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Working on the Train: Technology, Trade, and Wages in Italian Manufacturing*

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Abstract

This paper investigates the increase in demand for non-manual workers in Italian manufacturing during the 1990s. We find that within-firm skill upgrading is the main determinant of this shift in demand, whereas the reallocation of employment across firms reduces the relative demand for skills. Although the adjustment of skill premia is relatively small when referred to annual wages, hourly wage premia and skill intensity reveal substantial and offsetting contributions to wage responses. Within-firm skill upgrading is strongly and significantly related to investment in computers and R&D, suggesting skill biased technical change as the main explanation of the increase in the relative demand for non-manual workers.

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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, who were typically "busy" reading the financial and general press; second-class travellers, mainly families, tourists and economy-travellers, who were typically busy in conversations, generally about soccer or politics, with their fellow travellers. Nowadays, first-class travellers can be seen silently hunched over their laptops, or noisily talking business over their cellular phones. Second-class travellers still chat their way to their destination, although mostly over the phone. Academics, now travelling second-class, either read newspapers or work on their laptops (or sleep).[1]

This anecdotal evidence suggests three working hypotheses: first, technical progress in Italy, as in many other countries, has been skill-biased, that is, it has raised the relative productivity of more educated (skilled) workers; second, relative wages have not (fully) adjusted to the change in relative productivity; third, skill upgrading has operated, to some extent, by increasing the average number of hours worked by skilled workers, relative to those worked by the less skilled.

This paper explores these conjectures by presenting new evidence on the dynamics of manual and non-manual employment and wages in Italian manufacturing during the 1990s. Between 1989 and 1995 the non-manual share of the wage bill increased by 3.5 per cent in our overall sample of manufacturing firms. This reflected an increase in both the non-manual employment share and the non-manual relative wage, suggesting shifts in labor demand within manufacturing from manual to non-manual workers. We provide firm-level evidence on the sources and determinants of aggregate skill upgrading, and examine the respective roles of increased international competition and skill-biased technical change as its main determinants.

The analysis provides a number of interesting results. First, within-firm skill upgrading is the main determinant of the shift in relative demand in the nineties: Italian firms have substituted unskilled for skilled workers at a rate comparable to those experienced in other industrialized countries, with

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

high-tech firms playing a leading role in this process. Second, the reallocation of employment between firms has reduced the relative demand for skills: demand shifts, associated to trade, have shifted employment *away* from skill-intensive firms, contributing to moderate the change in relative factor prices. Third, although the adjustment of skill premia is relatively small when referred to annual wages, hourly wage premia and skill intensity reveal substantial and offsetting contributions to wage responses. Finally, within-firm skill upgrading is strongly and significantly related to investment in computers and R&D. This suggests that skill-biased technical progress was a key determinant of the increase in the relative demand for non-manual workers in Italian manufacturing in the last decade.

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 wage and employment dynamics in Italy in the last decade. In section 4 we present firm-level decompositions of aggregate changes in relative wage bill, employment and wages into their respective within and between components. Section 5 takes a closer look at wage dynamics, decomposing annual wages into hourly wages and number of hours worked. In section 6 we present evidence from firm-level regressions to provide an interpretation of the observed wage and employment dynamics. Section 7 concludes the paper 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. In the United States and the United Kingdom, both relative employment and wage differentials between skilled and unskilled workers have been growing since the early 1980s.[2] In continental Europe, relative wages have been more stable, while most of the adjustment seems to have taken place on the quantity side, with higher skilled employment shares and unemployment of unskilled workers growing faster than those of skilled work-

[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.

ers.[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.

Following these labor markets developments, in the past decade a growing number of economists have attempted to provide a theoretical interpretation.[4] Most studies have focused on factors underlying shifts in the relative demand for skilled workers, due to the observed simultaneous rise in skill-premia and employment shares, and to the evidence indicating that the relative supply of skills can only explain a small fraction of growing wage inequality.[5] The literature has pointed in particular to trade competition and skill-biased technological change as the main explanations for the rise in the relative demand for skilled labor.[6]

The "technology" view argues that changes in production practices, in particular those related to the computer revolution, have increased the relative productivity of more skilled workers, thus leading to higher relative demand, employment shares, and wage premia for skilled workers. This argument, based on the skill-bias of technological change, is consistent with the observed IT-induced growth in productivity observed in the United States. Empirically, an important implication of skill-biased technical change is an increased proportion of skilled labor *within* industries (or firms/plants, depending on the specific way new technologies are adopted).

The "trade" view points to Stolper-Samuelson effects of growing competition with developing countries.[7] According to proponents of this explanation, increased trade openness has lowered product demand in developed economies in sectors producing unskilled labor-intensive goods. As resources

[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 expanations often proposed are outsorcing (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)).

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

have shifted to skill-intensive sectors, the relative demand for unskilled workers has fallen. This argument is consistent with the trends towards "globalization" documented, for example, by the acceleration of the growth of trade in goods and services in the recent past. Empirically, an important implication of the trade view is shifts of employment *between* industries (or firms/plants, depending on the level of aggregation).

The broad consensus emerging from the early empirical literature, generally based on studies of *industry* data, is that, while international trade accounted for some of the rise in wage differentials, most of it could be attributed to 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 was based on two main findings. First, most of the increase in aggregate skilled employment and wage bill share could be accounted for by skill upgrading within industries, whereas employment shifts towards skill-intensive industries played a minor role. Second, many studies found a significant relationship between indicators of technological change and within-industry skill upgrading.

The explanation resting on skill-biased technical change, however, has been challenged recently both empirically and theoretically. At the empirical level, a number of studies based on firm- or plant-level data have cast doubts on the conclusions of previous studies based on industry data.[9] In particular, Bernard and Jensen (1997) found that within-industry increases in the demand for skilled labor can be largely attributed to shifts in employment *between plants* (see also Bernard and Jensen (1995)), with increases in employment at exporting plants playing a major role.[10] The general conclusion from this literature is that significant dynamics occur at the level of individual firms and establishments, so that the earlier studies using industry data may have underestimated the role of trade.

At the theoretical level, a further criticism came from the work of trade

[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).

theorists arguing that the factor bias of technological change may be relevant for wage dynamics in a one-sector closed economy, but is irrelevant in more general settings. In particular, it is argued, in a two-sector two-factor Heckscher-Ohlin economy it is the *sector* bias rather than the factor bias of technical progress that matters for wage dynamics (see e.g. Leamer (1994, 1998)). Krugman (1995), however, shows that this criticism rests on the assumption of local technical change affecting a small open economy. When we consider unilateral (pervasive) technical change, occurring simultaneously in many countries, these economies may be thought to behave as a closed economy, so that the reverse is true: it is indeed the *factor* bias of technical progress that matters for wage dynamics.[11]

Against this background, this paper presents new evidence on the trade vs technology debate, investigating the increase in demand for non-manual workers in Italian manufacturing during the 1990s. The paper contributes to the existing literature in a number of ways. First, by providing firm-level evidence, the paper helps to check the robustness of the results of the early literature based on industry data, while also addressing the factor-bias vs sector-bias debate. Second, we examine separately the dynamics of hours worked and hourly wages, rather than just those of annual wages. Third, with respect to previous studies on Italy, we consider a comprehensive data set, covering a representative sample of the manufacturing sector. Finally, with respect to methodology, we provide a more general approach to firm-level decompositions of aggregate wage and employment dynamics.

3 Skill upgrading in Italian manufacturing: data description

Most of the existing evidence for Italy on the effects of technology and trade on the dynamics of employment and wages for skilled and unskilled workers is based on industry-level data. Bella and Quintieri (2000) analyse a panel of manufacturing industries, arguing 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

[11]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.

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 employment. More recently, Manasse et al. (2001) analyze a panel of metal-mechanical firms and find that skill-biased technical change is the main determinant of skill upgrading, raising wage inequality *within* skilled workers (i.e. between managers and clerks) more than between manual and non-manual workers.[13]

The analysis presented in this paper is based on a firm-level data set for the Italian manufacturing sector.[14] The data set is drawn from the Statistical Information System on Enterprises (SISSI), developed by the Central Directorate of Statistics on Institutions and Enterprises (DCII) of the Italian Statistical Institute (ISTAT), and is based on four 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 Commercial Flows (COE), and the Archives of Active Firms (ASIA, SIRIO, NAI).[15]

Our data set consists of a sub-sample of the manufacturing sector, with annual observations from 1989 to 1995 for a balanced panel of 8441 firms, covering about 22 per cent of total manufacturing employment.[16] With respect

[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]This study also finds that trade has dampened the effects of technology on the labor market, as employment has shifted towards unskilled-intensive firms (see also Faini et al. (1999)).

[14]The data set provides information on the profit and loss account (sales, output, costs and outlays, value added, labor costs, capital depreciation and allowances, interests on debts, taxes, profits, etc.), balance sheet (real assets, financial assets and liabilities, financial and commercial credits and debits, etc.), employment and wages (for executives, clerks, manual workers and apprentices), fixed capital formation, R&D and exports.

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

[16]Higher numbers of observations were available for shorter panels (e.g. 14,683 observations for the 1993-95 period), but the choice of the smaller balanced panel was dictated by the need for a longer sample for the present analysis.

to the size of firms, measured by the number of employees, the majority of firms (63%) falls in 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] Data on employment and wages are available separately for manual workers (trainees and production workers) and non-manual workers (clerks and executives).[18]

Table 1 provides a preliminary description of the data set, reporting overall and sub-sample averages for a number of wage and employment indicators. Column 1 reports 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 non-manual wage rate over the average wage rate ($\frac{W_n}{W}$, henceforth "skill premium"), and the non-manual employment share ($\frac{E_n}{E}$, henceforth "skill intensity"). Between 1989 and 1995, in the overall sample of 8441 firms, the average non-manual wage bill share 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 4-7, the non-manual and overall average annual wage (68.2 and 50.2 millions Italian lira, respectively) and employment levels (43.3 and 136, respectively).

Looking at changes over time (rows 3 to 9), the non-manual share in the wage bill has risen by 3.5 percentage points between 1989 and 1995, from 40.8 to 44.3 per cent, implying an average yearly increase of 0.58 percentage points. This rise reflects a significant increase in the proportion of non-manual workers in employment (2.4 per cent), and a 0.8 per cent rise in the skill premium. The rise in skill-intensity, in turn, is due to a rise in non-manual employment (from 41.6 to 43.4) in the face of a contraction of overall employment (from 137.8 to 133.2). The slower growth of the skill premium reflects the fact that non-manual and manual wages have been rising at similar rates.

The following blocks in Table 1 document the significant heterogeneity of firms in the sample. First, "size matters": dividing the sample in three classes of small, medium, and large firms (rows 11 to 13), the non-manual

[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.

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

share in the wage bill and skill intensity are increasing in size, whereas skill premia are highest in medium-size firms (134.7 per cent) and lowest in small firms (128.5 per cent). Considering absolute wage levels, larger firms pay on average substantially higher annual wages, both non-manual and overall, than small and medium firms.

Second, dividing the sample in three groups of firms according to their geographic distribution (rows 15 to 17), firms located in the South are characterized by lower wage bill share (36%) and skill intensity (25.7%), but higher skill premia (140.2%) than those in the rest of the country. Looking at absolute levels of employment and wages, firms located in the South are on average smaller (119.5 employees) and pay substantially lower wages (58.7 and 41.9 millions for non-manual and average workers, respectively) than those in the rest of the country.

Third, we consider two further classifications aimed at characterizing the role of trade and technology for wage and employment dynamics. In the "trade" classification, we use the median of the ratio of exports to total sales to define "high-export" and "low-export" firms.[19] In the "technology" classification, we use the median ratio of computer stock to total capital stock to define "high-tech" and "low-tech" firms. The figures in the blocks at the bottom of table 1 show that, on average, high-export firms are larger than low-export firms but pay similar wages (both non-manual and overall). Wage bill shares, skill intensity and skill premia are virtually the same for high- and low-export firms. High-tech firms on average are larger and pay higher wages (both manual and non-manual), and are substantially more skill-intensive, while paying lower skill premia than low-tech firms. As a result, the non-manual wage bill share of high-tech firms is about 10 percentage points higher than low-tech firms.

Table 2 reports averages by size, allowing to check the robustness of the characterization obtained for the export and technology classifications in the overall sample.[20] The figures suggest that the characteristics of high-tech firms do not depend on their size: high-tech firms are on average more skill-intensive, pay lower skill premia, and have higher non-manual wage bill share than low-tech firms in all size sub-groups. On the other hand, the similar characteristics of high- and low-export firms in the overall sample turn out

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

[20]This check is particulary relevant, as differences in sub-groups by size are substantial, and sub-sample results might be spurious in the sense of reflecting different compositions by size.

to be a fallacy of composition: among small and medium firms, high export firms are more skill intensive and pay lower skill premia, while the opposite holds among large firms.

Table 3 presents sub-sector averages for the same set of wage and employment indicators. Overall, the figures indicate substantial heterogeneity among sub-sectors. In particular, Chemicals, Oil products and Electrical machinery are the sectors with highest non-manual wage bill shares (68.2, 58.2, and 56.8, respectively). These figures reflect correspondingly high skill intensity, whereas skill premia are highest in Leather, Textiles, and Rubber (156, 148.6 and 141.4 per cent, respectively). Looking at absolute wage rates, firms in the Oil products, Chemicals and Paper sectors pay highest wages (both non-manual and overall). Employment levels are highest on average in Transport, Chemicals, and Oil products.

4 Firm-level decompositions

In this section we attempt to identify firm-level determinants of the aggregate wage and employment dynamics described in section 3. We decompose the overall change in the non-manual share of the wage bill into the respective contributions of skill intensity and skill premia. We also split further each of these two components, into their respective *between* and *within* components, where the former reflects reallocations between firms, and the latter indicates changes within individual firms.

It should be observed that the existing literature generally focuses on the between-within decompositions for the non-manual shares of the wage bill and employment in isolation (see e.g. Berman et al., (1994), Bernard and Jensen (1997), Berman et al. (1998), Machin and Van Reenen (1998)). The standard approach, however, does not allow to identify the respective contributions of employment and wages to the change in the non-manual wage bill share. In addition, it provides only indirect information on the dynamics of relative wages. We therefore propose an approach that is more general and, we argue, more informative (see also Manasse et al., 2001).

Let there be $i = 1, ..., I$ firms, and define E^i = employment at firm i, E^i_n = non-manual employment at firm i, $E = \sum_i E^i$ = overall employment, $E_n = \sum_i E^i_n$ = overall non-manual employment, WB^i = wage bill at firm i, WB^i_n = non-manual wage bill at firm i, $W^i = \frac{WB^i}{E^i}$ average wage at firm i, $W^i_n = \frac{WB^i_n}{E^i_n}$ = average non-manual wage at firm i, $W = \frac{WB}{E} = \frac{\sum_i WB_i}{\sum_i E^i}$

aggregate average wage rate, $W_n = \frac{WB_n}{E_n} = \frac{\sum_i WB_i}{\sum_i E_n^i}$ = aggregate average non-manual wage rate. The change in the non-manual share of the total wage bill can be decomposed as follows:

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

$$= \sum_{i=1}^I \Bigg[\underbrace{\Delta\left(\frac{W_n^i}{W}\right)\overline{\left(\frac{E_n^i}{E}\right)}}_{Wtotw} + \underbrace{\Delta\left(\frac{E_n^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)}}_{Etotw} \Bigg] \qquad (2)$$

where Δ and upper-bar denote time differences and time-averages, respectively. The first term in (2) is the sum of firm-level changes in skill premia, weighted by time averages of non-manual employment shares (henceforth $Wtotw$). The second term is the sum of firm-level changes in skill intensity, weighted by time averages of relative wage rates (henceforth $Etotw$).

A positive employment component may be due to two different causes: either firms on average have become more skill-intensive (*within* effect), or employment on average has shifted towards skill-intensive firms (*between* effect). Similarly, a positive wage component may be due either to firms paying higher skill premia (*within* effect), or to overall wages growing more rapidly in firms paying higher skill premia (*between* effect). In order to separate these two effects, we decompose each term in (2) into its *between* and *within* components. The employment component can therefore be written as follows:

$$\sum_i \Delta\left(\frac{E_n^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)} = \sum_i \Delta\left(\frac{E_n^i}{E^i}\frac{E^i}{E}\right)\overline{\left(\frac{W_n^i}{W}\right)} =$$

$$= \sum_i \Big[\underbrace{\Delta P_n^i \overline{S^i}}_{Ewitw} + \underbrace{\Delta S^i \overline{P_n^i}}_{Ebetw}\Big]\overline{\left(\frac{W_n^i}{W}\right)} \qquad (3)$$

where $P_n^i = \frac{E_n^i}{E^i}$ denotes the proportion of skilled employment at firm i, and $S^i = \frac{E^i}{E}$ is the share of firm i in total employment. The first term in (3) is the weighted sum of changes in skill intensity *within* firms (employment within = $Ewitw$), keeping constant their relative size. It is positive if, on average, firms have substituted away from unskilled towards skilled workers. The second term in (3) is the weighted sum of changes in firms' employment shares (employment between = $Ebetw$), keeping each firm's factor proportions constant. It is positive if employment has, on average, shifted towards skill-intensive firms. Note that both employment components are weighted by the corresponding non-manual relative wages.

Similarly, the wage component in (2) can be decomposed as follows:

$$\sum_i \Delta\left(\frac{W_n^i}{W}\right)\overline{\left(\frac{E_n^i}{E}\right)} = \sum_i \Delta\left(\frac{W_n^i}{W^i}\frac{W^i}{W}\right)\overline{\left(\frac{E_n^i}{E}\right)}$$

$$= \sum_i \Big[\underbrace{\Delta D_n^i \overline{R^i}}_{Wwitw} + \underbrace{\Delta R^i \overline{D_n^i}}_{Wbetw}\Big]\overline{\left(\frac{E_n^i}{E}\right)} \tag{4}$$

where $D_n^i = \frac{W_n^i}{W^i}$ is the skill premium at firm i, and $R^i = \frac{W^i}{W}$ is the relative wage at firm i (the average wage at firm i relative to the average economy-wide wage rate). The first term in (4) is the weighted sum of changes in firms' skill premia (wage within = *Wwitw*), keeping constant their relative wage, and it is positive when on average firms raise the skill premium. The second term in (4) is the weighted sum of changes in firms relative wages (wage between = *Wbetw*), keeping their skill premium constant, and it is positive if, on average, wages rise faster in firms that pay higher skill premia. Note that both wage components are weighted by the corresponding relative non-manual employment levels.

Summing up, *within*-firm components presumably reflect factor-specific shocks, such as a change in the relative productivity of skilled workers due to skill-biased technical progress. *Between* components reflect firm and sector-specific shocks affecting relative market shares or average wage rates. These may originate on either the demand side (e.g., changes in consumer tastes, trade) or the supply side (e.g., sector-biased technical change) of product markets.

Table 4 presents the results of the decompositions in equations (2-4) for the overall sample and appropriately defined sub-samples.[21] The figures reported are the average annual change of the non-manual wage-bill share (*WBtot*) and its components: the weighted change in skill intensity (*Etotw*) and the weighted change in skill premia (*Wtotw*). Each component, in turn, is split into its respective between and within contributions (*Ebetw, Ewitw, Wbetw, Wwitw*).

[21]In order to allow a comparison with the existing literature, we report results for both wage bill share ("weighted") decompositions (tables 4-5) and for employment and wage ("unweighted") decompositions (tables 6-7). The appendix provides details on the derivation of the unweighted decompositions.

The first row displays the results for the overall sample of firms between 1989 and 1995.[22] The average annual change in the non-manual wage bill share (0.58 per cent) is largely accounted for by the employment component (0.51 per cent), with a small contribution of the wage component (0.07 per cent). Interestingly, the rise in the employment component is due to substantial *within*-firm substitution of unskilled with skilled labor (0.63 per cent). Shifts in employment associated with the *between* component have instead partially offset the within component (-0.12 per cent), implying that, on average, employment has moved towards *unskilled*-intensive firms.[23] Looking at the wage components, most of the overall change can be attributed to the between component (0.06 per cent): average wages have risen faster in firms paying higher skill premia.

Rows 2 and 3 report the decompositions obtained when splitting the overall 1989-95 sample into two four-year sub-periods (1989-92 and 1992-95). The results suggest that, for both employment and wages, changes were much larger in the first sub-period. As a result, the non-manual wage bill share rose at an average annual rate of 1 per cent between 1989 and 1992, as opposed to 0.17 per cent between 1992 and 1995. Looking at individual components, it is interesting to observe that both the employment between and wage within components were positive in the first sub-sample and negative in the second, accounting for most of the slowdown in the growth of the non-manual wage bill share.

The following blocks in table 4 present the contributions of individual sub-samples of firms to the overall decomposition. First, considering the sub-samples by size and region, for most components overall changes are largely accounted for by large firms, although they represent only 23% of the total number of firms. As a consequence, given that most large firms are located in the North, for all components the overall changes can be attributed largely to firms located in the North. These results suggest that particular attention should be paid to size in characterizing the dynamics of individual sub-samples of firms. Second, high-tech firms account for a substantial share of within-firm factor substitution, implying that these firms have been the most active in raising the proportion of skilled workers among their employees. This finding seems to support the hypothesis that skill-

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

[23]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.

biased technical change may be the driving force behind factor substitution. Third, high-export firms account for most of the negative employment between component. This seems to point to specialization in unskilled-intensive goods by exporters, as a possible explanation of the employment shift.[24]

This interpretation seems to be reinforced by the breakdown of overall changes into two sub-periods: 1989-92 and 1992-95 (rows 2-3 in table 4). These two sub-periods are characterized by large swings in the real exchange rate. During the first, the lira appreciated by 30% in real terms, while during the second it depreciated by roughly the same proportion. Between 1989-92, employment shifted from high-export to low-export firms (with high-tech exporters being particularly penalized), and with a net positive contribution to the yearly change in factor proportions ($Ebetw$ = 0.12). Conversely, during the second period, characterized by real depreciation, only traditional (non high-tech) exporters gained employment shares, with a negative overall contribution to the change in factor proportions ($Ebetw$ = -0.37).

Table 5 presents the contributions of individual sub-sectors to overall decompositions. The rise in the non-manual wage bill share and employment share is common to all sectors except for Transport (-0.06), with noticeable increases in Chemicals (0.17) and Electrical machinery (0.15). Interestingly, the positive employment within component is pervasive, in the sense that it is common to all sectors. The negative employment between component is also common to many sectors, although it largely reflects the substantial fall in the transport sector (-0.10). The wage components (both within and between) are close to zero in most sectors, with the major exception of the wage between component in the Chemicals sector (+0.05).

Tables 6 and 7 report results for employment and wage (unweighted) decompositions.[25] The results present a picture similar to the one for the wage bill decompositions, with some important qualifications. The average annual rise in skill intensity (0.4 per cent) is due to a large positive within component (0.5 per cent), partially offset by a negative between component (-0.1 per cent). The overall change in the wage skill premium (0.11 per cent) reflects positive between and within components (0.23 per cent) counterbalanced by a negative wage composition effect: on average non-manual

[24] Note that the negative employment between component is largely attributable to "Large" firms (-0.13 per cent). Within this sub-sample, high-export firms are indeed less skill intensive than low-export firms (relative skilled employment is 33.5 and 36.4, respectively).

[25] See the appendix for details on wage and employment (unweighted) decompositions.

employment shares have grown more in firms paying higher skill premia.[26] This indicates that changes in employment between firms partially offset not only the response of relative employment, but also that of relative wages.[27]

5 A finer decomposition: hourly wages and hours worked

In this section we take a closer look at wage dynamics, decomposing yearly wages into average hourly wages and yearly number of hours worked per employee. The average number of hours worked per employee is obtained by dividing the total number of hours worked by the number of employees: $(h^i = \frac{H^i}{E^i})$. Hourly wages are then obtained as yearly wages divided by the average number of hours worked: $(\omega_i = \frac{W^i}{h^i})$. This allows us to assess whether the adjustment of annual wages reflects actual changes in the return to labor (hourly wages), or rather changes in employment intensity (total number of hours worked).[28] Table 8 provides overall and sub-sample averages for manual and non-manual hourly wages (ω and ω_n, respectively), total number of hours worked per employee (h and h_n, respectively), and the corresponding hourly wage skill premium $(\frac{\omega_n}{\omega})$ and "hourly" skill intensity $(\frac{h_n}{h})$. In the overall sample, non manual employees work longer hours per year (1720.6 vs 1665.4), and earn higher hourly wages (39.6 vs 30.2 thousand lire) than manual workers. The average hourly skill premium and skill intensity are 131.5 and 103.3 per cent, respectively.

[26] This is an interesting result, considering that the wage composition component can be considered conceptually similar to the employment-between component: it measures the change in wages due to changes in the composition of overall non-manual employment, for a given non-manual employment share (see the appendix for details).

[27] As in the weighted decompositions, high-tech firms account for most of within-firm skill upgrading, while high-export firms account for most of the negative employment-between and wage-composition component. Considering individual sub-sectors, within-firm skill upgrading is common to all sectors. Employment between and wage composition components, as expected, are closely correlated across sectors. Chemicals, Electrical machinery and Transport are the main contributors to the aggregate dynamics of skill intensity and wage premium.

[28] Note that even if the values of both annual wages and hours are plausible, there is the possibility that some values of the resulting ratio are not plausible. This is a classic problem with hourly wage measures referred to as "division" bias when applied to the estimation of labor supply elasticities (see Borjas, 1978).

Looking at changes over time, the hourly wage skill premium rises by 1.2 percentage points, while hourly skill intensity is virtually unchanged between 1989 and 1995. Dividing the sample by size, large firms pay hourly wages significantly higher than small firms (both overall and non-manual), whereas the average number of hours worked is highest in small firms. High-tech firms pay higher hourly wages, but lower skill premia. Hourly wages and the number of hours are relatively similar in low- and high-export firms.

Having described changes in aggregate hourly wage premia and skill intensity, we can calculate their respective between and within components. Consider first the decomposition of the change in hourly skill intensity:

$$\begin{aligned}
\Delta \frac{h_n}{h} &= \Delta \frac{H_n}{E_n h} = \Delta \frac{\sum_i E_n^i h_n^i}{E_n h} \\
&= \Delta \sum_i \frac{h_n^i}{h^i} \frac{h^i}{h} \frac{E_n^i}{E_n} \\
&= \sum_i \left[\underbrace{\left(\Delta \frac{h_n^i}{h^i} \right) \overline{\frac{h^i}{h}}\, \overline{\frac{E_n^i}{E_n}}}_{hwit} + \underbrace{\left(\Delta \frac{h^i}{h} \right) \overline{\frac{h_n^i}{h^i}}\, \overline{\frac{E_n^i}{E_n}}}_{hbet} + \underbrace{\left(\Delta \frac{E_n^i}{E_n} \right) \overline{\frac{h_n^i}{h}}}_{hcom} \right]
\end{aligned} \tag{5}$$

where the three terms in (5) reflect the respective contributions to the change in overall hourly skill intensity of (i) within-firm changes in hourly skill intensity ($hwit$), (ii) between-firm changes in the relative number of hours ($hbet$), and (iii) a composition effect reflecting changes of firms' shares in total non-manual employment ($hcom$).

Similarly, the between-within decomposition of the change in the hourly wage premium can be written as follows:

$$\begin{aligned}
\Delta \frac{\omega_n}{\omega} &= \Delta \frac{WB_n}{H_n \omega} = \Delta \frac{\sum_i \omega_n^i H_n^i}{H_n \omega} \\
&= \Delta \sum_i \frac{\omega_n^i}{\omega^i} \frac{\omega^i}{\omega} \frac{H_n^i}{H_n} \\
&= \sum_i \left[\underbrace{\left(\Delta \frac{\omega_n^i}{\omega^i} \right) \overline{\frac{\omega^i}{\omega}}\, \overline{\frac{H_n^i}{H_n}}}_{\omega wit} + \underbrace{\left(\Delta \frac{\omega^i}{\omega} \right) \overline{\frac{\omega_n^i}{\omega^i}}\, \overline{\frac{H_n^i}{H_n}}}_{\omega bet} + \underbrace{\left(\Delta \frac{H_n^i}{H_n} \right) \overline{\frac{\omega_n^i}{\omega}}}_{\omega com} \right]
\end{aligned} \tag{6}$$

where the three terms in (6) reflect the respective contributions to the change in overall hourly wage skill premia of (i) within-firm changes in skill premia (ωwit), (ii) between-firm changes in relative hourly wages (ωbet), and (iii) a composition effect reflecting changes of firms' shares in the total number of non-manual hours worked (ωcom).

Table 9 presents the results for the decompositions in (5)-(6). While overall hourly skill intensity is virtually unchanged between 1989 and 1995, this actually hides positive within and composition components and a negative between component: firms using non-manual labor more intensively, on average, use overall labor less intensively. This negative between component of hourly skill intensity, particularly large for high-export firms, complements the negative employment-between component found earlier. Interestingly, the rise in the hourly wage skill premium also hides offsetting dynamics: a large negative within component, more than compensated by positive between and composition components. Within firms, hourly wage premia fall, but this is compensated by the fact that, on average, firms paying higher hourly skill premia use relatively more hours of non-manual labor. Note that for both hourly wages and hours it is high-export firms who account for most of the positive composition components (reallocation of employment and hours across firms).

While these decompositions contribute to the interpretation of the dynamics of hourly skill intensity and wage premia, they provide only indirect information on their respective contributions to aggregate employment and wage dynamics. In the following, we therefore decompose the wage between and within contributions to changes in the wage bill share, employment share, and relative wage, into the respective contributions of hourly wages and number of hours worked.

Consider first the contributions of hourly wages and hours to the (weighted) wage within component in equation (4):

$$\begin{aligned}
\sum_i^I \left[\underbrace{\left(\Delta D_n^i \overline{R^i} \right)}_{Wwitw} \frac{\overline{E_n^i}}{E} \right] &= \sum_i^I \left(\Delta \frac{W_n^i}{W^i} \overline{R^i} \right) \frac{\overline{E_n^i}}{E} = \qquad (7) \\
&= \sum_i^I \left(\Delta \frac{\omega_n^i h_n^i}{\omega^i h^i} \overline{R^i} \right) \frac{\overline{E_n^i}}{E} = \\
&= \sum_i^I \left[\underbrace{\left(\Delta \frac{\omega_n^i}{\omega^i} \frac{\overline{h_n^i}}{h^i} \right)}_{Wwitw\omega} \overline{R^i} \right] \frac{\overline{E_n^i}}{E} + \sum_i^I \left[\underbrace{\left(\Delta \frac{h_n^i}{h^i} \frac{\overline{\omega_n^i}}{\omega^i} \right)}_{Wwitwh} \overline{R^i} \right] \frac{\overline{E_n^i}}{E}
\end{aligned}$$

where the first term reflects wage-within dynamics associated with changes in hourly wage skill premia, and the second term reflects wage-within dynamics associated with changes in the ratio between non-manual and average hours worked per employee.

The respective contributions of hourly wages and hours to the (weighted) wage-between component in equation (4) can be obtained as follows:

$$\begin{aligned}
\sum_i^I \left[\underbrace{\left(\Delta R^i \overline{D_n^i} \right)}_{Wbetw} \frac{\overline{E_n^i}}{E} \right] &= \sum_i^I \left(\Delta \frac{W^i}{W} \overline{D_n^i} \right) \frac{\overline{E_n^i}}{E} = \\
&= \sum_i^I \left(\Delta \frac{\omega^i h^i}{\omega h} \overline{D_n^i} \right) \frac{\overline{E_n^i}}{E} = \\
&= \sum_i^I \underbrace{\left[\left(\Delta \frac{\omega^i}{\omega} \overline{\frac{h^i}{h}} \right) \overline{D_n^i} \right]}_{Wbetw\omega} \frac{\overline{E_n^i}}{E} + \sum_i^I \underbrace{\left[\left(\Delta \frac{h^i}{h} \overline{\frac{\omega^i}{\omega}} \right) \overline{D_n^i} \right]}_{Wbetwh} \frac{\overline{E_n^i}}{E}
\end{aligned} \tag{8}$$

where the first term reflects wage-between dynamics associated with changes in the relative hourly wage, and the second term reflects wage-between dynamics associated with changes in firms' relative number of hours worked per employee.

Table 10 presents the results for wage bill decompositions. The small positive between component (0.06) reflects changes in hourly wages (0.09), partially offset by a negative contribution of hourly wages. The results for the wage-within component are striking: on average firms with higher non-manual employment shares have used non-manual workers more intensively, with the relative number of hours worked by skilled workers and the hourly wage skill premium contributing 0.17 and -0.16 per cent a year, respectively. These results are largely confirmed by those for wage decompositions (table 11) and suggest that, although the adjustment of annual wage skill premia is relatively small, it actually hides substantial positive contributions of changes in skill intensity and negative contributions of changes in hourly wage premia.

6 Interpreting firm-level skill upgrading

In the previous sections we found that skill upgrading within firms explains most of the increase in the non-manual share of employment and wage bill, and is partially offset by between-firm employment dynamics. In this section we consider whether the data support the standard interpretation that within-changes reflect (skill biased) technical progress, and between-changes reflect demand shifts (possibly related to trade). We start with a reduced form specification where the between and within components of the changes in the wage bill share, skill intensity and skill premium, are regressed on variables intended to proxy for demand, trade, and technology shocks affecting individual firms. We then use a cost function framework to focus explicitly on skill-biased technical change and obtain an indication of its contribution to within-firm skill upgrading.

If the standard interpretation of firm-level wage and employment dynamics is correct, *within* 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 demand changes facing the firm, and we also interact this variable with the export dummy in order to capture specific effects of trade on high-export firms.[29] Technological change at firm level is proxied by two variables: the ratio of investment in computers over total investment, and the ratio of research and development expenditures over total sales.[30] All the regressions include size, region, and industry dummies to allow for different firm and industry characteristics. The general specification is therefore

$$\Delta C_d^i = \alpha + \beta_1 \Delta lS^i + \beta_2 \Delta lSX^i + \beta_3 ICI^i + \beta_4 RDS^i + \sum_j \gamma_j DUM^j \qquad (9)$$

where ΔC_d^i indicates firm i contribution to the between or within C component in the d decomposition ($d =$ wage bill, wage, employment), ΔlS is the growth rate of total sales, ΔlSX is ΔlS interacted with the export dummy, ICI is the ratio of investment in computers over total investment, RDS is the ratio of research and development expenditures over total sales, and DUM represents industry, size and geographic dummies.

Table 12 presents the results obtained estimating by OLS the equations for the change in the wage bill share and its components.[31] The growth rate of sales is positive and highly significant in all the between regressions,

[29]Due to data limitations (exports are only available for 1989), total sales cannot be broken down into domestic and export components.

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

[31]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

whereas it is negative and significant in the wage bill and employment within equations. The export-sales interaction term is positive and marginally significant in the wage bill within and employment between equations. There appears to be a positive and significant relationship between demand shocks and shifts of employment (and wages) across firms. This relationship appears to be significantly stronger for demand shocks occurring at high export firms.

Looking at the technology indicators, the computer share of investment is positive and significant in both the wage bill and employment within equations, while not significant in all the between equations. The R&D indicator is positive, although not significant, in the wage bill and employment within equations. To the extent that the interpretation of the computer intensity indicator is correct, technological change appears to be positively and significantly related to within-firm skill upgrading.

The results for the equations of the employment and wage (unweighted) components are presented in table 13:[32] the growth rate of sales is positive and highly significant in all the between and composition regressions, and the export-sales interaction term is positive and significant in the employment between and wage composition equations. Note that the positive coefficient on the wage composition component can also be considered an indication of a positive relationship between demand shocks and employment reallocations across firms. The computer share of investment is positive and significant in the employment within equation, while the R&D indicator is again insignificant in all equations.

These results can be taken as preliminary evidence that the observed rise in the share of skilled employment at firm level reflects (skill-biased) technological change, and that the shift of employment towards unskilled-intensive firms reflects changes in demand likely to be related to trade. This interpretation, however, is subject to a number of possible objections. First, suppose that the demand for *un*skilled-intensive goods rises, leading to higher relative prices for unskilled-intensive firms. As these firms expand relative output and employment, the relative demand for less educated workers rises, and the wage premium falls (this is the familiar Stolper-Samuelson theorem). As a consequence, all firms react by hiring relatively more skilled workers. In this case we would observe a negative employment between change and a positive

7830 observations, respectively, are available for the computer intensity and research and development indicators.

[32]The different sample size in the employment and wage equations is due to the fact that non-manual wages are not defined for firms who do not employ non-manual workers.

employment within change (as we actually do). Both should be attributed to demand/trade changes,[33] whereas our interpretation would lead us to attribute the within-firm change to technology, thus overestimating its role and underestimating that of demand shifts.[34] Second, changes in skill intensity might simply reflect capital deepening under skill-capital complementarity. More generally, in order to measure the effects of technical progress on factor shares, we need to control for changes in factor prices and capital intensity.

We therefore use an alternative procedure for measuring the bias in technical progress, that explicitly controls for changes in capital input and relative factor prices. The idea is to define technical progress as the reduction in unit-costs (the backward shift in the unit-isoquant) at *constant* factor prices (see Binswanger, 1974). If we observe that a firm raises skill intensity in employment, at constant relative wages (picking a new tangency point on an isocost line of the same slope), then there is a skill-bias in technical progress, since the change in factor intensity must reflect the rise in the relative marginal product of skilled labor.

Empirically, we implement this approach following Brown and Christensen (1981) in deriving the wage bill share equation of a quasi-fixed cost function. We assume that firms choose variable factors to minimize costs subject to an output constraint, with a translog specification for the cost function and a constant returns to scale production function. We also assume that the only variable factors of production are skilled and unskilled labor, and that capital is a quasi-fixed factor. We thus obtain the following equation for the firm-level change in the non-manual share of the wage bill (see e.g. Berman et al., 1994):

$$\Delta\left(\frac{WB_n^i}{WB^i}\right) = \alpha + \ \beta\Delta\ln(\frac{W_n^i}{W_m^i}) + \gamma\,\Delta\ln(\frac{K^i}{Y^i}) + \varepsilon^i \tag{10}$$

where K_i and Y_i represent capital and value added, respectively, and the specification also includes a set of industry, size and geographic dummies, as in (9). Note that if β is positive (negative) the elasticity of substitution between labor inputs is below (above) one. A positive (negative) estimate for

[33] The positive relationship between within components and indicators of technological change could be explained by the fact that although all firms face a fall in wage premia, it is firms with higher skill intensity (i.e. more innovative firms) who respond more by raising the demand for skills, thus explaining the positive relationship between within employment changes and indicators of technological change.

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

γ implies that capital is complement (substitute) to non-manual labor, since it raises (lowers) its wage bill share at *constant* factor prices. The intercept is a measure of the average bias in technical change, and the residual provides a measure of the firm-specific bias.

Table 14 reports the results of estimating equation (10) in its basic version, and adding (either individually or jointly) the two indicators of technological change defined above (computers as a share of total investment and R&D over sales). Starting from the basic equation without technology indicators, relative wages have a positive and statistically significant coefficient, implying a low elasticity of substitution between labour inputs. The capital intensity coefficient is also positive and significant, indicating complementarity between capital and skilled labor, and suggesting that skill upgrading has been strengthened by capital deepening.[35]

When we add to the basic model technology indicators individually (equations 1-2) or jointly (equation 3), both the computer share of total investment and R&D expenditures as a fraction of sales have positive and highly statistically significant coefficients. The estimated coefficients are also quantitatively relevant. The average share of computers in total investment was 8.6 per cent in 1995, and multiplying this figure by the corresponding coefficient (0.031) gives 0.26. Considering that the average non-manual wage bill share rises by 3.35 per cent between 1989 and 1995 (implying a 0.56 annual change), the fraction of investment devoted to computers accounts for over 40 per cent (0.26/0.56) of the shift in the average wage bill share in the same period. Similar calculations suggest that R&D has a smaller impact on the change in the average wage bill share (about 2 per cent). The inclusion of the R&D indicator does not affect the coefficient on computer intensity, so that the two technology indicators together account for about half of the change in the average non manual wage bill share.

One natural objection to the specification in (10) is that changes in relative wages are unlikely to be exogenous, as the relative wage variation might reflect different skill mixes of labor across firms (unobserved quality differences). In addition, the definitional relationship between the dependent variable (non-manual wage bill share) and the relative wage regressor (non-manual relative to manual wage), is likely to produce biased coefficient estimates (see Borjas, 1980). In the absence of convincing instruments for

[35] Firms have rapidily raised their capital-labor ratios in the last two decades, possibly due to tax reasons (see Daveri and Tabellini, 1997).

changes in relative wages, we also present the results of estimating equation (10) without the relative wage regressor (equations 4-6). Although the explanatory power of the regression falls substantially, the size and significance of all estimated coefficients is not affected. In particular, the technology indicators remain highly statistically significant and quantitatively relevant.

Summing up, after controlling for changes in labor input prices and capital intensity (and other firm and industry characteristics), residual within-firm skill upgrading is positively and significantly related to indicators of technological change. Quantitatively, such indicators account for almost half of the average change in the non manual wage bill share. Overall, these results suggest that skill-biased technological change, particularly for those firms that invested heavily in computers, was an important determinant of within-firm skill upgrading in the Italian manufacturing sector between 1989 and 1995.

7 Conclusions

This paper presented firm-level evidence on the dynamics of non-manual wage premia and employment shares in Italian manufacturing in the nineties. We considered alternative interpretations of these aggregate dynamics, focusing on trade competition and skill-biased technical change as possible determinants of higher demand for skilled workers.

The analysis provided a number of interesting results. Between 1989 and 1995, in our sample of manufacturing firms, the non-manual share of the wage bill increased by 3.5 per cent. This reflected an increase in both the non-manual employment share and, to a lesser extent, the non-manual relative wage. Within-firm skill upgrading was the main determinant of the shift in relative demand for skilled labor, whereas demand changes associated with exports reduced the relative demand for non-manual employment, partially offsetting the effect of technology and contributing to moderate the change in relative factor prices. Although annual wage skill premia did not respond much to the shift in the relative demand for labor, hourly wage premia and skill intensity revealed substantial and offsetting contributions to wage responses. Across firms, within-firm skill upgrading is found to be significantly related to proxies of technical change such as investment in computers and R&D.

Overall, these results point to skill-biased technical progress as the main determinant of skill upgrading in Italian manufacturing in the last decade.

This conclusion, based on firm-level evidence, complements and qualifies the findings in studies for other OECD economies based on industry data (e.g. Berman, et al. (1994), Berman et al. (1998), and Machin and Van Reenen (1998)), or firm/plant-level data (e.g. Krueger (1993), and Haskel and Heden (1998)). The results also seem to reject the conclusion of recent studies based on micro data indicating growing trade competition as a key determinant of rising non-manual wage premia (e.g. Bernard and Jensen (1997), Haskel and Slaughter (1999a)). In our sample of firms, demand shocks associated to trade shifted employment away from firms producing skill-intensive goods (see also Faini et al. (1999), and Bella and Quintieri (2000)).

Surely these results must be interpreted with care, given that they are restricted to the manufacturing sector of a single country, for a relatively short period, so that they cannot be taken as representative of a "continental European case". Despite these drawbacks, our results provide interesting information on the nature and causes of recent wage and employment dynamics, while underlining the importance of interpreting aggregate outcomes on the basis of microeconomic data. Future research will verify the robustness of these firm-level results extending the analysis to different sectors and samples.

8 Appendix

This appendix provides some details on the derivation of the wage and employment (unweighted) decompositions discussed in sections 4 and 5. Consider first the decomposition of the change in relative employment:

$$
\begin{aligned}
\Delta\left(\frac{E_n}{E}\right) &= \Delta\sum_i \frac{E_n^i}{E} = \Delta\sum_i \frac{E_n^i}{E^i}\frac{E^i}{E} = \\
&= \Delta\sum_i P_n^i S^i = \\
&= \sum_i \left[\underbrace{\Delta P_n^i \overline{S^i}}_{Ewit} + \underbrace{\Delta S^i \overline{P_n^i}}_{Ebet}\right]
\end{aligned}
\tag{11}
$$

The first term is the change in the non-manual employment share that is attributable to the change in the firms' factor proportions, P_n^i, keeping constant their relative size. This reflects shifts in factor intensity *within* plants. It is positive if skill upgrading has occurred in larger firms. The second term gives the part of the total change in the non-manual employment share that is attributable to the change in plant relative size (the change in the employment share, S^i), keeping each firm's factor proportions constant at the period's average. This reflects employment shifts *between* firms. It is positive if employment rises relatively more in skill-intensive plants.

Next, consider the decomposition of the change in non-manual relative wage:

$$
\begin{aligned}
\Delta\left(\frac{W_n}{W}\right) &= \Delta\frac{\sum_i W_n^i E_n^i}{W E_n} = \Delta\sum_i \frac{W_n^i}{W^i}\frac{W^i}{W}\frac{E_n^i}{E_n} = \\
&= \Delta\sum_i D_n^i R^i S_n^i = \\
&= \sum_i \left[\underbrace{\Delta D_n^i \overline{R^i}\ \overline{S_n^i}}_{Wwit} + \underbrace{\Delta R^i \overline{D_n^i}\ \overline{S_n^i}}_{Wbet} + \underbrace{\Delta\ S_n^i \overline{D_n^i}\ \overline{R^i}}_{Wcom}\right]
\end{aligned}
\tag{12}
$$

where $S_n^i = \frac{E_n^i}{E_n}$ is firm's i share of non-manual employment. The first term is the within component, and it is positive (negative), when the wage gap rises (falls) on average within firms. The second term is the relative wage change occurring between firms. It is positive when, on average, wages have been rising faster in firms that pay higher wage premia. The third term is a composition effect, reflecting changes in the composition of non-manual employment across firms. It is positive when, on average, non-manual employment shares rise more in firms that pay higher wage premia.

It is important to note that the wage composition component is conceptually similar to the employment between component. This can be can be seen by rewriting the change in the aggregate non-manual wage bill as follows:

$$\begin{aligned}
\Delta\left(\frac{WB_n}{WB}\right) &= \Delta\sum_i^I\left(\frac{W_n^i}{W^i}\frac{W^i}{W}\frac{E_n^i}{E^i}\frac{E^i}{E}\right) \qquad (13)\\
&= \Delta\sum_i^I\left(\frac{W_n^i}{W^i}\frac{W^i}{W}\frac{E_n^i}{E_n}\right)\frac{E_n}{E}\\
&= \Delta\left(\frac{W_n}{W}\frac{E_n}{E}\right) =\\
&= \Delta\left(\frac{W_n}{W}\right)\overline{\frac{E_n}{E}} + \Delta\left(\frac{E_n}{E}\right)\overline{\frac{W_n}{W}}
\end{aligned}$$

Equation (13) shows that employment shifts across firms that affect aggregate relative non-manual employment $\left(\frac{E_n}{E}\right)$ enter the unweighted employment between component, whereas employment shifts that affect shares within non-manual employment $\left(\frac{E_n^i}{E_n}\right)$, without affecting $\frac{E_n}{E}$, enter the unweighted wage composition component.

We now consider the respective contributions of hourly wages and hours to the wage within component in equation (12):

$$\begin{aligned}
\sum_i^I\left[\underbrace{\Delta D_n^i\overline{R^i}}_{Wwit}\ \overline{S_n^i}\right] &= \sum_i^I\left(\Delta\frac{W_n^i}{W^i}\overline{R^i}\right)\overline{S_n^i} = \sum_i^I\left(\Delta\frac{\omega_n^i h_n^i}{\omega^i h^i}\overline{R^i}\right)\overline{S_n^i} =\\
&= \sum_i^I\left[\underbrace{\left(\Delta\frac{\omega_n^i}{\omega^i}\overline{\frac{h_n^i}{h^i}}\right)}_{Wwit\omega}\overline{R^i}\right]\overline{S_n^i} + \sum_i^I\left[\underbrace{\left(\Delta\frac{h_n^i}{h^i}\overline{\frac{\omega_n^i}{\omega^i}}\right)}_{Wwith}\overline{R^i}\right]\overline{S_n^i}
\end{aligned}$$

where the first term reflects wage-within dynamics associated with changes in hourly wage skill premia, and the second term reflects wage-within dynamics associated with changes in the ratio between non-manual and overall average hours worked per employee.

Similarly, the contributions of hourly wages and hours to the (weighted) wage-between component in equation (11) can be obtained as follows:

$$\begin{aligned}
\sum_{i}^{I}\left[\underbrace{\Delta R^{i}\overline{D_{n}^{i}}}_{Wbet}\;\overline{S_{n}^{i}}\right] &= \sum_{i}^{I}\left(\Delta\frac{W^{i}}{W}\overline{D_{n}^{i}}\right)\overline{S_{n}^{i}} = \sum_{i}^{I}\left(\Delta\frac{\omega^{i}h^{i}}{\omega h}\overline{D_{n}^{i}}\right)\overline{S_{n}^{i}} = \\
&= \sum_{i}^{I}\underbrace{\left[\left(\Delta\frac{\omega^{i}}{\omega}\overline{\frac{h^{i}}{h}}\right)\overline{D_{n}^{i}}\right]}_{Wbet\omega}\overline{S_{n}^{i}} + \sum_{i}^{I}\underbrace{\left[\left(\Delta\frac{h^{i}}{h}\overline{\frac{\omega^{i}}{\omega}}\right)\overline{D_{n}^{i}}\right]}_{Wbeth}\overline{S_{n}^{i}}
\end{aligned}$$

where the first term reflects wage-between dynamics associated with changes in the relative hourly wage, and the second term reflects wage-between dynamics associated with changes in firms' individual shares in the overall number of hours worked.

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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
1990	41.7	134.8	30.9	59.4	44.1	43.4	140.4	8441
1991	42.5	135.3	31.4	65.3	48.2	44.1	140.4	8441
1992	43.8	136.2	32.1	69.9	51.3	43.6	135.7	8441
1993	44.4	135.5	32.8	71.8	53.0	43.4	132.4	8441
1994	44.5	135.1	32.9	75.3	55.8	43.6	132.2	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	134.5	35.4	68.6	51.0	54.5	153.8	29538
Low tech.	37.3	137.4	27.2	67.4	49.0	32.1	118.3	29549

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: Employment and wages: averages by sub-sector

Sample	$\frac{WB_n}{WB}$	$\frac{W_n}{W}$	$\frac{E_n}{E}$	W_n	W	E_n	E	N.Obs.
Food	41.1	133.5	30.8	69.6	52.1	50.8	164.8	4354
Textiles	31.0	148.6	20.8	57.9	38.9	20.7	99.6	8720
Leather	23.5	156.0	15.1	54.6	35.0	10.6	70.5	2535
Wood	21.4	135.5	15.8	53.2	39.3	9.0	57.1	1656
Paper	46.4	130.6	35.6	78.4	60.0	44.8	126.1	3808
Oil prod.	58.2	116.0	50.2	77.4	66.7	115.6	230.3	198
Chemicals	68.2	120.2	56.8	78.6	65.4	144.2	254.0	2738
Rubber	33.1	141.4	23.4	68.1	48.2	26.6	113.6	3298
Non-m. min.	31.7	133.7	23.7	66.9	50.0	25.9	109.1	4528
Metal min.	29.8	132.0	22.6	64.5	48.9	22.2	98.3	8649
Mech. mach.	43.9	131.7	33.3	67.2	51.0	50.2	150.8	7850
Elec. mach.	56.8	126.0	45.1	66.3	52.6	103.5	229.7	4222
Transport	40.4	137.6	29.4	64.7	47.1	119.3	405.9	1935
Other man.	29.5	131.0	22.5	52.4	40.0	14.7	65.0	4596

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 4: Wage bill share decompositions: overall and by sub-sample

Sample	WBtot	Etotw	Wtotw	Ebetw	Ewitw	Wbetw	Wwitw	N.Obs.
Overall	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
Small	-0.00	-0.00	-0.00	-0.02	0.01	0.00	-0.00	1104
Medium	0.15	0.14	0.01	0.03	0.11	0.01	0.00	5078
Large	0.43	0.37	0.06	-0.13	0.50	0.05	0.01	2021
North	0.39	0.33	0.05	-0.14	0.47	0.03	0.02	6637
Centre	0.18	0.17	0.01	0.02	0.15	0.03	-0.02	1214
South	0.01	0.01	0.00	-0.00	0.01	0.00	0.00	352
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.	0.34	0.31	0.04	-0.14	0.45	0.06	-0.02	4469
Low tech.	0.24	0.20	0.03	0.02	0.18	0.00	0.03	3734
Hexp-Htech	0.13	0.12	0.02	-0.15	0.26	0.03	-0.01	2486
Hexp-Ltech	0.14	0.10	0.04	0.03	0.07	0.01	0.04	1682
Lexp-Htech	0.21	0.19	0.02	0.01	0.18	0.03	-0.01	1983
Lexp-Ltech	0.10	0.10	-0.01	-0.01	0.12	-0.01	-0.00	2052

Note: $WBtot$ = non-manual share of wage bill, $Etotw$ = total employment, $Wtotw$ = total wage, $Ebetw$ = empl. between, $Ewitw$ = empl. within, $Wbetw$ = wage between, $Wwitw$ = wage within. All components are weighted (see sec. 4 for details).

Table 5: Wage bill share decompositions by sector

Sample	WBtot	Etotw	Wtotw	Ebetw	Ewitw	Wbetw	Wwitw	N.Obs.
Food	0.04	0.05	-0.01	-0.00	0.05	-0.00	-0.01	612
Textiles	0.01	0.02	-0.01	-0.02	0.05	-0.00	-0.01	1123
Leather	0.02	0.02	0.00	0.01	0.01	0.00	0.00	344
Wood	0.01	0.01	0.00	0.00	0.01	0.00	0.00	229
Paper	0.03	0.02	0.01	-0.03	0.04	0.01	0.00	534
Oil	0.03	0.01	0.01	0.00	0.01	0.00	0.01	32
Chem.	0.17	0.13	0.04	0.05	0.08	0.05	-0.01	385
Rubber	0.01	0.00	0.00	-0.01	0.01	-0.00	0.01	439
Non-m. min.	0.05	0.04	0.01	0.00	0.04	0.00	0.00	638
Metal min.	0.03	0.04	-0.01	0.00	0.03	-0.01	-0.00	1199
Mech. mach.	0.08	0.05	0.03	-0.03	0.08	0.02	0.01	1135
Elec. mach.	0.15	0.14	0.00	-0.00	0.15	0.02	-0.02	589
Transport	-0.06	-0.04	-0.02	-0.10	0.06	-0.02	0.01	288
Other	0.02	0.01	0.00	-0.00	0.01	-0.00	0.01	656

Note: $WBtot$ = non-manual share of wage bill, $Etotw$ = total employment, $Wtotw$ = total wage, $Ebetw$ = empl. between, $Ewitw$ = empl. within, $Wbetw$ = wage between, $Wwitw$ = wage within. All components are weighted (see sec. 4 for details).

Table 6: Employment and wage decompositions: overall and by sub-sample

Sample	*Etot*	*Ebet*	*Ewit*	*Wtot*	*Wbet*	*Wwit*	*Wcom*	N.Obs.
Overall	0.40	-0.10	0.50	0.11	0.20	0.03	-0.11	8441
89-92	0.65	0.08	0.57	0.36	0.24	0.28	-0.17	8441
92-95	0.15	-0.28	0.43	-0.12	0.18	-0.27	-0.03	8441
Small	0.00	-0.01	0.02	-0.02	0.01	-0.01	-0.02	1186
Medium	0.13	0.03	0.10	0.23	0.03	0.01	0.19	5228
Large	0.27	-0.11	0.38	-0.09	0.16	0.03	-0.28	2027
North	0.27	-0.10	0.37	-0.18	0.11	0.06	-0.35	6783
Centre	0.13	0.01	0.12	0.29	0.09	-0.05	0.25	1285
South	0.01	-0.00	0.01	-0.00	0.00	0.01	-0.02	373
High exp.	0.18	-0.08	0.25	-0.13	0.11	0.09	-0.33	4220
Low exp.	0.22	-0.02	0.25	0.24	0.08	-0.06	0.21	4221
High tech.	0.24	-0.11	0.35	-0.11	0.19	-0.08	-0.22	4546
Low tech.	0.16	0.01	0.15	0.22	0.01	0.11	0.11	3895
Hexp-Htech	0.10	-0.10	0.20	-0.28	0.09	-0.03	-0.34	2505
Hexp-Ltech	0.08	0.03	0.05	0.16	0.02	0.12	0.01	1715
Lexp-Htech	0.14	-0.01	0.15	0.18	0.10	-0.05	0.12	2041
Lexp-Ltech	0.08	-0.02	0.10	0.06	-0.02	-0.01	0.09	2180

Note: *Etot* = total employment, *Ebet* = employment between, *Ewit* = employment within, *Wtot* = total wage, *Wbet* = wage between, *Wwit* = wage within, *Wcom* = wage composition. See the appendix for details on the decompositions.

Table 7: Employment and wage decompositions by sector

Sample	$Etot$	$Ebet$	$Ewit$	$Wtot$	$Wbet$	$Wwit$	$Wcom$	N.Obs.
Food	0.04	-0.01	0.05	-0.01	-0.00	-0.02	0.01	623
Textiles	0.03	-0.02	0.05	-0.06	-0.01	-0.02	-0.03	1238
Leather	0.02	0.01	0.01	0.05	0.01	0.00	0.04	366
Wood	0.01	0.00	0.01	0.02	0.00	0.00	0.02	241
Paper	0.01	-0.02	0.03	-0.04	0.03	0.01	-0.08	540
Oil	0.01	0.00	0.01	0.07	0.01	0.03	0.03	32
Chem.	0.08	0.02	0.06	0.25	0.17	-0.04	0.12	386
Rubber	0.01	-0.00	0.01	-0.04	-0.01	0.02	-0.05	451
Non-m. min.	0.03	0.00	0.03	0.07	0.01	0.01	0.05	646
Metal min.	0.03	0.01	0.03	-0.03	-0.02	-0.00	-0.00	1215
Mech. mach.	0.04	-0.02	0.06	-0.02	0.05	0.04	-0.11	1141
Elec. mach.	0.12	0.01	0.11	0.18	0.05	-0.05	0.17	598
Transport	-0.04	-0.08	0.05	-0.34	-0.08	0.02	-0.28	295
Other	0.02	0.00	0.01	0.02	-0.01	0.02	0.00	669

Note: $Etot$ = total employment, $Ebet$ = employment between, $Ewit$ = employment within, $Wtot$ = total wage, $Wbet$ = wage between, $Wwit$ = wage within, $Wcom$ = wage composition. See the appendix for details on the decompositions.

Table 8: 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	1708.3	1653.3	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
Small	128.2	100.3	29.6	23.1	1746.5	1741.7	7969
Medium	132.3	101.8	33.2	25.1	1752.7	1721.2	37235
Large	128.9	104.1	41.1	31.9	1713.6	1646.1	13879
North	131.3	103.2	40.0	30.4	1714.2	1661.6	47436
Centre	131.2	104.0	39.1	29.8	1748.8	1682.1	9014
South	135.0	103.9	33.9	25.1	1731.5	1666.8	2633
Exp.	131.0	103.7	39.4	30.1	1723.7	1661.7	29538
Non exp.	132.3	102.8	39.9	30.2	1716.4	1670.1	29545
Tech	130.2	103.3	40.0	30.7	1716.2	1660.9	29536
No tech	132.8	103.4	39.0	29.4	1728.0	1670.8	29547

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

Table 9: Decompositions for hours and hourly wages

Sample	$\frac{h_n}{h}$wit	$\frac{h_n}{h}$bet	$\frac{h_n}{h}$com	$\frac{\omega_n}{\omega}$wit	$\frac{\omega_n}{\omega}$bet	$\frac{\omega_n}{\omega}$com	N.Obs.
Overall	0.02	-0.11	0.04	-0.58	0.20	0.54	8440
Exp.	0.00	-0.13	-0.14	-0.29	0.16	0.04	4220
Non exp.	0.02	0.02	0.19	-0.29	0.04	0.50	4220
Tech	0.04	-0.07	-0.13	-0.48	0.18	0.16	4218
No tech	-0.02	-0.04	0.18	-0.09	0.02	0.37	4222

Note: figures reported are within, between, and composition components of changes in $\frac{h_n}{h}$ and $\frac{\omega_n}{\omega}$ (see section 5 for details).

Table 10: Hours and hourly wages in wage bill decompositions

Sample	Wwitw$h$	Wwitwω	Wbetw$h$	Wbetwω	Wwitw	Wbetw	N.Obs.
Overall	0.17	-0.16	-0.02	0.09	0.01	0.06	8202
Exp.	0.10	-0.07	-0.03	0.07	0.03	0.04	4168
Non exp.	0.07	-0.09	0.01	0.02	-0.02	0.03	4034
Tech	0.13	-0.14	-0.02	0.07	-0.01	0.05	4154
No tech	0.04	-0.02	-0.01	0.01	0.02	0.01	4048

Note: Wwitw$h$ = contribution of hours to wage within, Wwitwω = contribution of hourly wage to wage within, Wbetw$h$ = contribution of hours to wage between, Wwitwω = contribution of hourly wages to wage between. Wwitw = wage within, Wbetw = wage between (see section 5 for details).

Table 11: Hours and hourly wages in unweighted decompositions

Sample	Wwit$h$	Wwitω	Wbet$h$	Wbetω	Wwit	Wbet	N.Obs.
Overall	0.53	-0.50	-0.08	0.28	0.03	0.20	8202
Exp.	0.32	-0.23	-0.11	0.22	0.09	0.11	4168
Non exp.	0.21	-0.27	0.03	0.05	-0.06	0.08	4034
Tech	0.41	-0.43	-0.06	0.23	-0.02	0.17	4154
No tech	0.12	-0.07	-0.02	0.05	0.05	0.03	4048

Note: Wwit$h$ = contribution of hours to wage within, Wwitω = contribution of hourly wage to wage within, Wbet$h$ = contribution of hours to wage between, Wwitω = contribution of hourly wages to wage between. Wwit = wage within, Wbet = wage between (see section 5 for details).

Table 12: Determinants of wage bill components

Dep. Var.	ΔlS	ΔlSX	ICI	RDS	R^2	N.Obs.
$WBbet$	0.62	0.18	-0.20	0.10	0.05	7377
	(6.58)	(1.26)	(-1.38)	(0.38)		
$WBwit$	-0.06	0.08	0.07	0.08	0.04	7377
	(-2.76)	(2.02)	(2.08)	(1.15)		
$Ebetw$	0.50	0.23	-0.19	0.20	0.04	7377
	(7.61)	(1.93)	(-1.50)	(0.82)		
$Ewitw$	-0.06	0.05	0.08	0.11	0.03	7377
	(-2.71)	(1.24)	(2.03)	(1.26)		
$Wbetw$	0.12	-0.05	-0.01	-0.10	0.02	7377
	(2.58)	(-0.99)	(-0.35)	(-0.66)		
$Wwitw$	-0.00	0.02	-0.01	-0.03	0.01	7377
	(-0.11)	(1.25)	(-0.80)	(-0.80)		

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; $\Delta lSX = \Delta lS$ * expdum;
ICI = Computer share of total investment; RDS = $R\&D$ / sales.

Table 13: Determinants of wage and employment components

Dep. Var.	ΔlS	ΔlSX	ICI	RDS	R^2	N.Obs.
$Ebet$	0.37	0.17	-0.13	0.10	0.04	7508
	(7.89)	(2.00)	(-1.61)	(0.63)		
$Ewit$	-0.04	0.03	0.07	0.07	0.03	7508
	(-2.38)	(1.02)	(2.34)	(1.10)		
$Wbet$	0.39	-0.15	-0.05	-0.33	0.02	7377
	(2.62)	(-0.98)	(-0.35)	(-0.67)		
$Wwit$	-0.01	0.07	-0.04	-0.09	0.01	7377
	(-0.25)	(1.14)	(-0.79)	(-0.79)		
$Wcom$	1.46	0.97	-0.60	0.80	0.03	7377
	(7.80)	(2.49)	(-1.36)	(0.97)		

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; $\Delta lSX = \Delta lS$ * expdum;
ICI = Computer share of total investment; $RDS = R\&D$ / sales.

Table 14: Determinants of within firm skill upgrading

Dep. Var.	$\Delta lWnm$	ΔlKY	ICI	RDS	R^2	N.Obs.
$\Delta wbsh$	0.109	0.003			0.237	8136
	(32.407)	(1.949)				
(1)	0.111	0.003	0.030		0.246	7742
	(32.335)	(1.975)	(5.145)			
(2)	0.112	0.004		0.032	0.243	7684
	(31.801)	(2.222)		(3.794)		
(3)	0.113	0.004	0.031	0.032	0.252	7321
	(31.869)	(2.252)	(5.101)	(4.014)		
(4)		0.003	0.027		0.007	7977
		(1.742)	(4.047)			
(5)		0.004		0.032	0.006	7872
		(1.976)		(3.524)		
(6)		0.004	0.029	0.030	0.008	7483
		(1.831)	(4.274)	(3.649)		

Note: t-statistics in parentheses. All specifications include size, geography, and industry sector dummies, as defined in section 3. Dependent variable: $\Delta wbsh$ = change in log relative wage bill; ΔlWnm = change in log relative wage; ΔlKY = change in log capital-output ratio; ICI = Computer share of total investment; RDS = $R\&D$ / sales.