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Technical Progress and Wage Dispersion in Italy: Evidence from Firms' Data

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ABSTRACT. – In this paper we test for the effect of technological progress on the labour demand and relative earnings by skill in Italy from 1986 to 1990. We consider a large panel of firms, about 36,000: the data allow us to construct a proxy of the use of new technology by each firm.

Our main conclusions are that: (i) wage dispersion in Italy did not increase by the same extent as in the US and UK; (ii) technological progress led to a remarkable increase in the employment of skilled (captured in our data by white-collars) vis-à-vis blue-collar workers. However relative earnings did not experience a similar rise. We suggest that both a shift in the supply of skills and the features of the Italian wage bargaining system counteracted the rise in earnings dispersion.

Progrès technique et dispersion des salaires en Italie : étude d'un panel d'entreprises

RÉSUMÉ. – Dans ce Papier on examine les effets du progrès technologique sur la demande de travail et sur les rémunérations en Italie de 1986 à 1990 avec un ensemble considérable d'entreprises (quelque 36 000).

Les conclusions principales sont les suivantes: (i) en Italie il n'y a pas eu la même croissance de la dispersion des salaires qu'on a enregistré dans les pays anglo-saxons; (ii) le progrès technologique a conduit à une très grande augmentation de l'emploi le plus qualifié et non pas à un développement du différentiel salarial entre les employés et les ouvriers. Notre hypothèse est que la croissance de la dispersion des salaires a été ralentie aussi bien par l'amélioration de la qualité de l'offre de travail que par le processus de négociation salariale.

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1 Introduction

Considerable attention has been devoted recently to the impact of technology on wage distribution. In particular, the increase in the overall wage dispersion and in the schooling premium, observed in both the US and the UK, has been frequently associated with a shift in the relative demand for skilled labour stemming from a wave of non-neutral technical progress. However, there is still no consensus on this view: other explanations, such as the increased openness of the economy, changes in the composition of labour supply and alteration of the institutional framework, have been put forward.

One way to shed more light on the issue is to compare the US and UK with other industrialized countries. This paper investigates the impact of new technology on the relative demand for skilled labour and wage premia in Italy. We do so by looking at a new set of firms' data, which originate from social security files and companies' balance sheets.

The data are unique, at least for Italy, in terms of industry coverage, size, quality of the earnings variable, and the availability of a large array of explanatory variables. Furthermore the data-set provides us with a specific proxy for the use of innovation in each firm (also derived from balance-sheet information). This is computed as the share of "intangible" assets, such as R&D expenditure, patents and licences, in the total capital stock: it aims at capturing the extent to which a firm *uses* computed-based new technology, such as packages for word processing, spreadsheets, softwares that command robots and machine-tools and the like. This variable allows to test directly whether new technologies have had a significant influence upon wages and the use of skills in the workplace. The two main shortcomings of the data are that, except for the number of blue- and white-collar workers in each firm, they do not include information on individual workers' characteristics and that the period covered is short (1986-1990).

As a consequence, the picture of the changes in earnings distribution that we are able to draw is partial at best. Nevertheless some interesting aspects emerge. In particular, the use of new technologies has a strong impact on the relative demande for skilled labour: this is an extremely robust result. On the other hand innovation does not affect earnings by skill to a comparable extent: the coefficient of the variable on both blue- and white-collar earnings is not always significant and sometimes goes the wrong direction. In general, however, white-collar workers' earnings seem to be more affected by new technologies than blue-collar workers'.

The increase in the white/blue-collar earnings differential has not matched the shift in relative labour demand. This result suggests that the wage pressure due to increased demand for higher skills may have been counteracted by the institutional framework of wage determination or by a corresponding shift in the supply of skills. The impact of technology on earnings is clearly increasing toward the end of our sample: one might expect that it has become stronger in the nineties.

The outline of the paper is as follows. In Section 2 we review the international debate. In Section 3 we examine the pattern of earnings dispersion in the second half of the eighties and investigate the impact of technical progress across different skills and firm characteristics, by way of variance decompositions. In Section 4 we run a set of regressions to identify the effect of the use of innovation on earnings and labour demand by skill, after controlling for firms' characteristics. Our results are then discussed and possible interpretations offered. Conclusions follow.

2 Technical Progress and Wage Dispersion: The International Debate

The increase in wage inequality during the eighties in the US and a number of other countries [1] has received widespread attention. The evidence shows an increase in earnings differentials related to both education and experience during the past decade (see BOUND and JOHNSON [1992], and KATZ and MURPHY [1992]) along with an increase in dispersion within each experience and education group (see JUHN, MURPHY and PIERCE [1993]). DAVIS and HALTIWANGER [1991] and BERMAN *et al.* [1994] document a substantial widening of the wage differential between white- and blue-collar workers in the manufacturing sector.

The contemporaneous rise in white-collar workers' relative wages and employment suggests a shift in the demand of labour towards more skilled jobs [2]. Two likely candidates have emerged: (i) demand shifts away from low-skilled production processes (mainly within the manufacturing sector) and (ii) skill-biased technical change.

The first of these is often associated with international trade and the globalisation of the economy. According to the standard argument, cheap unskilled labour intensive imports from less developed countries have displaced low-skilled domestic production and have consequently reduced

1. LEVY and MURNANE [1992] provide an extensive survey of the US literature. DAVIS [1992] and BLAU and KAHN [1994] provide cross-country comparisons. Further international evidence is included in FREEMAN and KATZ [1995].
2. KATZ and MURPHY [1992] show in fact that supply factors alone cannot account for the observed changes in relative wages. Another potential explanation of the rise in wage inequality considered in the literature is institutional changes, such as the decline in unionisation, which has disproportionately affected blue-collar workers: according to FREEMAN and KATZ [1994], this factor explains about a fifth of the overall increase in wage dispersion. DI NARDO *et al.* [1994], on the other hand, find a substantial impact of the changes in the minimum wage on wage dispersion.

the demand for less skilled US workers [3]. The argument in favour of skill-biased technical change, on the other hand, is that the new computer-based technology relies heavily on highly educated and highly skilled workers: consequently, the adoption of new production techniques has led to an increase in the demand for skilled workers.

In general, empirical studies support the view of skill-biased technical change [4]. The recurrent argument is that industrial shifts should be mirrored by a strong increase of the variance of wages *between* industries; on the other hand, the evidence suggests that most of the rise in wage dispersion has occurred *within* industries (see for example BERMAN *et al.*, 1994, who decompose the variance of wages across industries to 4 digits).

As is pointed out by MISHEL and BERNSTEIN [1994], one problem with the technical change hypothesis is that much of the evidence has been of the residual kind: that is, the only explanation left after all the others have been discarded for one reason or the other [5]. In the face of this criticism, the role of technical progress in wage and employment determination deserves further investigation. This can come either by looking at direct evidence on the impact of new technologies or by comparing the US experience with that of other countries.

On the first account, recent work by DOMS *et al.* [1994], who match employer and employee data, finds a significant positive relationship between the use of technologically advanced production methods, on the one hand, and the share of highly skilled non-production workers and the average wage at the plant level, on the other hand. Note that the effect of technology on wages remains significant even once workers' characteristics have been controlled for. This is consistent with the results of KRUEGER [1993] and ENTORF and KRAMARZ [1994], who also find a wage premium from the use of advanced technology, after controlling for workers' characteristics.

As to international comparisons, an increase in wage dispersion along the skill dimension comparable to that found for the US has been detected for the UK by MACHIN [1993]. The evidence for Germany and France is less clear: ABRAHAM and HOUSEMAN [1993] for GERMANY and DAVIS [1992] and KATZ *et al.* [1994] for France fail to discover a significant increase in wage dispersion across different occupations and skills. In general, comparative studies find that the widening of the skill differentials in other industrialized countries is far less dramatic than in the US and in the UK.

Italy has been present only marginally in the debate. We hope to fill this gap, by presenting some new evidence on the changes in earnings dispersion in this country. The data (fully described in the Appendix) come from a newly constructed data-set of firms, which is unique both in size and

3. On this issue see LAWRENCE and SLAUGHTER [1993], SACHS and SHATZ [1994], BERNARD and JENSEN [1994] and KRUGMAN [1995].
4. See, among others, DAVIS and HALTIWANGER [1991], KATZ and MURPHY (1992), JUHN *et al.* [1993], LAWRENCE and SLAUGHTER [1993] and BERMAN *et al.* [1994].
5. In the same spirit, JUHN [1994] and BERNARD and JENSEN [1994] suggest that the explanation based on technical progress is only partial and can be usefully supplemented by consideration of product demand shifts.

in information on firms' characteristics. The data have several interesting features: a wide sectoral coverage (the whole non-farm private business sector [6]); large sample size (we have more than 20,000 firms per year, covering between 1.6 and 1.9 million employees); and a good measure of earnings (annual earnings as registered in the fully comprehensive social security files). However, our data offer only a partial picture of wage dispersion, as they consider *average* annual earnings at the firm level, separately for blue and white-collar workers: we are therefore unable to take individual workers characteristics into account. The period covered is also quite short (1986-1990). On the other hand, given the size of the data set, we are able to investigate earnings dispersion across firms in great depth.

3 Earnings Dispersion

We begin by considering the distribution of incomes by *households* in Italy (see BRANDOLINI and SESTITO [1994], for a fuller account). Table 1 shows the changes in income distribution between 1977 and 1993. The data come from the Bank of Italy's Survey of Household Income and Wealth, which was conducted annually up to 1987, every other year thereafter; incomes, which include both earned and unearned components, are reported after-tax and have been equivalized by dividing by the square root of family size.

TABLE 1

Income distribution across households (1)

	1977	1982	1986	1987	1988	1989	1990	1991	1993
Mean log deviation	0.2106	0.1381	0.1585	0.1707	n.a.	0.1500	n.a.	0.1481	0.1957
Theil index	0.2443	0.1410	0.1556	0.1726	n.a.	0.1519	n.a.	0.1488	0.1805
Gini coefficient	0.3485	0.2874	0.3016	0.3193	n.a.	0.2974	n.a.	0.2918	0.3254

Source: Based on Bank of Italy Survey of Households' Income and Wealth.

(1) Total household income net of taxes and social security contributions and equivalized across households dividing by the square root of family size.

According to the set of different measures we compute, overall income inequality was reduced between the end of the seventies (1977 is the first year for which figures are available on a comparable basis) and the early nineties: for instance, the Gini coefficient falls from 0.35 in 1977 to 0.33 in 1993 (0.29 in 1991). Several phases can be discerned. Between 1977 and 1982 income differentials contracted. From the mid-eighties to the beginning of the nineties, which is the period we are directly concerned

6. A sample selection bias toward larger firms and the manufacturing sector has been at least partially, corrected by ex-post weighting (the procedure is described in the Appendix).

with, income dispersion among households is relatively constant: it first undergoes a modest increase, then a small decline (in 1989 and 1991). Finally, between 1991 and 1993 inequality increases quite rapidly, although income dispersion is still lower than in the seventies. The recent increase is probably linked to the 1993 recession, one of the most severe of the last half-century (real consumption fell for the first time since the war): the dramatic rise is unemployment is likely to have caused households' income differentials to widen. This counter-cyclical pattern of income inequality is a new feature for Italy, however: in the past (during the recession of the early eighties, for instance) cyclical effects were far less clear and, if anything, the pattern was pro-cyclical (see BRANDOLINI and SESTITO [1994]).

Evidence on the earnings distribution of individual *employees* has been collected by SESTITO [1992] and ERICKSON and ICHINO [1993]. Both papers consider the period from 1977 to 1987. They find that dispersion across employees slightly declines; moreover, premia for education and experience are basically invariant.

These figures suggest a different pattern of income dispersion in Italy in the eighties from that of the US and UK. There is hardly any increase in income differentials and changes are mainly confined to the self-employed and pensioners (see BRANDOLINI and SESTITO [1994]). Do our firms' data confirm this picture?

From the data, we construct two sets of measures of earnings dispersion. The first is based simply on the average earnings for each firm; the second considers the average blue-collar and white-collar earnings within each firm separately. The reason for computing two sets of measures is that some firms lack one of the two categories of worker. This distinction turns out to be useful when we look at the variance of earnings by skill.

Measures of earnings dispersion based on *firms'* data provide a picture similar to that emerging from data on households' incomes (Table 2). The increase in earnings dispersion over the period is small: (log) variance across firms rises from 0.055 in 1986 to 0.065 in 1990; that across blue and white-collar groups within firms from 0.068 to 0.079. Earnings dispersion increases between 1986 to 1988 whereas it falls in 1989 and in 1990. The time pattern is thus akin to the one observed on households incomes [7]. The other inequality measures (also reported in Table 2), which are typically less sensitive to extreme values, display a similar pattern. Unfortunately our data do not extend past 1990, so we cannot test whether the earnings distribution by firm widened during the recession of the early nineties, as data on households seem to suggest.

Is the observed pattern of earnings dispersion similar across different groups of workers and firms? In order to answer this question we break down the earnings distribution into its within and between components [8]. We focus

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7. In 1988 no household survey was carried out, so we cannot compare households' income and firms' earnings distribution directly.
8. Since all measures of inequality lead to similar conclusions (and only a few can be decomposed exactly into the within and between components), from now on we will concentrate on the log variance.

TABLE 2

Earnings Distribution in the Sample

	1986	1987	1988	1989	1990
			Across firms		
Coefficient of variation	24.1	26.0	27.6	25.7	25.9
Variance of (log) earnings	0.0552	0.0621	0.0694	0.0633	0.0650
Mean log deviation	0.0277	0.0314	0.0352	0.0316	0.0323
Theil index	0.0279	0.0319	0.0359	0.0317	0.0323
Gini coefficient	0.1312	0.1387	0.1464	0.1402	0.1412
Quintile ratio	1.447	1.476	1.499	1.528	1.516
Decile ratio	1.776	1.820	1.803	1.841	1.850
			Across cells (1)		
Coefficient of variation	26.7	28.5	30.1	28.3	28.7
Variance of (log) earnings	0.0676	0.0754	0.0825	0.0764	0.0786
Mean log deviation	0.0346	0.0387	0.0426	0.0389	0.0400
Theil index	0.0343	0.0386	0.0425	0.0385	0.0395
Gini coefficient	0.1625	0.1697	0.1771	0.1711	0.1732
Quintile ratio	1.542	1.567	1.602	1.625	1.621
Decile ratio	1.949	1.948	2.006	1.975	1.988
Number of firms	20,968	22,754	24,282	25,893	25,092
Number of cells (1)	38,939	42,035	44,487	47,773	46,328
Number of workers in the sample (2)	1,577	1,760	1,814	1,867	1,817

(1) Each firm represents two cells when both white- and blue-collars are present. (2) Thousands.

on the earnings dispersion according to skill. The data do not contain detailed information on skills, so we are obliged to identify higher skills with non-manual (white-collar) and lower skills with manual (blue-collar) occupations: this is quite a restrictive assumption, although a common one in the literature.

In order to decompose total variance of earnings we use the following formula:

$$Total\ variance = \sum_j \frac{\ell_j^{bc}}{L}(\overline{w}_j^{bc} - \overline{w})^2 + \sum_j \frac{\ell_j^{wc}}{L}(\overline{w}_j^{wc} - \overline{w})^2$$
$$= \underbrace{\sum_j \frac{\ell_j^{bc}}{L}(\overline{w}_j^{bc} - \overline{w}^{bc})^2 + \sum_j \frac{\ell_j^{wc}}{L}(\overline{w}_j^{wc} - \overline{w}^{wc})^2}_{within}$$
$$+ \underbrace{\frac{\sum_j L_j^{bc}}{L}(\overline{w}^{bc} - \overline{w})^2 + \frac{\sum_j L_j^{wc}}{L}(\overline{w}^{wc} - \overline{w})^2}_{between}$$

where j denotes the firm; bc stands for blue-collar and wc for white-collar. $\overline{w}_j^{bc}$ and $\overline{w}_j^{wc}$ are average earnings for blue-collar and white-collar workers in firm j (our elementary units of observation) respectively; $\overline{w}^{bc}$ and $\overline{w}^{wc}$ are average blue- and white-collar earnings in the economy and $\overline{w}$ are total average earnings. ℓ_j^{bc} and ℓ_j^{wc} are the number of blue-collar and white-collar workers in firm j; $L^{bc}(= \sum_j \ell_j^{bc})$ and $L^{wc}(= \sum_j \ell_j^{wc})$ are the overall number of blue- and white-collar workers; $L(= L^{bc} + L^{wc})$ is total employment in the economy.

This variance decomposition focusses on the variance within and between *groups* (occupations, in this case), weighted by their employment shares, rather than within and between *firms*, as in DAVIS and HALTIWANGER [1991] for instance. In other words, we treat blue-collar and white-collar workers within each firm as separate units. As we mentioned, this enables us to include also those firms that only have either blue-collar or white-collar workers, but not both: for instance, many firms in the service sector typically employ only non-production workers. Note also that the between component depends on the average white/blue-collar earnings differential.

Table 3 summarizes the results of the variance decomposition. Several features are worth noting. First, the white-collar employment share in the economy increases regularly over the period. The white/blue-collar earnings differential increases substantially between 1986 and 1987 and then starts falling since 1988.

TABLE 3

Variance Decomposition: White VS. Blue Collar Earnings (1)

Years	Total variance	Within variance		White-collar employment share (%)	White/blue log earnings differential	Between variance as % of total
		White-collar workers	Blue-collar workers			
1986	0.0676	0.0635	0.0398	39.84	0.2770	27.18
1987	0.0754	0.0696	0.0429	40.26	0.3007	28.85
1988	0.0825	0.0838	0.0443	41.19	0.3005	26.53
1989	0.0764	0.0696	0.0455	41.30	0.2941	27.44
1990	0.0786	0.0751	0.0462	42.24	0.2880	25.72

(1) The decomposition considers 2 groups (white- and blue-collar workers)

Secondly, the share of total variance due to the dispersion between groups is small (less than 30%). Most of the action occurs within each of the two groups. The variance within the blue-collar group grows smoothly over time, whereas the variance within the white-collar segment peaks in 1988. Its contribution to the overall variance is systematically larger than that of blue-collar workers. From this step of the analysis we can conclude that the pattern in earnings dispersion we observe between 1986 and 1990 is driven largely by changes which occur within the white-collar earnings [9].

9. In principle these results could be affected by the weights we used to correct for the under-representation of employees in the service sector and in small firms (see the Appendix for details). In order to check the sensitivity of our results to these factors we re-computed the same measures on unweighted data, where we considered only the firms that remain in the sample for the whole 5-year period. We expected sample selection (in favour of the fittest and largest firms) to lead to a higher average wage and a smaller dispersion: this is exactly what we find. However, the pattern of earnings dispersion over time remains substantially unaffected.

A natural question is whether the pattern of earnings dispersion is linked to technological innovation. Our hypothesis is that Italy was affected by the introduction of new technology in the eighties in the same way as other industrialized countries. Although the adoption of technology is difficult to measure, the evidence supports this view. Over the period, R&D intensity at the aggregate level increases rapidly: R&D expenditure as a percentage of value added has risen by over 40% from 1986 to 1991.

From our data we can also construct a direct measure of the use of new technology by each firm. This measure consists of the share of "intangible" assets, such as R&D expenditure, patents and licences, in the total capital stock. It captures the extent to which a firm *uses* computer based technologies (think of packages for word processing). It does not capture instead whether a firm *develops* innovations that it later sells or uses in-house. But it is a plausible assumption that the main effects on labour demand, if any, should come from users of new technology rather than from their developers [10].

The use of innovation at the aggregate level increases substantially between 1986 and 1990 (from .074 to .100 on average; the median value from .027 to .036), which confirms the diffusion of new technologies in Italy.

In other to test the impact on earnings, we follow the same methodology as before and decompose the variance of earnings into two further classes, according to whether firms use innovations to a large extent or not (Table 4) [11]. A firm is defined as "technologically advanced" if its stock of patents and licenses exceeds the industry (3 digit) annual median. It emerges that the firms that use computer-based technologies more aggressively pay a higher premium to white-collar workers: this premium is increasing up to 1988. The same firms also have a comparatively larger (and increasing) share of white-collar staff [12].

10. The variable, constructed on the basis of balance sheets' information, includes items which are not directly related to the use of technology, such as advertisement and goodwill (see the Appendix for details). For a small sub-sample of firms in our dataset, however, a detailed breakdown of the various components is available. In the Appendix we examine to what extent our results are affected by the inclusion of items unrelated to technology.

11. The variance decomposition now leads to a within component which is equal to:

$$\sum \frac{\ell_j^{bc,t}}{L}(\overline{w}_j^{bc,t} - \overline{w}^{bc,t})^2 + \sum_j \frac{\ell_j^{bc,nt}}{L}(\overline{w}_j^{bc,nt} - \overline{w}^{bc,nt})^2$$
$$+ \sum_j \frac{\ell_j^{wc,t}}{L}(\overline{w}_j^{wc,t} - \overline{w}^{wc,t})^2 + \sum_j \frac{\ell_j^{bw,nt}}{L}(\overline{w}_j^{wc,nt} - \overline{w}^{wc,nt})^2$$

and to a between component equal to:

$$\frac{L^{bc,t}}{L}(\overline{w}^{bc,t} - \overline{w})^2 + \frac{L^{bc,nt}}{L}(\overline{w}^{bc,nt} - \overline{w})^2 + \frac{L^{wc,t}}{L}(\overline{w}^{wc,t} - \overline{w})^2 + \frac{L^{wc,nt}}{L}(\overline{w}^{wc,nt} - \overline{w})^2$$

where the subscript t refers to innovative firms and nt to non-innovative ones, as defined in the text.

12. However, the increase in the share is even faster in non-innovative firms.

TABLE 4

Log Variance Decomposition: Use of New Technologies (1)

Years	Within variance: Blue-collar workers	Within variance: White-collar workers	White/blue collar log earnings differential	White-collar employment share (%)
		Technologically advanced firms		
1986	0.0395	0.0599	0.2933	43.14
1987	0.0424	0.0724	0.3271	43.11
1988	0.0422	0.0947	0.3261	44.02
1989	0.0471	0.0684	0.3161	45.42
1990	0.0465	0.0791	0.2944	44.55
		Non technologically advanced firms		
1986	0.0398	0.0659	0.2449	35.38
1987	0.0432	0.0614	0.2609	36.81
1988	0.0466	0.0647	0.2623	37.80
1989	0.0436	0.0679	0.2554	36.01
1990	0.0459	0.0693	0.2787	39.48

(1) The decomposition considers 4 groups (white- and blue-collar workers; technologically advanced and non-technologically advanced firms)

The between component of the total variance is only slightly greater than that computed on the basis of the white/blue-collar distinction alone. Again, most of the action occurs within cells, especially that representing white-collar workers in advanced firms; their within-group dispersion is the largest (on average) and, like the overall dispersion, peaks in 1988 and then falls.

In short, variance decomposition allows us to discover that most of the changes in earnings dispersion occurs within the group of white-collar workers in the segment of firms that use advanced technology more intensively. This is the segment that drives the entire profile of the earnings distribution over time.

We have also tried to break down our cells further by using different combinations of skills, size, degree of technological progress and industries (2 and 3 digit) [13]. Partly because each group is quite small, we are not able to detect special patterns in any industry; however, the increase in earnings dispersion looks more pronounced among small firms.

13. This is to take into account that on average some industries use more technical innovation than others.

4 The Impact of New Technology: Estimates

Compared to variance decompositions, regressions enable us to quantify the impact of innovation on earnings and employment more precisely, by controlling for location, industry and firm size. We consider the effect of the use of innovation on both earnings and employment by skill in each firm. We run separate regressions for each year, in order to exploit all the information available in our (unbalanced) panel, including those firms which are present for a single year only. However, since the cross-sectional results may be affected by unobserved heterogeneity, we also run fixed-effects panel estimates [14].

If innovation is complementary to skill, one would expect a more intense use of new technology to increase the relative demand for skilled labour (captured in our sample by white-collar workers). Hence firms that make greater use of innovation should have a larger share of white-collar workers (or, equivalently, an increase in innovation should lead to greater demand for white-collar employees, reflected in panel estimates). Whether more advanced firms pay higher wages to the white-collar group depends also on the relative supply of skilled workers.

A further issue concerns the skill content of white- and blue-collar labour. It is quite possible that technical progress affects not only the ratio between white- and blue-collar staff within each firm, but also the composition of each group by skill, which we do not observe directly. If this is the case, the finding that blue-collar (or white-collar) workers earn a premium in innovative firms would still be consistent with a skill bias of technical progress. The relevant differential would then be the one between average earnings in this group of firms and in the rest of the economy, as suggested by the variance decomposition of the previous section.

In order to test for this possibility, we run regressions on white- and blue-collar earnings separately, in addition to their earnings differential and employment share [15]. We also include the ratio between the shares of the total wage bill paid to white-collar and to blue-collar workers among the variables to be explained: if relative labour demand is elastic with respect

14. We thank a referee for suggesting that we compute fixed-effects panel estimates.

15. The number of observations is slightly different since not all firms have both blue- and white-collar workers.

to the earnings differential by skill, the impact of the new technology onthe wage shares should be greater than that on the employment shares alone [16].

In the cross-sections (Table 5) for each year we estimate the following equations (in logs):

(1) $$\overline{w}_{jt}^{bc} = \alpha_{1t} + \beta_1 \tau_{jt} + \gamma_1 Z_{jt} + \varepsilon_{1jt} \qquad Blue\text{-}collar\ earnings$$

(2) $$\overline{w}_{jt}^{wc} = \alpha_{2t} + \beta_2 \tau_{jt} + \gamma_2 Z_{jt} + \varepsilon_{2jt} \qquad White\text{-}collar\ earnings$$

(3) $$\frac{\overline{w}_{jt}^{wc}}{\overline{w}_{jt}^{bc}} = \alpha_{3t} + \beta_3 \tau_{jt} + \gamma_3 Z_{jt} + \varepsilon_{3jt} \qquad Earnings\ ratio$$

(4) $$\frac{\ell_{jt}^{wc}}{\ell_{jt}^{bc}} = \alpha_{4t} + \beta_4 \tau_{jt} + \gamma_4 Z_{jt} + \varepsilon_{4jt} \qquad Employment\ ratio$$

(5) $$\frac{\overline{w}_{jt}^{wc}\ell_{jt}^{wc}}{\overline{w}_{jt}^{bc}\ell_{jt}^{bc}} = \alpha_{5t} + \beta_5 \tau_{jt} + \gamma_5 Z_{jt} + \varepsilon_{5jt} \qquad Wage\ shares\ ratio$$

for t =1986,...,1990. τ is our measure of technical innovation. In all equation Z includes (3 digit) industry dummies, location (95 provinces) dummies and firm size, expressed as the log of the total number of workers (we also allow for a quadratic term). The regressions we report are weighted, the weights being given by the overall number of employees in each firm ($\ell_j^T = \ell_j^{bc} + \ell_j^{wc}$) over total employment [17]. We experimented also with unweighted regressions: the results are generally similar, but for blue- and white-collar earnings in the first early part of the sample, as we will discuss later. In the final column of Table 5 regressions on pooled data are presented, in which all right-hand side variables have been interacted

16. In principle the earnings should be included as a regressor in the relative demand equation. A simultaneity bias may, however, arise. This could be overcome by using instrumental variables: unfortunately we could find no reasonably good instrument. The alternative strategy, which we follow, is to consider wage shares (see also BERMAN *et al.* [1994]). If the elasticity of substitution between skills is close to unity (as in the case of a Cobb-Douglas), the bias which arises from omitting the earnings differential from the right hand side disappears.

17. Employment weights have been further multiplied by a coefficient k_i, based on the frequency distribution of firms by size and industry in the universe (see the Appendix for a description), which attenuate the sample bias towards manufacturing and large size.

TABLE 5

Impact of Innovation on (log) Earnings and Employment by Skill (cross sectional estimates-weighted data)

Dependent variable (a)	1986	1987	1988	1989	1990	Test of equality (b)
Blue-collar earnings (β_1):	0.0143	0.0278	–0.0040	–0.0179	–0.0181	F=11.86 (**)
	(2.04)	(4.02)	(0.60)	(2.75)	(2.87)	(4; 103,127)
R^2	0.511	0.518	0.516	0.523	0.526	
White-collar earnings (β_2):	0.0134	0.0017	–0.0010	–0.0116	–0.0056	F=2.23 (*)
	(1.63)	(0.21)	(0.12)	(1.62)	(0.78)	(4; 113,577)
R^2	0.454	0.478	0.522	0.493	0.491	
White blue-collar earnings	0.0072	–0.0176	0.0138	0.0300	0.0165	F=4.59 (**)
ratio (β_3):	(0.83)	(2.05)	(1.67)	(3.80)	(2.13)	(4; 99,136)
R^2	0.248	0.271	0.261	0.258	0.288	
White blue-collar employment	0.4591	0.4410	0.4155	0.5954	0.4690	F=2.43 (*)
ratio (β_4):	(9.54)	(9.35)	(9.41)	(14.06)	(11.26)	(4; 99,140)
R^2	0.461	0.457	0.470	0.472	0.465	
White blue-collar wage shares	0.4663	0.4240	0.4300	0.6256	0.4858	F=3.18 (*)
ratio (β_5):	(9.52)	(8.86)	(9.52)	(14.37)	(11.37)	(4; 99,136)
R^2	0.444	0.437	0.447	0.450	0.439	

(a) Coefficient of the measure of technical innovation (see text). t-statistics in brackets. The other regressors are: log size and its square, 3-digit industry dummies and 95 provincial dummies (in the pooled estimates the coefficients of the dummies are allowed to vary by year).

(b) The F test refers to the hypothesis of equality of the coefficients on technical innovation over the 5 years. Degrees of freedom in brackets.

(*) Significant at the 10% confidence level.

(**) Significant at the 1% confidence level.

with time dummies: their only purpose is to test whether the coefficient on τ is the same over the whole sample [18]; as we shall see, this hypothesis is generally rejected.

The use of new technology has a positive and significant impact on the white/blue-collar employment ratio (eq. (4)) and on the wage shares ratio (eq. (5)). In both instances, the coefficient β cannot be restricted to be the same over the five years (F-tests are significantly different from zero at the 95% confidence interval, although only marginally so in eq. (4)); it is also very similar in the two equations, thereby suggesting that the impact on the wage shares is mainly driven by that on relative employment. In the

18. For instance, eq. (1) become now:

$$\overline{w}_{jt}^{bc} = \alpha_{1t} + \beta_{1t}\tau_{jt} + \gamma_{1t}Z_{jt} + \varepsilon_{1jt}$$

where α, β and γ are allowed to vary over time. Differently from before, this equation is estimated over the entire sample. In Table we report the test that $\beta_{1,1986} = .. = \beta_{1,1990} = \beta_1$.

unweighted estimates the impact of innovation on the relative demand for white-collars is clearly increasing over the sample; on weighted data this pattern is less clear, although the coefficient in 1989 is significantly above those of the other years.

The use of innovation affects blue- and white-collar earnings in a similar way (eqs. (1) and (2)). In both equations the coefficient β is positive at the beginning of the sample, whereas it turns negative in 1988, although it is never statistically significant for white-collar earnings. However, the same regressions on unweighted data offer a slightly different picture: innovation has a permanent positive effect on earnings of both skills and it is greater (and more significant) for white-collars. The difference between weighted and unweighted estimates suggests that most of the effect of innovation on earnings occurs in small firms at one (or both) ends of the distribution: this is consistent with the findings of the variance decomposition.

Finally, the effect of innovation on the wage premium for white-collar workers (eq. (3)) is on the verge of significance in most cross-sections. The coefficients of the control variables (not reported here) are in line with what we expected [19].

Overall there is thus strong evidence that the use of innovation brought about a shift in the relative demand for white-collar labour. However, the impact on the earnings differential (β_3) is not significant and it is certainly less strong than one would have expected on the basis of what we observe in the labour demand. Moreover, if we consider blue- and white-collar earnings separately, innovation has an ambiguous sign (the coefficients are first positive, then negative) and is not very precisely estimated. These results are unaffected by the introduction of a larger set of covariates including value added and financial variables [20].

Do our results, especially that on the labour demand, support the view that new technologies require more educated and more skilled labour, as argued for instance by KRUEGER [1993] and DOMS *et al.* [1994]? One problem with our data, as we stressed earlier, is that we cannot control for workers' characteristics. Hence, the distinction between white- and blue-collar workers is probably too blunt to assess the "true" skill requirements of technologically advanced firms [21].

The findings of equations (1) and (2) show that, at least until 1988, the use of innovation affected both blue- and white-collar earnings positively: hence they are consistent with the view of ENTORF and KRAMARZ [1994] that firms tend to select abler workers, both blue- and white-collars, in order to man new technologies. Firms select workers by choosing those who are already better paid: high wages therefore represent a signal of greater ability.

19. Industry effects are remarkably stable from one year to the other and display a similar ranking for both blue- and white-collar workers. Size has the usual positive effect on earnings.

20. However, this exercise has the drawback that the sample size is significantly reduced because many firms lack information on the additional covariates.

21. For instance one can think that firms that want to pay their workers more, simply shift them up along the scale established by collective agreements: in the data this might show up as an increase in white-collar staff.

In order to test this hypothesis we would require panel data on individual workers, as in ENTORF and KRAMARZ [1994]. Nevertheless, by controlling for firms' fixed effects, we can check to what extent are the findings of the cross-sections driven by unobserved heterogeneity across firms, which is related to the average "ability" of the workforce in each firm.

Hence we replicate the previous exercises by exploiting the panel nature of our data (Table 6). In order to control for unobserved heterogeneity we use a fixed-effects estimator. The sample is smaller than in the annual cross-sections, as firms have to be present for at least two years (not necessarily consecutive) in order to identify their time-invariant effects. We also allow for time-variant industry and location effects, by introducing a full set of interactions between time dummies and industry and location dummies (we exclude the firm size). As before we use weighted data. The regressions now become:

$$(1') \quad \overline{w}_{jt}^{bc} = \mu_j + \lambda_{1t} + \beta_1 \tau_{jt} + \gamma_{1t} Z_{jt} + \varepsilon_{1jt} \qquad \textit{Blue-collar earnings}$$

$$(2') \quad \overline{w}_{jt}^{wc} = \mu_j + \lambda_{2t} + \beta_2 \tau_{jt} + \gamma_{2t} Z_{jt} + \varepsilon_{2jt} \qquad \textit{White-collar earnings}$$

$$(3') \quad \frac{\overline{w}_{jt}^{wc}}{\overline{w}_{jt}^{bc}} = \mu_j + \lambda_{3t} + \beta_3 \tau_{jt} + \gamma_{3t} Z_{jt} + \varepsilon_{3jt} \qquad \textit{Earnings ratio}$$

$$(4') \quad \frac{\ell_{jt}^{wc}}{\ell_{jt}^{bc}} = \mu_j + \lambda_{4t} + \beta_4 \tau_{jt} + \gamma_{4t} Z_{jt} + \varepsilon_{4jt} \qquad \textit{Employment ratio}$$

$$(5') \quad \frac{\overline{w}_{jt}^{wc} \ell_{jt}^{wc}}{\overline{w}_{jt}^{bc} \ell_{jt}^{bc}} = \mu_j + \lambda_{5t} + \beta_5 \tau_{jt} + \gamma_{5t} Z_{jt} + \varepsilon_{5jt} \qquad \textit{Wage shares ratio}$$

where the μ's represent firms' fixed effects and the λ's time effects common to all firms.

The panel estimates are slightly different from those of cross-sections [22]. The coefficient for the white/blue-collar employment ratio remains significant, supporting the case for a shift in the relative labour demand; however, the impact of new technologies is now much smaller, by about a factor of 8. The coefficient is varying over time, although the

22. Introducing a wider set of covariates in the fixed-effects estimates does not affect the results.

TABLE 6

Impact of Innovation on (log) Earnings and Employment by Skill (weighted fixed effects)

Dependent variable	Coefficient (a)	R^2	Number of observations	Test of equality (b)	Time varying according to a linear trend (c)
Blue-collar earnings (β_1):	–0.0027 (0.97)	0.668	99,077	F=2.82 (*) (4; 97798)	0.0047 (2.51)
White-collar earnings (β_2):	0.0074 (2.35)	0.625	108,845	F=3.68 (**) (4; 107563)	0.0056 (2.61)
White blue-collar earnings ratio (β_3):	0.0050 (1.45)	0.061	95,276	F=3.37 (**) (4; 93999)	0.0023 (1.03)
White blue-collar employment ratio (β_4):	0.0624 (5.63)	0.108	95,280	F=2.88 (*) (4; 94003)	–0.0031 (0.42)
White blue-collar wage shares ratio (β_5):	0.0673 (5.96)	0.108	95,276	F=3.97 (**) (4; 93999)	–0.0007 (0.10)

(a) Coefficient of the measure of technical innovation (see text). Absolute-value t-statistics in brackets. The other regressors are: 3-digit industry dummies and 95 provincial dummies (the coefficients of the dummies are allowed to vary by year).

(b) F test of equality of the coefficient for innovation over the 5 years. Degrees of freedom in brackets.

(c) Coefficient of the interaction of innovation with a linear trend (trend x $\tau_{it.}$). Other regressors are the same as in note (a). t-statistics in brackets.

(*) Significant at the 10% confidence level.

(**) Significant at the 1% confidence level.

hypothesis that it follows a linear trend is rejected by the data (see the last two columns of Table 6) [23].

Differently from the cross-sections, white-collar earnings are now clearly affected by the use of innovation [24]: β_2 has a trend-like pattern over time.

23. In the first experiment we interacted the β coefficients with time dummies and tested whether they are significantly different across years; in the second one, we interacted them with a time trend and tested whether the latter was significant. So, in the first experiment equation (1′) becomes:

$$\overline{w}_{jt}^{bc} = \mu_j + \lambda_{1t} + \beta_{1t}\tau_{jt} + \gamma_{1t}Z_{jt} + \varepsilon_{1jt}$$

and we test whether $\beta_{1,1986} = .. = \beta_{1,1990} = \beta_1$.
In the second experiment we regress instead:

$$\overline{w}_{jt}^{bc} = \mu_j + \lambda_{1t} + \beta_1\tau_{jt} + \beta_1' \cdot trend \cdot \tau_{jt} + \gamma_{1t}Z_{jt} + \varepsilon_{1jt}.$$

In this case only β_1' is reported in Table 6.

24. On unweighted data the coefficient is still positive, although no longer significant.

On the other hand, when we control for firms' unobserved heterogeneity, the effect of innovation on blue-collar earnings tends to disappear: β_1 is now negative and insignificant [25]. Interestingly, we cannot reject the hypothesis that also β_1, increases over time according to a trend [26] (see the last column of Table 6). Taken together, these findings point to changes in the composition of workers within both occupations over the sample: innovative firms have paid their workers, presumably the best skilled ones, increasingly more. On average a significant effect can be detected only for white-collar workers: this might be due simply to the small size of the sample. Finally, the white/blue-collar earnings differential is not significantly affected by the use of innovation, altough the t-statistic is above 1. There is therefore limited evidence that new technologies inpinge on the skill premium, similarly to what we found in the cross-sections.

To sum up, we find robust evidence that the use of technology leads to a shift in the relative labour demand towards higher, non-manual skills in the second half of the eighties. However there is a limited evidence that an increase in the wage premium (for both blue- and white-collar workers and for the latter *vis-à-vis* the former) occurs at the same time. This is not altogether surprising, given that the overall earnings dispersion is relatively constant over the period.

Why does the shift in relative labour demand not lead to a substantial increase in the white-collar wage premium? A possible answer is that the supply of skilled labour has risen as to match the shift in relative demand [27]. Table 7 offers some indirect evidence on this point: skilled labour (measured by the share of high school or college graduates in total employment) increases by 5 percentage points in the period we consider, after having grown by more than 10 points in the previous decade. It is interesting to note (and it may turn out to be relevant for the future) that this shift tends to decelerate progressively; the slowdown is partly due to

TABLE 7

Schooling by Degree. Share of Total Workers who Achieved the Corresponding Degree

	1977	1986	1987	1988	1989	1990	1992
14-29 years:							
Primary or no degree	33.9	11.0	9.3	8.0	7.4	6.8	5.3
High school or college	20.1	31.5	33.1	33.7	34.5	35.5	35.9
all ages:							
Primary or no degree	57.5	36.3	34.1	32.0	30.1	27.6	24.1
High school or college	17.0	28.2	29.8	31.0	32.3	33.7	34.8

Source: Labour Force Survey

25. On unweighted data it is positive with a t-statistic of 1.5.
26. Although the average effect, not reported in Table 6, is still negative.
27. A similar explanation is provided by ABRAHAM and HOUSEMAN [1993] for Germany.

demographic reasons (the reduction in the size of the better educated young cohorts) and partly to a levelling of educational attainment of the youths.

Another line of argument follows from the institutional characteristics of wage determination in Italy, which has been traditionally dominated by nationwide collective bargaining. Contracts are signed at the industry level, cover both white- and blue-collar workers and typically allow for modest wage differentials by occupation [28]. Employers have to apply the union contracts to their entire workforce [29]. Bargaining at the industry level represents a powerful obstacle to the increasing returns to skill within each industry. Both because of the wage indexation system (*scala mobile*) and the explicit egalitarian stance of the unions (particularly in the seventies), the wage scales fixed by contracts were gradually compressed.

The narrowing of the wage scales is partially counteracted (across firms, not necessarily across skill groups) by supplementary bargaining at the firm level, which typically takes place mid-way between national contracts and mainly involves large companies, and by bonuses granted to individual workers. Both components have become more important in the last decade. Since 1982, earnings dispersion across white-collars occupations in the engineering industry has risen, while the dispersion of contractual wages has remained basically constant; since the mid-eighties earnings dispersion has also increased within blue-collar occupations (see Sestito, 1994, for details). The decline in the share of the total wage bill determined at the industry level explains this difference: the ratio of contractual to total earnings has been falling more rapidly for white-collar workers. Extrapolating this trend, one might expect bargaining institutions to play a less important role in attenuating the impact of new technology in the future. The observed increase in income dispersion across households in 1993 and the growing

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28. In the past, national industry-wide wage agreements were signed every 3-4 years. Coordination across sectors was not explicit; but the main contracts, each involving a large and diversified array of branches, were typically signed no more than 6-12 months apart.
    Until recently a cost-of-living indexation clause (the *scala mobile*) applied to all industries was operating. In the seventies wages and salaries were indexed to consumer prices with a 3-month lag and were increased by equal steps for all employees, thus contributing to wage compression. The mechanism was reformed in the mid- eighties lenghtening the lag to 6 months and differentiating to some extent the inflation compensation according to salary level. The degree of coverage of the average wage with respect to price increases gradually declined from around 100% in 1977-1978 to 50% in the mid-eighties, and hovered around that level after the 1986 reform. The wage indexation mechanism was finally dismantled in 1993.
    A new bargaining framework has been in place since July 1993, following an agreement between unions, employers' associations and the Government. The new system retains the two levels of bargaining but duration of the wage clauses in the national contracts has been reduced to 2 years (so making wage negotiations more frequent). Company level bargaining ought to be explicitly linked to "profit-sharing" schemes. Our data refer, anyway, to the period when the old system was still in place.
29. Even those few firms that do not belong to the employers associations that stipulate the contracts often use nationwide contract wages as a benchmark. Union contracts, which used to include a cost of living indexation mechanism, provide in fact a useful yardstick in an inflationary environment. Also, in the case of disputes over the fair amount of the wage, courts tend to refer to collective agreements. Moreover, State subsidies (such as rebates in social security contributions) are usually made conditional on compliance with the wage scales set in the national contracts.

effect of innovation on earnings toward the end of the sample may indicate that Italy is on its way to a widening of the wage distribution, in the same direction, if not of the same scale, as other industrialized countries.

5 Conclusions

Households' data suggest that Italy has not experienced a substantial widening of earnings differentials in the eighties. We try to find confirmation of this evidence by looking at the other side of the labour market, i.e. firms. In particular, we investigate the profile of earnings paid by a large sample of Italian firms in the second half of the eighties: the analysis is carried out at increasing degrees of detail. Firms' data allow to test the impact of innovation on both earnings and labour demand, which is the centrepiece of the current international debate on returns to skill.

Our main results can be summarized as follows:

(i) Our evidence confirms that earnings dispersion in Italy does not show the dramatic widening experienced in the US and the UK. The overall earnings dispersion across firms is basically constant: it rises slightly between 1986 and 1988, but that increase is halved in the following two years. A detailed breakdown of the variance of earnings suggests that the pattern is driven by changes *within* the group of white-collar workers in technologically advanced firms.

(ii) We find a robust positive correlation between the relative demand for more skilled labour and the use of new technology; on the other hand, there is little evidence of a corresponding wage premium. In order to reconcile these results we invoke the institutional aspects of wage setting in Italy and the large shifts in the supply of skills. As the impact of these forces is likely to diminish in the future, whereas innovation technology is not likely to slow down, we suspect that Italy may soon experience increasing earnings dispersion linked to the use of new technology. This view is supported by our evidence on the increasing impact of innovation on earnings over the sample.

The Data

The data set is an unbalanced panel of 35,174 firms operating in the non-farm private sector in 1986-1990. It is the outcome of merging two main sources, both containing information at the firm level (Table a1).

TABLE a1

Distribution of Firms by Year of Presence in the Matched Sample

years	number of firms	% of the total number of firms in the sample	total years of presence
1986-1990	14,196	40.4	5
1987-1990	1,988	5.7	4
1986-1989	2,025	5.8	4
1988-1990	2,301	6.5	3
1987-1989	383	1.1	3
1986-1988	1,664	4.7	3
1989-1990	3,831	10.9	2
1988-1989	481	1.4	2
1987-1988	524	1.5	2
1986-1987	1,550	4.4	2
1990	2,795	7.9	1
1989	707	2.0	1
1988	741	2.1	1
1987	444	1.3	1
1986	1,543	4.4	1
total	35,174	100.0	
	total number of firms considered in each year		
1986	20,978		
1987	22,774		
1988	24,303		
1989	25,912		
1990	25,112		

The first one is the archive of Italian Social Security Administration (INPS) which contains data on average annual earnings, separately for blue- and white-collar workers, together with information on the sector of activity (3-digit code), location, date of entry and employment. The INPS data set covers five years (1986-1990) and encompasses the entire population of private firms that pay social security contributions (i.e. which have at least one employee). At the end of 1990 the archive covered over 1 million firms and more than 9 million workers, practically the whole of private-sector employees. The definition of blue- and white-collar workers in INPS data follows that of collective agreements within each industry. Agreements tend to make reference to the nature of the task performed (manual *vis-à-vis* non-manual), although there may be differences across industries. The definition is likely to be accurate, since companies pay slightly different social security contributions for blue- and white-collar workers.

The second source is the Company Accounts Data Service (*Centrale dei Bilanci*), which provides information on companies' balance sheets for about 30,000 firms each year, collected by a network of banks that use the information for business assessments. The data set includes a large number of variables on the economic situation of the individual firm, its profitability, assets, liabilities and so forth. The sample, which is an unbalanced panel, is not fully representative of the population of Italian firms, as it is biased towards manufacturing, large size, location in the North or Centre and probably also towards more profitable firms.

The merging of the INPS and *Centrale dei Bilanci* data was carried out on the basis of each firm official identification code. The initial data set (43,509 firms) was then reduced on the basis of a procedure aimed at: *a)* dropping false matches due to errors in the codes and *b)* excluding firms that may not be active in any particular year. To check whether firms were correctly identified we compared the number of employees from the two sources. We discarded those cases in which the discrepancy was greater than 10 per cent, for firms over 50 employees in the INPS files, or 5 units, for firms with under 50 employees. Since employment in the *Centrale dei Bilanci* may refer to either the date of closure of the balance sheets (usually in December) or to the annual average, we accepted those observations for which at least one of the two comparisons produced a good match with INPS files. We also excluded firms that did not display a positive wage bill. Overall we dropped 10.9 per cent of the previously matched sample. The final data set was made up of 35,174 firms.

The matched data set follows the *Company Accounts Data Service* in not being a representative sample of Italian firms. In particular, it underestimates the non-manufacturing sectors and small firms. This is quite troublesome, given the weight of firms up to 20 employees in the Italian economy (more than 90 per cent of the population of firms and almost 40 per cent of total employment, Table a2).

To overcome this problem, we reweighted each observation in our sample by using the INPS distribution of firms and employment. The factor of correction is then given by $k_i = fu_i/fs_i$, i.e. by the ratio between the frequency of group i of firms in the universe and in the sample. The groups we considered are formed on the basis of the firm size and sector of activity (2 digits) for each year. To implement the procedure we actually used five size classes: 1-19 employees, 20-49, 50-99, 100-199 and 200 and over (Table a3). This partition implies a certain degree of approximation, as the lowest class is quite large with respect to the structure of the INPS universe

TABLE a2

Distribution of Firms and Employees by Size (Social security universe and sample, 1990)

Firm size (a)	Social Security		Matched sample	
	% firms	% employees	% firms	% employees
1-19	94.0	39.2	46.7	5.9
20-49	4.0	13.7	27.8	11.8
50-99	1.1	8.2	12.7	12.2
100-199	0.5	7.5	7.1	13.3
200 and more	0.4	31.4	5.7	56.8
total	100.0	100.0	100.0	100.0

(a) number of employees

(see again Table a2). Unfortunately the structure of the *Centrale dei Bilanci* data set prevents us from doing otherwise [30].

The weighting procedure provides good results as judged in comparison with the National Accounts. Average annual earnings *per capita* computed on the basis of weighted data for the whole sample are very close to annual earnings estimated by the National Accounts for the corresponding sectors (Table a4).

The technology variable we use is the ratio of "intangible" assets to total capital (which also includes plant and equipment). Intangible capital includes software licences, patents and R&D expenditure, business goodwill from mergers, other expenditures on intangibles and other deferred charges. In order to check how are our results affected by the inclusion of items not directly related to technology, we use a sub-sample of about 600 firms, for which detailed information on patents and licenses *vis-à-vis* other intangibles are available. The sub-sample is clearly tilted towards large and technologically advanced firms; the share of white-collar workers and the white/blue-collar differential are also significantly bigger than in our data set. Hence the results of our experiments do not necessarily carry over to the entire sample [31].

30. The partition theoretically gives 250 cells per year. A further source of approximation in the weighting procedure arises from the fact that some cells are empty in our sample, but not in the universe. In those cases we joined two adjacent size classes. This operation involved a reassignment of 155 size cells over the whole period (an average of 30 per year).

31. The average size in the sub-sample is twice as much than in our data set; the white-collar employment share is 70% bigger and the white/blue-collar premium is 8% larger; the use of innovation 2% more widespread.

TABLE a3

Distribution of Firms and Employees in the Matched Sample and Sample Coverage of the INPS Files.

Firm size (number of employees)	matched sample		coverage of INPS (%)	
	firms	employees	firms	employees
		1986		
1-19	9,310	87,239	1.02	2.65
20-49	5,907	184,201	15.7	16.6
50-99	2,871	200,682	27.9	28.4
100-199	1,641	225,564	35.2	35.3
200 and more	1,249	898,726	34.9	31.0
total	20,978	1,596,412	2.18	18.47
		1987		
1-19	10,306	94,111	1.1	2.7
20-49	6,370	198,748	16.2	17.2
50-99	3,037	212,994	29.1	29.7
100-199	1,704	234,875	36.0	36.1
200 and more	1,375	1,041,373	37.6	36.0
total	22,774	1,782,101	2.3	20.2
		1988		
1-19	11,478	101,910	1.2	2.9
20-49	6,546	204,130	16.0	17.0
50-99	3,117	218,724	29.1	29.7
100-199	1,774	244,137	36.3	36.5
200 and more	1,388	1,067,343	37.8	36.7
total	24,303	1,836,244	2.3	20.2
		1989		
1-19	12,175	115,539	1.2	3.0
20-49	7,196	233,480	16.6	17.6
50-99	3,238	227,687	29.3	30.1
100-199	1,852	255,154	36.6	36.9
200 and more	1,451	1,072,708	38.5	36.3
total	25,912	1,890,568	2.4	20.2
		1990		
1-19	11,729	108,622	1.2	2.9
20-49	6,991	217,844	15.8	16.8
50-99	3,177	223,028	28.0	28.6
100-199	1,775	244,810	34.4	34.7
200 and more	1,440	1,045,635	35.2	37.5
total	25,112	1,839,939	2.3	19.4

We run the same regressions as in Table 5 (annual cross-sections) and in Table 6 (fixed- effects panel) on the sub-sample, by using both the narrow (patents, licences and R&D expenditure only) and the more general definition of use of technology, which includes the non-technological items. On a year

TABLE a4

Per Capita Annual Earnings in the Non Farm private Sector: Comparison of National Accounts and Matched Sample (thousands of lire and percentage changes)

	1986	1987	1988	1989	1990
National Accounts					
level (1)	18,827	20,423	21,948	23,546	5,395
– growth rate (1)	–	8.5	7.5	7.3	7.9
level (2)	19,720	21,413	23,050	24,748	26,735
– growth rate (2)	–	8.6	7.6	7.4	8.0
Sample					
level	19,836	21,654	23,403	24,971	26,815
– growth rate	–	9.2	8.1	6.7	7.4

(1) Overall standard units of labour. It includes both regular and irregular (black economy) full-time and part-time workers, all computed as full time equivalent.

(2) Regular standard units of labour. It includes only regular full-time and part-time workers, all computed as full time equivalent.

to year basis, the impact of the variable is similar in both definitions: as in the regressions on the whole sample, it is significant for employment and wage shares, not for the remaining equations. The coefficients are numerically different from those on the whole sample, although reasonably close across the two definitions. In panel estimates, all coefficients are largely insignificant, probably due to the limited size of the sub-sample.

We also checked whether the difference between the narrowly- and widely-defined technology variable displays any pattern across industries or firms. We find that non-technological items in our variable are basically constant over time: when we regress them on firm-fixed effects, the R^2 is 0.84. This is good news for panel estimates, since it implies that the (spurious) impact of these items is taken care by firm-fixed effects and does not affect the coefficient of innovation. On the other hand, time-variant industry and province effects explain no more than 28% of the variability of these residual items: cross-sectional estimates of the impact of innovation are thus more strongly affected by the inclusion of non-technological items.

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