demand for unskilled workers.

A large body of literature has attempted to provide an interpretation of these developments,[4] with most studies concentrating on the determinants of the relative *demand* for skilled labor.[5] In particular, trade integration and technological change have been considered the main factors behind the rise in the demand for skilled workers.[6] The "technology" view argues that technical progress has been *skill-biased*: new production practices associated to the introduction of computers have increased the relative productivity of skilled workers. This has led to higher relative demand, and in turn to higher employment shares and wage premia for skilled workers. Empirically, skill-biased technical change is consistent with increased employment shares of skilled labor within individual sectors (or firms/plants, depending on the

[2]See e.g. Katz and Murphy (1992)), Bound and Johnson (1992), Lawrence and Slaughter (1993), Berman, Bound, and Griliches (1994)) for the United States, and Haskel (1998), Haskel and Slaughter (2001b)) for the United Kingdom.

[3]See e.g. Freeman and Katz (1996), OECD (1997), Berman, Bound and Machin (1998), Machin and Van Reenen (1998), Card, Kramarz, and Lemieux (1998).

[4]For recent surveys of this literature see Haskel (2000) and Slaughter (1999).

[5]Katz and Murphy (1992) argue that lower relative supply of skills could account only for a small part of the observed changes in relative wages in the United States between 1963 and 1987. See also Topel (1997) for an analysis of the supply-side determinants of wage inequality.

[6]Other explanations often proposed are outsourcing (see e.g. Haskel (1996), Feenstra and Hanson (1999)), and changes in institutional factors such as the decline of the influence of unions, collective bargaining, and lower minimum wages (see e.g. Gosling and Machin (1993) and Fortin and Lemieux (1997)).

level of aggregation and the specific way new technologies are adopted). The "trade" view points to Stolper-Samuelson effects of increased exposure to international trade.[7] According to advocates of this explanation, competition from developing countries has lowered the relative price of unskilled-intensive goods. As resources have shifted to sectors producing more profitable skill-intensive products, the relative demand for manual workers has fallen. This argument thus "blames" the growth of trade in goods, services and factors in the past three decades (i.e. "globalization"). Empirically, the trade view is consistent with employment in developed countries moving from skill-unintensive towards skill-intensive sectors (firms/plants).

The broad consensus emerging from the early empirical literature, generally based on studies of *industry* data, is that, while international trade accounts for no more than 15-20% of the rise in wage differentials, the rest can be explained by skill-biased technical progress (see *e.g.* Bound and Johnson (1992) and Berman et al. (1994) for the United States, but also Berman et al. (1998) and Machin and Van Reenen (1998) for an international perspective).[8] This conclusion is supported by two main findings. First, most of the aggregate skill upgrading is due to changes *within* industries, whereas the reallocation of employment *between* industries plays a smaller role. Second, within-industry skill upgrading is significantly related to a number of indicators of technological change.

This explanation has been recently challenged, both empirically and theoretically. At the empirical level, a number of studies based on firm-level or plant-level data reach conclusions significantly different from those obtained on the basis of industry data.[9] Bernard and Jensen (1997), for example, find that *within-industry* increases in the demand for skilled labor can be largely attributed to shifts in employment *between plants* of the same industry (see also Bernard and Jensen (1995)), with exporting plants playing a major role.[10] Earlier studies, it is argued, have ignored important dynamics occur-

[7]See Richardson (1995), Wood (1995) and Slaughter (1998) for recent surveys on the effects of trade on wage dynamics.

[8]A similar conclusion has been reached using both price (e.g. Leamer (1996), Feenstra and Hanson (1996)) and volume (e.g., Borjas, Freeman and Katz (1997)) data to capture the effect of trade on the labor market.

[9]Most plant- and firm-level analyses aim at assessing the links between exporting activity and productivity (see e.g. Bernard and Jensen (1999) and Bernard et al. (2000)) or the existence of learning effects associated with the exports status of firms (see e.g. Clarides, Lauch and Tybout (1998)).

[10]For a theoretical explanation of this evidence see Manasse and Turrini (2001).

ring at the level of individual firms and establishments, and thus have largely underestimated the role of demand and trade. At the theoretical level, trade theorists have argued that what matters for factor prices (in a two-sector two-factor Heckscher-Ohlin economy) is the *sector* bias of technical progress, rather than its *factor* bias (see e.g. Leamer (1994, 1998)).[11]

There are relatively few studies on the Italian case. Most of the existing evidence for Italy is based on industry-level data. Bella and Quintieri (2000) analyze a panel of manufacturing industries, and argue that trade competition has had a small impact on employment changes, whereas technological progress has played a major role. Faini et al. (1999) reach similar conclusions on the limited role of trade for labor market dynamics, using a panel of fourteen manufacturing sectors between 1985 and 1995. Among firm-level studies, Dell'Aringa and Lucifora (1994) look at a cross section of metal-mechanical firms to discuss the role of trade unions in affecting wage differentials.[12] Casavola et al. (1996) consider a large panel of firms between 1986 and 1990, finding that technological change explains most of the increase in relative skilled employment. More recently, Manasse et al. (2001) analyze a panel of metal-mechanical firms observed from 1992 to 1995 and find that skill-biased technical change is the main determinant of skill upgrading.[13] The study also finds that trade has *dampened* the effects of technology on wage differentials, as employment has shifted towards unskilled-intensive firms (see also Faini et al. (1999)). This anomaly is due to the fact that Italy mainly trades with more "advanced" European partners, and firms are specialized in relatively "low tech" goods. The present study on one hand confirms these results for the entire manufacturing sector, and for a much longer time horizon (1989-1995). On the other, the new data set enables us to separate hours worked and from the number of employees of each category,

[11]Krugman (1995), however, shows that this criticism rests on the assumption of local technical change affecting a small open economy. See Haskel (2000) for an interpretation of this debate, and Haskel and Slaughter (2001a) for empirical evidence on the role of sector bias for the dynamics of wage differentials.

[12]Erickson and Ichino (1995) and Dell'Aringa and Lucifora (2000) discuss the role of labor market institutions in explaining a compressed wage structure in Italy. Ferragina and Quintieri (1998) examine the relationship between export activity, productivity and performance. See also Quintieri and Rosati (1995) for an investigation of inter-industry wage differentials.

[13]In particular, technology has contributed to raise wage inequality *within* the category of skilled workers (i.e. making managers better and clerks worse off) rather than between manual and non-manual workers.

and thus to distinguish the relative price of an hour of work from the relative earnings. The paper adds another anomaly to the Italian case: despite working more *hours,* the earnings of non manual workers *within firms* have failed to adjust, so that relative *hourly wages* have actually fallen. The possible explanations for this "rigidity" are discussed in the concluding section.

Against this background, our paper contributes to the literature in several respects: data, methodology and, we think, results. As to the first aspect, we exploit a new and much more comprehensive data set for Italy, filling an important gap for assessing the role of technology and trade for this country; as to methodology, we provide a general and consistent approach to firm-level between/within decompositions; moreover, we show how previous estimates of the role of technical progress may contain a "bias of the bias", due to the fact that changes in relative hours are reflected in changes in factor prices rather than quantities.

3 The data

Our analysis is based on firm-level data for the Italian manufacturing sector. The data set is drawn from the Statistical Information System on Enterprises (SISSIEI), a network of databases developed by the Italian Statistical Institute (ISTAT, Central Directorate of Statistics on Institutions and Enterprises), that combines statistical information from four main sources: the System of Accounts of Firms (SCI) and the Survey on Technological Innovation of Industrial Enterprises (INN), both collected on a yearly basis; the monthly statistics on Foreign Trade Flows (COE), and the Archives of Active Firms (ASIA, SIRIO, NAI).[14] Our sample consists of a balanced panel of 8441 manufacturing firms with annual observations from 1989 to 1995, covering about 22 per cent of total manufacturing. The sample includes all the firms with at least 20 employees who responded continuously to the ISTAT surveys between 1989 and 1995.[15]

The data set provides information on the income statement (sales, out-

[14]See Sorce and Fazio (1999) and Corsini, Di Francescantonio and Monducci (1998) for a more detailed description of the construction of the data set.

[15]Note that the System of Accounts of Firms, the main component of SISSIEI, is based on a survey which is conducted by ISTAT on all Italian firms with at least 20 employees and on a representative random sample for firms with less than 20 employees (see Corsini et al. (1998)).

put, costs and outlays, value added, labor costs, capital depreciation and allowances, interests on debts, taxes, profits, etc.), the balance sheet (real assets, financial assets and liabilities, financial and commercial credits and debits, etc.), firms' employment and wages, fixed capital formation, R&D and exports. Data on employment and wages are available separately for manual workers (trainees and production workers) and non-manual workers (clerks and executives).[16] The majority of firms in the sample (63%) falls into the category of "medium" firms (between 25 and 100 employees), while 23% are "large" (more than 100 employees) and the remaining 14% are "small" (below 25 employees). As for the geographic distribution, 80% of the firms in the sample are located in Northern Italy, 15.5% in Central Italy and the remaining 4.5% in the South.[17]

Table 1 provides a preliminary description of the data, reporting sample and (appropriately defined) sub-sample averages for a number of wage and employment indicators. Column 1 shows the share of non-manual workers in the wage bill ($\frac{WB_n}{WB}$), while columns 2 and 3 display its components: the ratio of the wage rate of non-manual workers over the average wage ($\frac{W_n}{W}$, henceforth "skill premium"), and the share of non-manual workers in employment ($\frac{E_n}{E}$, henceforth "skill intensity"). In the period 1989-1995, on average, the share of non-manual workers in the wage bill was 43.3 per cent, the skill premium 135.9 per cent, and skill intensity 31.8 per cent. Table 1 also reports, in columns 4 and 5, the average annual wage rate of non-manual and average workers ($W_n = 68.2$ and $W = 50.2$ millions Italian lira, respectively), and, in columns 6 and 7, the average number of non-manual and total employees in the sample ($E_n = 43.3$ and $E = 136$ thousands, respectively).

Between 1989 and 1995 the share of non-manual workers in the wage bill rose by 3.5 percentage points (0.58 per cent a year, on average). This rise reflects a significant increase in skill intensity (2.4 per cent), with a relatively modest 0.8 per cent rise in the skill premium. Hence, relative wages in our sample conform to the "sticky" pattern found in other studies for earlier periods (e.g. Erickson, Ichino (1995)). The rise in skill-intensity, in turn, reflected an absolute increase of average non-manual employment (from 41.6

[16]Wages include salaries, social contributions paid by the firm, and contributions paid by the firm to the severance-payment fund (TFR).

[17]The three geographic areas are defined as follows. North: Piemonte, Valle D'Aosta, Lombardia, Alto Adige, Veneto, Friuli Venezia Giulia, Liguria, Emilia Romagna. Center: Toscana, Umbria, Lazio, Marche, Abruzzo, Molise. South: Campania, Basilicata, Puglia, Calabria, Sicilia, Sardegna.

to 43.4 thousands) despite the contraction of total employment from 137.8 to 133.2 thousands (note that this implies that manual employment fell by 6.4 thousand units in our sample of firms).

The following blocks in Table 1 document the significant heterogeneity of firms in the sample. Grouping firms according to their size, larger firms pay substantially higher wages than small and medium firms. Skill premia are highest in medium-size firms (134.7 per cent) and lowest in small firms (128.5 per cent), while the wage bill share and skill intensity are increasing in size. Considering a classification based on the geographic distribution, firms located in the South are on average smaller (119.5 employees) and pay substantially lower wages than those in the rest of the country. Also, they appear to pay higher skill premia (140.2%) than those in the rest of the country, although they are characterized by lower wage bill shares (36%) and skill intensity (25.7%).

Next, we consider two further classifications, according to their export activity and computer intensity. "High-export" ("low-export") firms are defined as those whose share of exports in total sales is above (below) the median.[18] Similarly, "high-technology" ("low-technology") firms are defined as those whose share of computer stock over total capital stock is above (below) the median.[19] High- and low-export firms pay similar wages and have similar wage bill shares and skill intensity (despite the former being larger). "Technology-intensive" firms (henceforth "high-tech") employ a substantially higher proportion of skilled workers (35.4% against 27.2%). Despite paying higher salaries for both types of workers, the wage differentials are surprisingly lower in high-techs. The share of skilled workers in the wage bill is about 10 percentage points higher for high-tech than for low-tech firms.

Table 2 groups high/low-tech firms and high/low-export firms by size, since some of the features previously observed may be simply due to differences in scale. The figures suggest that the features of high-tech firms do not depend on their size: high-tech firms are more skill-intensive, pay lower premia, and have higher non-manual wage bill share than low-tech firms in *all* size groups. On the other hand, the similarities between high- and low-exporters in the total sample turn out to be a fallacy of composition: small and medium high-exporters are more skill intensive and pay lower skill premia than low-exporters of the same size, while the converse is true for large

[18] Due to data limitations, the ratio of exports to total sales is only available for 1989.

[19] Thus this classification is based on firms' inputs, rather than on their output.

high-exporters.

4 Firm-Level Decompositions

In this section we present firm-level decompositions in order to provide an interpretation of the aggregate annual wage and employment changes described above. We decompose the change in the relative wage bill into the respective contributions of employment skill-intensity and wage skill-premium. Each of these is further disaggregated into a *between* and a *within* component. The former reflects reallocations of employment and wages that occur between different firms; the latter identifies changes in the employment and wage structure that occur within individual firms. We depart here from the literature in an important aspect: instead of focusing on the decompositions for the relative wage bill and employment intensity taken in isolation (see e.g. Berman et al., (1994), Bernard and Jensen (1997), Berman et al. (1998), Machin and Van Reenen (1998)) we proceed by nesting the wage bill with employment and wage decompositions. Unlike the standard approach, our methodology allows us to identify the respective contributions of annual wages and employment to the change in the wage bill share. Moreover, our approach provides direct information on the changes of relative wages (see also Manasse et al., 2001).

Let the firms in the sample be indexed by superscript $i = 1, ..., I$, and denote manual and non-manual workers with subscripts m and n, respectively (so that E_n^i and W_n^i denote non-manual employment and annual wage in firm i). Firm i employs $E^i = E_n^i + E_m^i$ workers. Total employment is $E = \sum_i E^i$, and total non-manual employment is $E_n = \sum_i E_n^i$. The average wage at the firm is defined as $W^i = \frac{W_n^i E_n^i + W_m^i E_m^i}{E_n^i + E_m^i} = \frac{WB^i}{E^i}$ and the non-manual wage at the firm is defined as $W_n^i = \frac{W_n^i E_n^i}{E_n^i} = \frac{WB_n^i}{E_n^i}$. Finally, let $W = \frac{\sum_i W^i E^i}{\sum_i E^i} = \frac{WB}{E}$ and $W_n = \frac{\sum_i W_n^i E_n^i}{\sum_i E_n^i} = \frac{WB_n}{E_n}$ denote the (sample-wide) average and non-manual mean wage, respectively.

The change in the share of non-manual workers in the wage bill can be decomposed as follows:

$$\Delta(\frac{WB_n}{WB}) = \Delta \sum_{i}^{I} \left(\frac{W_n^i}{W} \frac{E_n^i}{E} \right) = \sum_{i=1}^{I} \left[\underbrace{\Delta \left(\frac{W_n^i}{W} \right) \overline{\left(\frac{E_n^i}{E} \right)}}_{Wtot} + \underbrace{\Delta \left(\frac{E_n^i}{E} \right) \overline{\left(\frac{W_n^i}{W} \right)}}_{Etot} \right] \tag{1}$$

where Δ denotes time difference and the upper bar denotes an average over time. The first term in the square brackets in (1) is the sum of changes in wage premia, weighted by the time-averaged share of non-manuals in employment (*Wtot*). The second term is the sum of changes in skill intensities, weighted by the corresponding time-averaged wage premia (*Etot*).

Consider first the employment component (*Etot*). This may rise for two reasons: either individual firms have, on average, become more skill-intensive (*within* effect), or employment has shifted towards firms that are relatively intensive of skilled workers (*between* effect). Similarly, for the wage component, higher wage premia may be due either to the fact that individual firms have, on average, paid higher skill premia (*within* effect), or to the fact that wages have grown more rapidly in firms paying relatively higher premia (*between* effect). In order to disentangle these different sources, we decompose the two terms in equation (1) into their respective *between* and *within* components.

The (weighted) employment component can be written as follows:

$$\underbrace{\sum_i^I \Delta\left(\frac{E_n^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)}}_{Etot} = \sum_i^I \left[\underbrace{\Delta P_n^i \overline{S^i}}_{Ewit} + \underbrace{\Delta S^i \overline{P_n^i}}_{Ebet}\right]\overline{\left(\frac{W_n^i}{W}\right)} \tag{2}$$

where $P_n^i = \frac{E_n^i}{E^i}$ is the proportion of skilled workers in firm i's employment, and $S^i = \frac{E^i}{E}$ is the share of firm i in total employment. The first term in square brackets represents the change in the non-manual employment share that can be attributed to changes in firms' *factor proportions*, P_n^i, keeping constant their relative size, S^i. This reflects shifts in factor intensity *within* firms (henceforth denoted with *Ewit*): if positive, it suggests that on average firms have substituted unskilled with skilled workers. The second term gives the part of the total change that can be attributed to the change in firms' employment share or relative *size*, S^i, keeping each firm's factor proportions constant. This reflects movements of employment *between* firms (and is denoted by *Ebet*): if positive, it suggests that employment has shifted, on average, towards skill-intensive firms.

Similarly, the (weighted) wage component can be disaggregated as follows:

$$\underbrace{\sum_i^I \Delta\left(\frac{W_n^i}{W}\right)\overline{\left(\frac{E_n^i}{E}\right)}}_{Wtot} = \sum_i \left[\underbrace{\Delta D_n^i \overline{R^i}}_{Wwit} + \underbrace{\Delta R^i \overline{D_n^i}}_{Wbet}\right]\overline{\left(\frac{E_n^i}{E}\right)} \tag{3}$$

where $D_n^i = \frac{W_n^i}{W^i}$ is the wage differential paid by firm i, and $R^i = \frac{W^i}{W}$ is the relative wage paid by firm i as a ratio of the average (sample-wide) wage rate. The first term in square brackets is the part that can be attributed to changes in firms' wage differentials, D_n^i, keeping constant their relative wages, R^i. This is the wage-*within* component (*Wwit*): if positive, it suggests that on average firms have raised skill premia. The second term accounts for the changes in firms' relative wage rates, keeping their wage premia constant. This is the *between* component (*Wbet*): it is positive if, on average, wages have risen faster in firms that pay higher premia.

Summing up, *within*-firm movements presumably reflect *factor*-specific shocks, such as changes in the relative factor productivity and/or wage premia, due to skill-biased technical progress. *Between* movements presumably reflect *firm* and *sector*-specific shocks, such as changes in domestic and foreign demand affecting market shares and/or average wage rates.[20]

Table 3 presents the results of the decompositions in equations (1-3): the average annual change of the share of non manual workers in the wage bill (*WBtot*), and the contributions of the change in skill intensity (*Etot*) and the change in the skill premium (*Wtot*), split further into their respective between and within contributions (*Ebet, Ewit, Wbet, Wwit*). The first row displays the results for the overall sample of firms.[21] Between 1989 and 1995 the share of non manual workers in the wage bill rises by 0.58 per cent a year on average. This is largely accounted for by the skill intensity component ($Etot$ = 0.51 per cent), with a smaller contribution of the wage premium component ($Wtot$ = 0.07 per cent). Interestingly, the rise in the proportion of skilled workers in employment is due to substantial *within*-firm substitution of unskilled with skilled labor ($Ewit$ = 0.63 per cent a year), whereas the *between* component is *negative* ($Ebet = -0.12$ per cent), partially offsetting the effect of the within component.

This means that, on average, employment has moved towards *unskilled*-intensive firms, thus moderating the rise in the proportion of skilled workers in employment.[22] Looking at the wage components, most of the (small) total change can be attributed to the between effect ($Wbet$ = 0.06 per cent): on

[20] Clearly, demand and trade may indirectly affect within-firm changes through their impact on factor prices (see below).

[21] Note that the lower number of observations (compared to table 1) is due to the presence of firms employing only manual workers.

[22] This result confirms the findings in Manasse et al. (2001) for the metal-mechanical sector. See also Faini et al. (1999) for similar results based on industry data for Italy.

average wages have risen faster in firms paying higher skill premia.

Rows 2 and 3 of table 3 divide the 1989-95 sample into two four-year sub-periods (1989-92 and 1992-95). The results indicate that, for both relative employment and wages, changes were much larger in the first sub-period: the share of non-manual workers in the wage bill rose at an average annual rate of 1 per cent between 1989 and 1992, as opposed to just 0.17 per cent between 1992 and 1995. It is interesting to observe that this deceleration is largely explained by the employment component. In particular, the relative expansion of employment in *unskilled*-intensive firms (the negative *Ebet*) occurs only in the second sub-period, 1992-95, a period of booming manufacturing exports, particularly for low-skill firms, spurred by a rapidly depreciating real exchange rate (see Manasse et al. (2002)). In the same period skill-upgrading (the positive *Ewit* component) also slows down.

The next blocks in table 3 show the contributions of individual sub-samples of firms to the overall decomposition. Looking at the classification of firms by their computer-intensity, two interesting features appear from the table. First, high-tech firms account for a large share of the within-firm rise in skill intensity (*Ewit* about 0.40 per cent as opposed to 0.24 per cent for low-tech firms). This finding is consistent with the hypothesis that new technologies (computers) and skills are complement, so that technical change has indeed been skilled-biased. Second, high-tech firms also entirely account for the negative employment between component, *Ebet*. Thus high-tech firms, the most active in raising their skill intensity, have lost market shares during this period. Looking at the classification of firms by their export activity, we observe an important result: high-export firms account entirely for the negative employment between component. The last two findings suggest that the Italian specialization pattern in international trade is shifting employment towards unskilled-intensive goods and away from computer-intensive firms.[23] Notice also that, when we classify firms jointly for computer-intensity and export-activity, skill-upgrading (*Ewit*) occurs equally for all high-tech firms (irrespective of being high or low exporters), whereas the loss of employment share (*Ebet*) is more evident among high-tech exporters.

[23] It should be noted that the negative employment between component is largely attributable to large firms (-0.13 per cent). Within these firms, high-exporters are indeed less skill intensive than low-exporters (relative skilled employment is 33.5 and 36.4, respectively).

5 Hours and hourly wages

In this section we examine our "working on the train" conjecture that technical progress affects the relative number of hours worked by non manual workers. The point here is that considering *annual* rather than *hourly* wages, that is lumping together the number of hours with the hourly wage rate, as generally done in the literature, is potentially misleading. When hours change, this erroneously shows up in factor prices (annual wages) rather than in factor quantities (total hours employed). Thus the previous decompositions may be misleading, and the estimated skill-bias of technical progress may be biased (see below).

We obtain the average number of hours worked per employee in firm i (h^i) by dividing the number of hours worked in firm i (H^i) by the number of its employees (E^i): $h^i = \frac{H^i}{E^i}$. The hourly average wage at the firm is then defined as the ratio between the annual wage rate and the average number of hours per employee: $\omega^i = \frac{W^i}{h^i}$. Average non-manual hours (h_n^i) and hourly wage rates (ω_n^i) at firm i are calculated similarly.

Table 4 shows sample and sub-sample means across firms for average worker's and non-manual worker's hours (h and h_n, respectively), hourly wage rates (ω and ω_n), and the corresponding "hourly" skill intensity ($\frac{h_n}{h}$) and wage premium ($\frac{\omega_n}{\omega}$). In the entire sample, non manual employees work longer hours per year (1720.6 vs. 1665.2), and earn higher hourly wages than average workers (39.6 vs. 30.1 thousand lire per hour, corresponding to Euro 20.45 and 15.6 respectively). The average hourly skill premium and hourly intensity are thus 131.5 and 103.3 per cent, respectively. Looking back at Table 1, we see that in the total wage premium of 135.9 (first row, second column), only 131.5 (Table 4) is the actual price differential, the rest simply reflecting differences in hours. Looking at changes between 1989 and 1995, the hourly wage premium rises by 1.2 percentage points, while hourly skill intensity rises until 1993 and then falls back to just below the initial level. Comparing this with the change in relative annual wages ($\frac{W_n}{W}$), Table 1 second column, we see that the modest rise in relative annual wages is (more than) entirely due to the rise in the hourly premium ($\frac{\omega_n}{\omega}$). The hourly wage premium is smaller in high-tech and high-export firms, while hourly skill intensity is relatively more uniform across firms.

Proceeding as before, we aim at separating the (*between*) changes resulting from compositional effects from those occurring at firm level (*within*). Thus we calculate between/within decompositions for the three components of the relative wage bill (see the Appendix for details), employment (E), hours worked (H) and hourly wages (HW):

$$\Delta(\frac{WB_n}{WB}) = (Ewit + Ebet) + (Hwit + Hbet) + (HWwit + HWbet) \quad (4)$$

The results, presented in Table 5, are revealing, particularly when compared with those reported in Table 3 . The apparent stability of annual wage premia within firms ($Wwit = 0.01$ in table 3), hides the offsetting contributions of hours and hourly wages: relative non-manual hours have risen at the annual rate of $Hwit = 0.19$, while, given the lack of adjustment in salaries, the hourly premium ($HWwit$) has *fallen* at the same rate. Given that the relative price of an hour of skilled labor has actually declined, firms have substituted manual with non-manual workers not only in terms of employment levels (on the *extensive* margin), at the annual rate of $Ewit = 0.63$, but also in terms of hours (on the *intensive* margin), at the annual rate of $Hwit = 0.19$. The latter phenomenon is simply obscured when the standard definition of annual wages is used. Within firms, relative non-manual hours have therefore risen approximately at the annual rate of 0.63 + 0.19 = 0.82 which is about one third above the estimate in Table 3. We now turn to the interpretation of these decompositions.

6 Interpreting the decompositions

So far we have interpreted the within and between components as reflecting technology and demand shocks, respectively. This interpretation, however, is not warranted: within-firm changes may also be due to demand shocks. Suppose, for example, that the domestic relative price of unskilled-intensive ("traditional") goods rises, due to a change in preferences or to trade liberalization.[24] As new firms enter the "traditional" sector, the share of unskilled workers in employment rises (*between* effect). The resulting excess demand for unskilled workers lowers the wage premium, and induces firms to substitute manual with non-manual workers (a positive employment *within* effect). In this case, a demand shock (*between* firms) indirectly causes a (*within*-firm) change in factor proportions. Attributing the latter to technology would be incorrect, and it would result in overestimating the role of technology (and underestimating that of demand or trade).

[24] We thank Paolo Epifani for raising this point.

In this section we therefore examine whether it is correct to interpret within and between components as reflecting technology and demand, respectively. We regress the between and within firm-level changes in wages (both annual and hourly), employment and hours, on variables that proxy for firm-level demand and technology. If our assumed interpretation is correct, *within*-firm changes should be significantly related to technology but not to demand variables, while the converse should be true for *between* changes.

We use the rate of growth of total sales as an indicator of the change in demand for a firm's output, and consider two alternative indicators of technological change at firm-level: the ratio of investment in computers over total investment, and the ratio of research and development expenditures over total sales.[25] All regressions include size, region, and industry dummies to allow for different firm and industry characteristics. The general specification is therefore:

$$\Delta C_d^i = \alpha + \beta_1 \Delta lS^i + \beta_2 ICI^i + \beta_3 RDS^i + \sum_j \gamma_j DUM_j \qquad (5)$$

where ΔC_d^i indicates firm i's contribution to the overall change in the relative wage bill, employment and (annual and hourly) wage ($\Delta C = WB$, E, W, HW, H), and the subscript $d = bet, wit$ denotes between and within components, respectively; ΔlS is the growth rate of total sales, ICI is the ratio of the firm's investment in computers over total investment, RDS is the ratio of Research and Development expenditures over total sales, and DUM represents a set of industry, size and geographic dummies.

The results of OLS estimation of equation (5) are presented in table 6.[26] The growth rate of sales has a positive and highly significant coefficient in all between regressions (with the exception of the hourly wage equation): demand shocks are positively related to between-firm changes in both employment and annual wages, but not to within changes (with the exception of hours, $Hwit$, and hourly wages, $HWwit$). Looking at the technology indicators, the computer share of investment ICI is positive and significant in the wage bill and employment within equations, while negative but never significant in the between equations. The research and development indicator

[25] The R&D variable also contains expenditures for patents, concessions, and copyrights.

[26] The lower number of observations (from 8203 in the decompositions to 7377 in the regressions) is largely due to data limitations on the technology indicators: only 8005 and 7830 observations, respectively, are available for the computer intensity and research and development indicators.

RDS is positive, although not significant, in the wage bill and employment within equations. Interestingly, it is positive and strongly significant in the equation for the within firm relative number of hours, *Hwit*. The results for hourly wages are less clear-cut: the within component is significantly related to both the growth of sales (positively) and the R&D indicator (negatively); the between component is not significantly affected by either demand or technology indicators.[27]

Overall, the evidence suggests that between-firm changes for all the indicators examined are positively and significantly related to changes in demand. In addition, there is a positive and significant relationship between technical change, as measured by investment in computers and R&D intensity, and within-firm skill upgrading both on the extensive margin (number of employees) and the intensive margin (number of hours worked per employee).

7 The (biased) bias of technical change

In the previous sections we found that the main determinant of the rise of non-manual employment and wage bill shares is firms substituting non-manual for manual workers. In this section, we use a cost function framework to measure the effect of technical change on the relative productivity of non-manual workers (the so called skill-bias of technical change). We find a positive and significant skill-bias. Also, we show that defining relative wages in terms of annual, rather than hourly, salaries, produces a downward bias in the estimates of the skill-bias as well as of the elasticity of factor substitution.

In order to isolate the effect of technical progress on factor shares, one needs to control for changes in factor prices and capital intensity: the rise in the share of skilled workers within firms may be simply due to a fall in their relative factor prices or to capital deepening when skills and capital are complement. We define technical progress as a reduction in unit cost (an inward shift of the unit-isoquant) at *constant* factor prices and capital intensity (see Binswanger, 1974). Technical progress is *neutral* if, despite lower unit costs, firms on average do not change factor proportions, at given factor prices and capital intensity. However, if they increase on average the proportion of skilled workers in employment (when they pick a new tangency

[27]In order to address the possible endogeneity of the proxies for demand and technology, we also estimated the equations by instrumental variables, using the initial levels of the regressors as instruments, and obtained qualitatively similarly results.

point on an lower isocost line of the *same* slope), then technical progress raises the relative productivity of non-manual workers and is defined *skill-biased.*

Empirically, we implement this approach following Berman et al. (1994). An equation for the wage bill share can be derived from a translog cost function with quasi-fixed factors of production (Brown and Christensen (1981)). Assume that firms choose variable factors, manual and non manual labor, in order to minimize costs, subject to an output constraint. Production requires (manual and non-manual) labor and capital, which is fixed in the short run. The cost function has the translog functional form, and returns to scale are constant. Under these assumptions the change in the share of non-manuals in the wage bill share can be written as follows:

$$\Delta(\frac{WB_n^i}{WB^i}) = \alpha + \beta\,\Delta\ln(\frac{w_n^i}{w_m^i}) + \gamma\,\Delta\ln(\frac{K^i}{Y^i}) + \varepsilon^i \tag{6}$$

where K_i and Y_i represent capital and value added, respectively (the actual specification also includes a set of industry, size and geographic dummies, as in (5)). Note that the intercept α measures the *average bias in technical change*, and the residual $\widehat{\varepsilon}^i$ provides an estimate of the firm-specific bias. If the slope coefficient β is positive (negative) a change in the relative price of non-manual labor raises (lowers) its cost share, implying that the elasticity of substitution between inputs is below (above) unity ($\sigma = \frac{-\beta + s_n(1-s_n)}{s_n(1-s_n)}$, where $s_n = \frac{WB_n}{WB}$). A positive (negative) estimate for γ implies that capital is complement (substitute) to non-manual labor, since it raises (lowers) its wage bill share at *constant* factor prices. In the following we present results obtained estimating the above equation using either annual or hourly wages ($w = W$, ω) as factor price.

Table 7 reports OLS estimation results using annual wages. We estimate equation (6) in its basic version, and subsequently add, either individually or jointly, the two indicators of technological change described above (computers as a share of total investment and R&D over sales). Starting from the basic specification, we see that the constant is positive and significant: the increase in the relative productivity of non manual workers (the average bias of technical progress) occurs at an annual rate of 0.48 and thus raises the wage bill share of skilled workers by almost half of a percentage point per year. The change in relative wages has a positive and statistically significant coefficient, implying an elasticity of substitution between labor inputs of $\sigma = 0.49$. The coefficient of the capital-value added ratio is also positive and significant, indicating complementarity between capital and skilled labor. Capital deepening has thus contributed to skill upgrading. When we add to the basic model technology indicators individually (equations 2-3) or jointly (equation 4), both the computer share of total investment and R&D expenditures as a fraction of sales have positive and highly statistically significant coefficients. The estimate of the average skill bias falls slightly (to 0.44) when explicit proxies of technical progress are included in the equation, while the estimated elasticity of substitution is robust across different specifications.[28]

Next we re-estimate the previous equation with hourly wages on the right hand side, and obtain the results shown in Table 8. Compared with those in Table 7, the parameters for capital deepening and the computer share in investment are virtually unchanged, while the estimates for the ratio of R&D expenditures over sales are almost double in size. Using hourly wages has two more important consequences: the estimated average skill-bias rises consistently in all specifications, respectively from α in the range (0.48-0.44) to α' in the range (0.52-0.48). Similarly, the estimated elasticity of substitution rises from $\sigma = 0.49$ to $\sigma' = 0.67$. The reason for the larger estimated skill bias is the following: technical progress raises, as we saw, the relative number of non-manual hours, but when wages are incorrectly measured (on an annual, rather than hourly basis), this effect is attributed to higher relative factor prices, rather than to the bias. As for the larger elasticity of substitution, note that in the second specification this elasticity effectively measures the change in total hours (employment *plus* average hours) induced by a change in relative factor prices, so that the estimated elasticity must also be larger. If technical innovation and skilled hours are complement, estimates of the skill-bias and of the elasticity of substitution based on annual wages (e.g. Berman et al., 1994, Berman et al., 1998) are therefore likely to underestimate the skill-bias of technical change.

Summing up, our estimates suggest that skill-biased technological change has raised the relative productivity of non manual workers at an annual rate of roughly half of a percentage point, and thus was the key determinant of the increase in the demand for non-manual workers in Italian manufacturing during the 1990s. We also found that in order to assess the role of technical progress on wage inequality and skill upgrading, it is important to disaggre-

[28]The results are also robusts to the use of beginning-of-period levels for the technology indicators.

gate annual wages into the number of hours worked and their hourly price. The current practice in the literature fails to do so, and therefore erroneously attributes changes in hours to factor prices rather than quantities. This produces a downward bias in the estimated skill-*bias* of technical progress.

8 Discussion and conclusions

This paper has presented firm-level evidence on the dynamics of wage premia and relative employment and hours in Italian manufacturing in the nineties. We have exploited a new data set, previously unavailable for research, that covers a balanced panel of 8441 manufacturing firms between 1989 and 1995. The analysis has reached a number of interesting results on the effects of technology and trade on employment and wages in Italian manufacturing firms.

First, Italian firms have substituted unskilled for skilled workers at a rate comparable to those experienced in other industrialized countries, with high-tech firms playing a leading role in this process (*within-firm* skill upgrading is the main determinant of the shift in relative labor demand in the nineties). This is a new, and somewhat unexpected, result, given that most studies on European economies find significant effects of technical progress at sector level only after 1995 (e.g. Daveri, 2000).

By contrast, demand changes associated to trade have moved manufacturing employment *away* from skill-intensive firms, contributing to moderate the change in relative factor prices (*between-firm* employment shifts have reduced the relative demand for skills). This anomaly is consistent with the finding in Manasse et al. (2002), obtained from a much smaller sample of (metal-mechanical) firms and a shorter time horizon. The anomaly is probably due to the specialization pattern of Italian trade. During the nineties firms have become increasingly specialized in unskilled-intensive "traditional" goods (such as shoes, textiles, furniture etc., see Chiarlone, 2001), and have been increasingly exporting to more "technology abundant" European countries.

Second, the relative stability of wage differentials within firms hides a second anomaly: when composition effects are taken care of, the relative number of *hours* worked by skilled workers has risen whereas relative *hourly wages* have fallen. The narrowing of hourly skill premia in the face of technical progress may come unexpected, particularly to readers unfamiliar with the features of the Italian labor market. Yet it is well known the Italian centralized system of wage bargaining systematically fails to tailor wages to firms and workers productivity, with unions acting as a powerful instrument of wage equalization. For example, salaries in the South are equalized to salaries in the North, despite large productivity gaps, and this is generally regarded as an explanation of a rate of unemployment which is four times larger in the South than in the North. In addition, possibly as a result of this compression in relative hourly wages, Italy has been exporting college graduates and skilled workers ("the brain drain") at a rate that has no comparison in Europe (see Becker, Ichino and Peri (2002)).

Third, *within-firm* skill upgrading, measured by changes in both relative employment and number of hours, is strongly and significantly related to investment in computers and R&D. This suggests that the skill bias of technical change has been a key determinant of the increase in the relative demand for non-manual workers in Italian manufacturing in the last decade.

Finally, the paper makes an important methodological point: in order to assess the role of technical progress on wage inequality and skill upgrading, it is essential to disaggregate hours worked from their price. Failing to do so, and attributing hours to factor prices rather than quantities, biases downward the estimates of the skill *bias* whenever technical progress and hours are complement. Properly measured, technical progress is found to raise the relative productivity of non-manual worker by half a percentage point every year.

Whether these results extend beyond the manufacturing sector is one of the questions to be investigated in further research. Finally, notice that our finding that total relative hours have risen (within firms) while hourly relative wages have fallen, suggests that labor *supply* effects can no longer be ruled out as a possible explanation of the Italian case. In order to assess the role of factors such as ageing labor force, female participation, immigration, education, changes in preferences away from leisure and so on, data on individual workers should be merged with firms' data: another important project for further research.

9 Appendix

This appendix provides some details on the derivation of the contributions of employment, hours worked and hourly wages to the wage bill presented in section 5:

$$\Delta\left(\frac{WB_n}{WB}\right) = \Delta\sum_{i}^{I}\left(\frac{E_n^i}{E}\frac{W_n^i}{W}\right)$$

$$= \sum_{i}^{I}\left[\Delta\left(\frac{E_n^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)} + \Delta\left(\frac{W_n^i}{W}\right)\overline{\left(\frac{E_n^i}{E}\right)}\right] =$$

$$= \sum_{i}^{I}\left[\begin{array}{c} \Delta\left(\frac{E_n^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)} + \Delta\left(\frac{h_n^i}{h}\right)\overline{\left(\frac{\omega_n^i}{\omega}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)} + \\ \Delta\left(\frac{\omega_n^i}{\omega}\right)\overline{\left(\frac{h_n^i}{h}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)} \end{array}\right] =$$

$$= \sum_{i}^{I}\left[\begin{array}{c} \underset{Ewit}{\Delta\left(\frac{E_n^i}{E^i}\right)\overline{\left(\frac{W_n^i}{W}\right)}} + \underset{Ebet}{\Delta\left(\frac{E^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)}} + \\ \underset{Hwit}{\Delta\left(\frac{h_n^i}{h^i}\right)\overline{\left(\frac{\omega_n^i}{\omega}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)}} + \underset{Hbet}{\Delta\left(\frac{h^i}{h}\right)\overline{\left(\frac{\omega_n^i}{\omega}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)}} + \\ \underset{HWwit}{\Delta\left(\frac{\omega_n^i}{\omega^i}\right)\overline{\left(\frac{h_n^i}{h}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)}} + \underset{HWbet}{\Delta\left(\frac{\omega^i}{\omega}\right)\overline{\left(\frac{h_n^i}{h}\right)}\ \overline{\left(\frac{E_n^i}{E}\right)}} \end{array}\right]$$

The first, second and third line above correspond to the first, second and third term of equation (4) in the text.

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Table 1: Employment and wages: overall and sub-sample averages

Sample	$\frac{WB_n}{WB}$	$\frac{W_n}{W}$	$\frac{E_n}{E}$	W_n	W	E_n	E	N.Obs.
Overall	43.3	135.9	31.8	68.2	50.2	43.3	136.0	59087
1989	40.8	135.1	30.2	55.1	40.8	41.6	137.8	8441
1995	44.3	135.9	32.6	79.8	58.7	43.4	133.2	8441
Small	25.8	128.5	20.1	51.6	40.2	4.5	22.2	7969
Medium	31.7	134.7	23.5	58.3	43.3	11.5	48.8	37238
Large	46.5	134.2	34.7	70.5	52.5	150.9	435.3	13880
North	43.4	135.4	32.0	68.5	50.6	43.1	134.5	47438
Centre	44.1	136.4	32.4	68.3	50.1	48.1	148.7	9015
South	36.0	140.2	25.7	58.7	41.9	30.7	119.5	2634
High exp.	43.1	135.9	31.8	67.9	50.0	49.9	157.1	29540
Low exp.	43.4	136.0	31.9	68.6	50.4	36.7	114.9	29547
High tech.	47.6	134.7	35.3	68.2	50.6	55.0	155.8	29526
Low tech.	37.4	137.6	27.2	68.2	49.5	31.6	116.2	29561

Note: $\frac{WB_n}{WB}$ = non-manual wage bill share; $\frac{W_n}{W}$ = skill premium; $\frac{E_n}{E}$ = skill intensity; W = average wage; W_n = non-manual wage; E = employment; E_n = non-manual employment. See section 3 for sub-sample definitions.

Table 2: Employment and wages: sub-sample averages by size

Sample	$\frac{WB_n}{WB}$	$\frac{W_n}{W}$	$\frac{E_n}{E}$	W_n	W	E_n	E	N.Obs.
Small								
High exp.	28.9	126.2	22.9	51.5	40.8	5.1	22.4	3006
Low exp.	23.9	130.0	18.4	51.8	39.8	4.1	22.1	4963
High tech.	29.8	126.7	23.6	51.9	41.0	5.2	22.2	3497
Low tech.	22.6	129.8	17.4	51.4	39.6	3.9	22.2	4472
Medium								
High exp.	34.0	133.1	25.5	58.7	44.1	13.0	50.8	18226
Low exp.	29.2	136.1	21.5	57.7	42.4	10.1	46.9	19012
High tech.	35.7	132.9	26.9	58.2	43.8	13.3	49.6	18336
Low tech.	27.6	136.5	20.2	58.3	42.7	9.7	48.1	18902
Large								
High exp.	45.3	135.3	33.5	69.9	51.6	147.1	439.1	8308
Low exp.	48.2	132.3	36.4	71.3	53.9	156.6	429.7	5572
High tech.	50.3	133.6	37.7	70.2	52.6	177.0	469.7	7693
Low tech.	40.8	135.3	30.2	71.0	52.5	118.4	392.5	6187

Note: $\frac{WB_n}{WB}$ = non-manual share of wage bill; $\frac{W_n}{W}$ = skill premium; $\frac{E_n}{E}$ = skill intensity; W = average wage; W_n = non-manual wage; E = employment; E_n = non-manual employment. See section 3 for sub-sample definitions.

Table 3: Wage bill share decompositions: overall and by sub-sample

Sample	WBtot	Etot	Wtot	Ebet	Ewit	Wbet	Wwit	N.Obs.
1989-95	0.58	0.51	0.07	-0.12	0.63	0.06	0.01	8203
89-92	1.00	0.83	0.16	0.12	0.72	0.08	0.09	8205
92-95	0.17	0.20	-0.02	-0.37	0.57	0.06	-0.08	8267
High exp.	0.28	0.22	0.06	-0.11	0.33	0.04	0.03	4168
Low exp.	0.30	0.29	0.01	-0.01	0.30	0.03	-0.02	4035
High tech.	0.29	0.24	0.05	-0.15	0.39	0.05	-0.01	4154
Low tech.	0.29	0.27	0.02	0.03	0.24	0.01	0.02	4049
Hexp-Htech	0.14	0.11	0.03	-0.10	0.21	0.02	0.01	2273
Hexp-Ltech	0.14	0.11	0.03	-0.01	0.12	0.01	0.02	1895
Lexp-Htech	0.15	0.14	0.02	-0.05	0.19	0.03	-0.01	1881
Lexp-Ltech	0.15	0.16	-0.01	0.04	0.12	-0.00	-0.00	2154

Note: $WBtot$ = non-manual share of wage bill, $Etot$ = total employment, $Wtot$ = total wage, $Ebet$ = empl. between, $Ewit$ = empl. within, $Wbet$ = wage between, $Wwit$ = wage within. See section 4 for details on the decompositions.

Table 4: Hours and hourly wages: overall and sub-sample averages

Sample	$\frac{\omega_n}{\omega}$	$\frac{h_n}{h}$	ω_n	ω	h_n	h	N.Obs.
Overall	131.5	103.3	39.6	30.1	1720.6	1665.2	59083
1989	131.2	102.9	32.1	24.4	1718.7	1669.8	8441
1990	130.4	103.3	34.8	26.7	1708.7	1653.4	8440
1991	130.1	104.0	38.1	29.3	1714.6	1648.6	8441
1992	131.9	103.3	40.6	30.8	1723.6	1668.2	8441
1993	130.1	104.1	41.6	32.0	1724.1	1655.6	8439
1994	131.4	102.8	43.8	33.4	1718.8	1671.6	8440
1995	132.4	102.7	46.0	34.7	1736.1	1690.8	8441
High exp.	131.0	103.7	39.4	30.1	1723.7	1661.7	29538
Low exp.	132.3	102.8	39.9	30.2	1716.5	1670.1	29545
High tech.	130.5	103.2	39.9	30.6	1709.2	1656.8	29523
Low tech.	132.5	103.8	39.2	29.5	1740.5	1676.5	29560

Note: ω_n = non-manual hourly wage per worker; h_n = non-manual average number of hours worked per employee (see section 5).

Table 5: Hours and hourly wages in wage bill decompositions

Sample	WBtot	Ewit	Ebet	Hwit	Hbet	HWwit	HWbet	N.Obs.
1989-95	0.58	0.63	-0.12	0.19	-0.00	-0.18	0.06	8203
89-92	1.00	0.74	0.11	0.41	0.04	-0.34	0.04	8204
92-95	0.17	0.57	-0.38	-0.03	-0.09	-0.06	0.16	8267
High exp.	0.28	0.33	-0.11	0.12	-0.01	-0.09	0.05	4168
Low exp.	0.30	0.30	-0.01	0.07	0.01	-0.09	0.01	4035
High tech.	0.29	0.39	-0.15	0.14	-0.00	-0.15	0.06	4154
Low tech.	0.29	0.24	0.03	0.05	0.00	-0.03	0.00	4049

Note: $WBtot$ = non-manual wage bill share, $Ewit$ = Employment within, $Ebet$ = Employment between, $Hwit$ = Hours within, $Hbet$ = Hours between, $HWwit$ = Hourly wage within, $HWbet$ = Hourly wage between.

Table 6: Determinants of wage bill components

Dep. Var.	ΔlS	ICI	RDS	R^2	N.Obs.
$WBwit$	-0.02	0.07	0.09	0.04	7377
	(-1.24)	(2.09)	(1.29)		
$WBbet$	0.72	-0.20	0.12	0.04	7377
	(9.91)	(-1.37)	(0.46)		
$Ewit$	-0.04	0.08	0.12	0.03	7377
	(-1.69)	(2.04)	(1.34)		
$Ebet$	0.62	-0.19	0.23	0.04	7377
	(10.07)	(-1.50)	(0.92)		
$Wwit$	0.01	-0.01	-0.03	0.01	7377
	(0.94)	(-0.79)	(-0.71)		
$Wbet$	0.10	-0.01	-0.11	0.02	7377
	(3.98)	(-0.35)	(-0.69)		
$Hwit$	-0.02	0.02	0.34	0.00	7377
	(-1.87)	(0.64)	(3.78)		
$Hbet$	0.11	-0.07	-0.03	0.01	7377
	(3.52)	(-1.23)	(-0.17)		
$HWwit$	0.03	-0.03	-0.37	0.01	7377
	(2.22)	(-1.02)	(-3.87)		
$HWbet$	-0.01	0.06	-0.07	0.00	7377
	(-0.50)	(1.41)	(-1.43)		

Note: t-statistics in parentheses. All specifications include size, geography and industry sector dummies, as defined in section 3. Legend: ΔlS = growth rate of sales; ICI = Computer share of total investment; RDS = $R\&D$ / sales.

Table 7: Determinants of within firm skill upgrading

Equation	α	$\Delta lWnm$	ΔlKY	ICI	RDS	R^2	N.Obs.
(1)	0.48	0.11	0.34			0.23	8136
	(31.21)	(32.51)	(2.10)				
(2)	0.43	0.11	0.36	0.56		0.24	7742
	(24.84)	(32.32)	(2.22)	(5.91)			
(3)	0.49	0.11	0.40		0.52	0.24	7684
	(30.87)	(31.89)	(2.39)		(3.36)		
(4)	0.44	0.11	0.43	0.58	0.51	0.25	7321
	(24.53)	(31.82)	(2.52)	(5.94)	(3.62)		

Note: t-statistics in parentheses. Dependent variable: $\Delta wbsh$ = change in log relative wage bill; $\Delta lWnm$ = change in log relative annual wage; ΔlKY = change in log capital output ratio; ICI = Computer share of total investment; RDS = $R\&D$ / sales.

Table 8: Determinants of within firm skill upgrading (hourly wages)

Equation	α	$\Delta lHWnm$	ΔlKY	ICI	RDS	R^2	N.Obs.
(1)	0.52	0.07	0.46			0.14	8135
	(32.14)	(20.48)	(2.71)				
(2)	0.47	0.07	0.46	0.59		0.14	7741
	(25.67)	(19.86)	(2.66)	(5.76)			
(3)	0.53	0.07	0.50		0.97	0.14	7684
	(31.53)	(19.98)	(2.82)		(5.46)		
(4)	0.48	0.07	0.50	0.63	0.97	0.15	7321
	(25.03)	(19.50)	(2.77)	(5.92)	(5.57)		

Note: t-statistics in parentheses. Dependent variable: $\Delta wbsh$ = change in log relative wage bill; $\Delta lHWnm$ = change in log relative hourly wage; ΔlKY = change in log capital output ratio; ICI = Computer share of total investment; RDS = $R\&D$ / sales.