Trends in the Italian Earnings Distribution, 1985-1996*

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Abstract
Using a panel of administrative Italian data (source: INPS), this paper provides new empirical evidence on the changes in the earnings distribution that occurred in Italy over a relatively long time period (1985-1996). Various statistical indicators have been used to document a slight, but not negligible, increase in earnings inequality. Decompositions by population subgroups have shed light on the underlying causes of the observed distributional changes.

1. Introduction

Recent studies on earnings inequality remark that only a relatively few OECD countries experienced a significant increase in earnings inequality over the first half of the 1990s. Contrary to the fears emerging from the trends documented at the end of the 1980s, only the United Kingdom and the United States continued to feature persistent and strong widening earnings differentials throughout the 1990s (OECD, 1996). As about Italy, the prevalent indications coming from existing research point to a modest or negligible increase in earnings inequality, mainly documented on the basis of the Bank of Italy survey.

In this paper we re-asses the case of Italy drawing on a different dataset, which covers a relatively longer period, from 1985 to 1996.

The study of the earnings distribution is a fundamental part of economic enquiry, not least because of its relevance for a large number of decisions taken by various economic actors. The relative wages of different category of workers are important for such firm's choices as hiring, training, investments and the like. Individual workers, too, look at wage differentials when deciding their human capital investments or searching for jobs in a specific occupation. Financial institutions often ask potential borrowers about their

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earnings, which assume a crucial role as collaterals. Needless to say, the levels and growths of individual earnings, as well as the distribution of these earnings, impinge on the individual's economic well-being and his perception of the overall social welfare and justice in the community where s/he lives and works. Moreover, indicators describing the earnings evolution of different groups of workers, for example those employed in low-paid jobs, are of significance for public policy purposes. The availability of this kind of information is likely to benefit the targeting and efficient designing of programs aimed at reducing the impact on the individuals of adverse outcomes in the labour market.

Observed earnings distributions tend to present a number of empirical regularities. Their density functions are always skewed to the right, asymmetric and display a long right tail and positive skewness measure. They are also leptokurtic and have a "fat tail". Put in non- technical jargon, this means that mean earnings always exceed median earnings and the top percentiles of earners account for quite a disproportionate share of total earnings. Groups of workers homogeneous with respect to some observed traits – for instance, occupation, education, experience and the like – generally differ in their mean earnings and, in some cases, these differences are large. Earnings vary within each sub-group too, implying that unobserved differences also account for differential pays within observationally similar workers. Another observed fact is that earnings dispersion for a particular cohort of workers is greater among experienced workers than among workers that are at the beginning of their career.

Economic theory has proposed various theoretical explanations of the observed regularities.[1] Some of these theories describe how workers decisions (e.g., human capital acquisition) and endowments (of talent, wealth, information) generate a distribution of individual productivities that gives rise to a distribution of earnings. Human capital theories focus on how workers acquire their skills and demonstrate that earnings inequality is a necessity in an economy where some activities require more costly investments. Other theoretical approaches tend to emphasise the role played by firms' optimal decisions, as when efficient wage structures are those that elicit desired levels of individual productivity. Highly skewed earnings distributions within firms would in this case be an incentive device. On the other hand, not all income differences at a point in time may be justified by the underlying differences in productivities and investments, or felt as "just". At the very minimum, the influence of luck in accounting for the large fortunes of some individuals may be recognised. Theoretical explanations on why earnings inequality may increase over time have also been put forward, emphasising the role of changes in both market forces and institutional factors. The links between inequality in the personal distribution of income and economic growth have also been addressed by recent research, challenging the conventional wisdom that inequality is always beneficial for economic growth.[2]

A more detailed discussion of these models is beyond the aims of this work and in the following pages we will mainly be in the business of providing new empirical evidence on the Italian earnings distribution. The basic questions we aim to answer are: To what extent does the Italian earnings distribution follow the empirical regularities generally observed in other countries? What distributional changes occurred in the Italian earnings distribution from the second half of the 1980s to the second half of the 1990s? How can we account for the observed trends?

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[1] See the Handbook of Income Distribution (2000)
[2] See Aghion and Williamson (1998).

2. Changes in the Italian wage distribution, 1985-1996

2.1 A preliminary look

For our analysis of the wage distribution in Italy we use administrative data from the Italian Institute for Social Security (INPS), containing information on a sample of employees over a period of twelve years – from 1985 up to 1996.[3]

Our data include not only individuals' wage and career histories but also a certain number of characteristics of each worker and of the firm where s/he currently works and has held previous jobs. We can therefore investigate both the general trends in the overall sample and how different subgroups – homogeneous with respect to selected characteristics – were affected by the main structural and cyclical factors that occurred in the Italian economy during the time period considered. Among personal characteristics, we have information about the employee's gender, age, geographical region where s/he was employed, along with his/her job qualification. We can also link these individual-level characteristics to information about the firm where the job is held, in particular the firm's sector of activity and its size.

The income variable used in this paper will mainly be real *monthly* earnings at 1996 prices, the latest available year. As we do not observe the actual number of hours worked by an employee, we cannot compute hourly wages. We do however know the number of days worked by each employee in each job spells and his/her total remuneration, which allows us to compute the employee's monthly wage after a suitable normalization.[4] Arguably, this is the distribution of interest if one is investigating the monetary incentives that the labor market offers to different sectors of the population and in different activity sectors. However, in Box 4 of the paper and for reasons that will be made clear, we will also pay attention to the distribution of *annual* earnings, i.e. the income measure that results from consideration of both the daily wage and of the number of days actually worked during the year. Further explanations about the way our earnings variable has been derived are provided in Box 1.

A final remark concerns our focus on the distribution of positive earnings, which should not be confused with the distribution of 'potential' earnings – i.e. the distribution that includes the earnings that zero earners would have received if they had worked. Nor are we allowed, by the very nature of our data, to make inference on the wage distributions in sectors of activity not covered by the INPS, as explained in chapter xx. It is with these qualifications in mind that we refer to the distribution analyzed below as to the Italian earnings distribution.

BOX 1 Earnings derivation

The gross monthly wage, *W*, is the ratio between gross *annual earnings* of the employee, *YW*, and the total number of days s/he worked and got paid for, *PD*, during the year. The result is then multiplied by an average working month of 26 days.

[3] See chapter XX of a description of the INPS data.

[4] We will tend to speak of 'wages' and 'earnings' as synonymous, referring in each case to the flow of monetary compensation that the employee receives in a month for his/her work, gross of income tax and of the social security contributions paid by the worker.

$$W = \frac{YW}{PD} * 26 \qquad (1)$$

A monthly wage calculated as in (1) is assigned to each employee for each year s/he is observed in the panel. *W* implicitly refers to the worker's 'typical' monthly earnings – had s/he worked full-time and full-year - and can be compared across employees, independently of the number of days they actually worked in a year. Finally *W* has been deflated by the consumer prices index for white and blue collar worker households (source: ISTAT), so as to obtain a variable in real terms, measured at 1996 prices.

In practice, though, not everybody in our sample works full-time and full-year, which entails two complications. First, for those who work only a fraction of the year, our monthly wage may not fully reflect the worker's economic situation, which might be better summarized by his/her annual earnings. If there are many employees who are not recorded as working full-year in the INPS data, the distribution of monthly earnings and annual earnings may well look different. We will come back to this issue in Box 4.

An additional problem is brought about by the presence of individuals that work part-time. In this case, an adjustment is necessary to PD if the part-timers' wage is to be fully comparable with the full-timers'. In the INPS data the exact number of hours worked in a day is not recorded. However, from the week-level information available in the data, we can recover a coefficient – call it q – that multiplies the number of days worked in part-time jobs and converts them in terms of full-time equivalent. Specifically, q is defined as the ratio between the number of hours worked during a week in a part-time job and the number of hours scheduled in the collective national contract for the same full-time job, for example 40 hours per week. The coefficient q is equal to one - by definition - if the employee's j-th job is full-time; otherwise q is less than one. The total number of days worked by an individual in the whole year in full-time or part-time jobs is then given by:

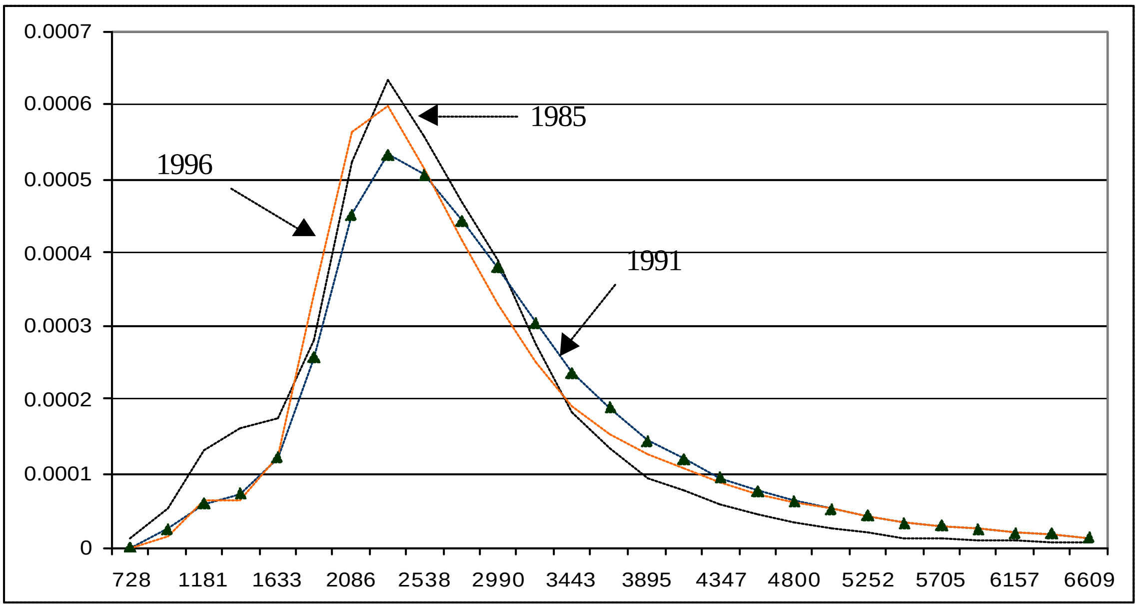
$$PD = \sum_{j=1}^{J} PD_j * q_j$$

where $j = 1,\ldots, J$ refers to the J job spells that the employee has had in the year.

We start our analysis by focusing on the population as a whole, while in section 3 we will move on to our decomposition exercise, breaking down the population in various subgroups. Various papers have performed similar exercises for other countries and represent therefore natural starting points for our research in a cross-national perspective. In particular, the framework of analysis used by Jenkins (1996) in his study of the UK income distribution trends has inspired the present work.

By way of first acquaintance with our data, let us consider three reference years only, 1985, 1991 and 1996, i.e. the start, an intermediate and the final year in our sample. Figure 1 illustrates graphical representations of the density functions of the earnings distributions in those three years, calculated with the Kernel estimation method[5]. The heights of the curve show the concentration of people at different points along the wage scale, and the area under the curve between two wage levels shows the proportion of the population with wages between those two levels (the area under the whole curve is equal to 100 per cent). To describe an income distribution analysts often focus on its location, spread and modality, which are respectively related to real income levels, income inequality and income clumping. A universal increment to wages – due for example to a generalized economic growth – would result in a shift of the curve along to the right. An increase in inequality could be generated in several ways, including, for example, a "squashing down" of the curve, flattening it and stretching it away from the average wage in both directions. Changes in wage clumping are revealed by changes in the "bumps" of income concentration at different points along the wage scale. Various statistical and graphical devices will be used below to describe how these three traits of an income distribution changed in Italy over the time period considered, and why.

Figure 1
Frequency Density Functions: 1985, 1991 and 1996.



Note: the horizontal axis measures monthly wages. The wage frequency density function (vertical axis) shows the concentration of people at each wage level. Wages greater than 6.7 million of Italian liras[6] are not shown (but have been used to compute the kernel density) so as to improve the picture's readability. *Source*: INPS panel data 1985, 1991, 1996.

Figure 1 puts in evidence some important aspects of the earnings distribution in Italy in the reference years. Firstly, at both ends of each density function, the curve is relatively low: there are relatively few people with the very low wages, and also relatively few with the very high wages. The vast majority of the population have monthly wages between about two millions and four millions of Italian liras, and the greatest concentration – the mode – is at about L2,4 million p.m. Secondly, all three curves are strongly asymmetrical towards the right hand side, so that the proportion of

[5] For a non-technical explanation of the kernel density estimation methods used in this paper, and their advantages over more commonly used methods such as histograms, see Cowell *et al.* (1996).
[6] 1936.27 Italian Liras are equal to 1 EURO.

employees earning more than the modal wage is larger than the proportion earning less. The "fat" and long tail on the right also points to the existence of a relatively small number of very well paid individuals, a fact that is confirmed below by a mean wage exceeding the median. Note how the right tail has become even thicker towards the end of the period, a circumstance that hints to an increase in overall wage dispersion/inequality. Thirdly, though the density curb appears to be relatively smooth and unimodal, some wage clumping can be observed – particularly so in 1985 – in the left tail. In subsequent years, this "bump" of wage concentration gets flatter but does not disappear completely. Finally, observe how the 1991 density function resembles a shift to the right of the 1985 density, while the 1996 density appears to be located in between. As we show below, this pattern is consistent with the business cycle that the Italian economy went through during the period.

The patterns revealed by figure 1 deserve a more-in-depth investigation, which we undertake below by showing the year-to-year changes in various statistical indicators for the whole sample and – in section 3 – for various sub-groups as well.

Table 1
Wage Distribution Indicators

	Mean	*Std*	*p10*	*p50*	*p90*	*p90/p10*	*p90/p50*	*p50/p10*
1985	2674	988	1635	2519	3790	2.32	1.50	1.54
1986	2759	1046	1710	2574	3948	2.31	1.53	1.50
1987	2831	1134	1749	2612	4124	2.36	1.58	1.49
1988	2852	1174	1759	2607	4212	2.39	1.62	1.48
1989	2918	1222	1871	2621	4328	2.31	1.65	1.40
1990	2962	1265	1880	2645	4441	2.36	1.68	1.41
1991	3065	1341	1918	2742	4579	2.39	1.67	1.43
1992	3078	1359	1930	2733	4633	2.40	1.70	1.42
1993	3075	1337	1948	2735	4596	2.36	1.68	1.40
1994	3054	1329	1934	2710	4578	2.37	1.69	1.40
1995	2988	1312	1884	2633	4550	2.41	1.73	1.40
1996	2977	1314	1888	2612	4544	2.41	1.74	1.38
% change 1985-96	11.3	33	15.4	3.7	19.9	3.9	15.6	-10.4

Note: values in the first part of the table are expressed in thousands of Italian lire. *Source*: our elaborations on INPS panel data.

In Table 1 we report the temporal sequences of the mean, standard deviation, median (also referred to as p50), and the tenth and ninetieth percentiles[7] of the wage distribution – denoted by p10 and p90, respectively. Ratios of these percentile points are also commonly used, as they help gauging how wages changed in different parts of the distribution.

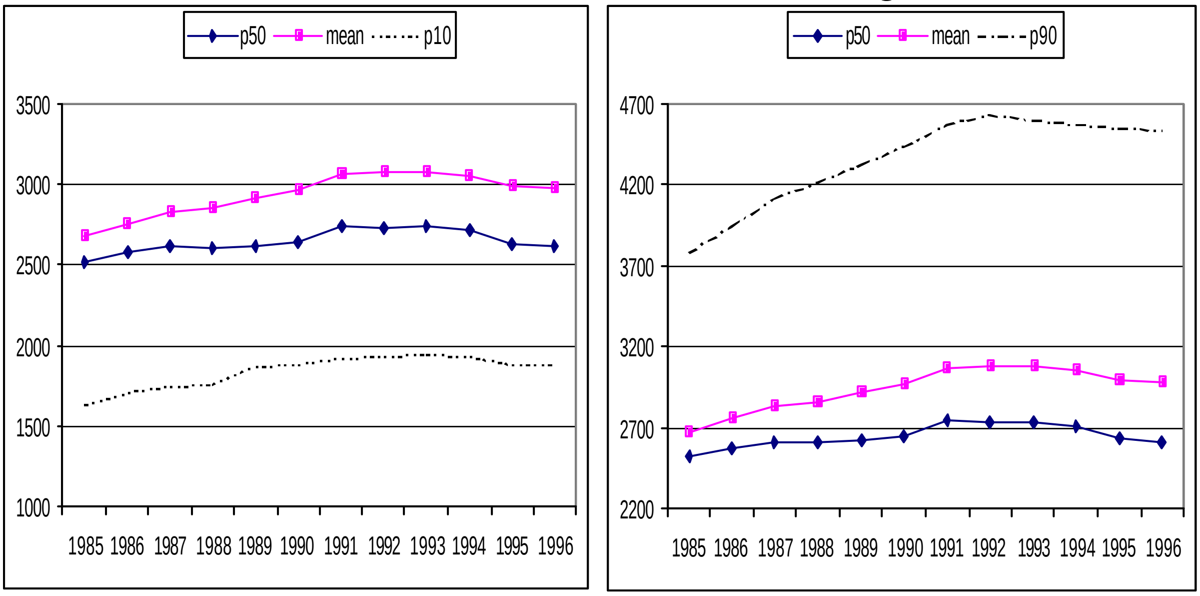
[7] Percentiles divide the earnings distribution - with wages ordered form the lowest to the highest - in groups of equal numerousness. For each of these groups, the value of the corresponding percentile is the highest income within the group. For example, deciles split the distribution in ten equal parts, so that p10 is the largest wage in the poorest tenth of workers.

The temporal path of mean real earnings reported in column 2 is consistent with the growth the Italian economy experienced until 1992, when it reaches its maximum value, and its substantial slowdown thereafter. The mean's decline is such that it reaches in 1996 almost the same value it had in 1990. Despite that, over the twelve years in our data average earnings grew by about 11%.

A similar path can be observed for median earnings – which is always lower than mean income – and for the bottom and top percentiles. Note, though, that p90 and p50 started to decline at least one year earlier than p10, this latter reaching its maximum in 1993. The economic slowdown seems, then, to have hurt medium/high earnings prompter than earnings at the bottom of the distribution. Notwithstanding this, the earnings of the richest 10% have grown by a stunning 20% over the 1985-1996 period, compared with a more modest 15% of the poorest 10% of the population. Workers in the median position saw, on the other hand, an earnings growth of 4% only.

These trends can be visualized with the help of Figure 2, which plots mean earnings, p50, p10 and p90 over time. Both the poorest and the richest tenth exhibit a growing path in the first part of the period, although after 1992 they become flatter and downward sloping. The richest tenth had a steeper growth than the bottom tenth, which in turn grew slightly faster than the median. For instance, in the 1985 distribution, the monthly wage of the person at the richest tenth of the population was 2.3 times the wage of the person at the poorest tenth; by 1996, the ratio had enlarged at 2.4 (a 4% rise). Even more increased the distance between the richest tenth and the median, as their ratio was 1.5 in 1985 and 1.7 in 1996 (a 15% rise). On the other hand, the poorest tenth gained ground with respect to the median, with a ratio that exhibited a 10% drop from 1985 to 1996. Overall, the evidence presented points to a reduction in inequalities in the poorest half of the distribution, to be set against an increase in the richest half.

Figure 2
Mean, 10th Percentile, Median and 90th Percentile in the Wages Distribution



Source: INPS panel data.

2.1 Assessing earnings inequality[8]

There would seem to be enough empirical evidence to conclude that earnings differences in the Italian distribution have been enlarging over the 1980s and 1990s[9], though the increase may appear a modest one when compared to the changes experienced by other developed countries, the US in particular.[10]

However, this is only partly confirmed by a look at the behavior of the earnings shares of deciles groups of the population. Table 2 depicts in more detail the changing fortunes in different parts of the distribution and shows, a bit surprisingly, a substantial static pattern for the earnings shares in different deciles. Small drops in the earnings share of deciles 2-8 are to be set against the more substantial gains recorded by the bottom and top deciles. With the evocative image of a big cake representing the total earnings to be distributed in a given year, we can say that the poorest tenth of the population has, over time, got a bigger slice. The same is true for the richest tenth of the Italian employees, while those situated in more central parts of the distribution have received slice smaller and smaller. These findings suggest that a limited amount of polarization towards the extremes of the Italian earnings distribution might have taken place over the time period studied, with the best well-paid jobs – but also the least well-paid ones – improving their situation at the expenses of those in the median position. OECD (1996) reports that real wages of low paid workers (first decile) have risen for most countries during the second half of the 1980s and the first half of the 1990s (the United States and, to a lesser extent, New Zealand and Australia are exceptions). However only in a small group of OECD countries (Germany, Finland and Canada) among the 13 studied is the growth of p10 higher than that of the median and p90. Interestingly, the results therein shown for Italy (deriving from the Bank of Italy survey and referring to the period 1983-93) are at variance with ours own as p10 is shown to grow by less than both p50 and p90 (OECD, 1996, Chart 3.3).

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[8] Needless to say, the study of earnings inequality is only one of the ingredients for the broader – and, to some, more appealing – objective of assessing economic inequality. The latter is however beyond the aims of the present work.

[9] The same conclusion is reached by Brandolini and Sestito (2000), using the Bank of Italy's *Survey of Household income and Wealth*. Comparing their percentile ratios for the years 1986, 1987, 1989, 1991, 1992, 1993 and 1995 with our figures in Table 1, one notes that our p90/p50 is systematically higher while our p50/p10 is always lower, pointing to a greater polarization of the INPS earnings distribution than in the Bank of Italy's. The differences in the nature of the two date sets (administrative data rather than survey data), as well as the income variable used (gross monthly earnings rather than net monthly earnings) are likely to be responsible for the observed differences.

[10] The p90/p50 and p50/p10 ratios for the US in 1995 were both equal to 2.1, compared to the value of 1.7 and 1.4 we obtain for Italy for the same year. During the period 1985-95 in the US, p90/p50 changed by about 17% and p50/p10 had a *positive* growth of about 7-8% (our calculations from Table 3.1 in OECD, 1996).

Table 2
Earnings shares for Decile Earnings groups: 1985-1996

	Decile earnings groups									
	(poorest)									***(richest)***
year	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
85	0.049	0.069	0.079	0.085	0.091	0.098	0.105	0.115	0.130	0.180
86	0.049	0.069	0.078	0.084	0.090	0.097	0.105	0.115	0.131	0.183
87	0.049	0.069	0.076	0.083	0.089	0.096	0.104	0.114	0.131	0.190
88	0.049	0.068	0.075	0.081	0.088	0.095	0.104	0.114	0.133	0.193
89	0.053	0.068	0.074	0.080	0.086	0.094	0.102	0.114	0.133	0.196
90	0.053	0.067	0.073	0.079	0.086	0.093	0.102	0.114	0.134	0.198
91	0.052	0.067	0.073	0.079	0.086	0.093	0.102	0.114	0.134	0.200
92	0.053	0.067	0.073	0.079	0.085	0.093	0.101	0.113	0.134	0.202
93	0.054	0.067	0.074	0.079	0.086	0.093	0.101	0.113	0.133	0.201
94	0.054	0.067	0.074	0.079	0.085	0.093	0.101	0.113	0.134	0.201
95	0.054	0.067	0.073	0.079	0.085	0.092	0.101	0.113	0.135	0.203
96	0.054	0.067	0.073	0.079	0.084	0.092	0.100	0.113	0.136	0.203
% change 1985-96	10.2	-2.9	-7.5	-7.0	-7.6	-6.1	-4.7	-1.7	4.6	12.7

At the same time, the improvement of the economic situation of the least advantaged prevents us to predicate that inequality has unambiguously increased in the Italian earnings distribution. Economic inequality is often quantitatively assessed by resorting to summary measures that aggregate information on the individuals' incomes and come up with a number comprised between a minimum (often zero) - representing a perfectly equal distribution of earnings among workers - and a maximum (generally 1) - for the case in which one individual in the whole population holds alone total income. It is clear, then, that alternative summary measures use a different way of aggregating that information, putting different weights on different parts of the distribution. When comparing a set of income distributions, then, different indices may rank them differently. In the case of the Italian earnings distribution, then, it might well be possible that any measure that puts enough weight to the improved economic situation of the bottom tenth ends up declaring that earnings inequality, has indeed lowered over the time period 1985-1996. However, for less extremist views on the ways inequality is to be measured, the above analysis points to a modest, but not negligible, worsening of earnings inequality. This is pictured in Figure 3 that shows the increasing path of the most commonly used inequality indices (see box 2 for their formulae).

The inequality indices considered differ in their sensitivity to income differences in different parts of the distribution. For instance, the Theil index is more sensitive than Mean Logarithm deviation (MLD) to income differences at the top of the distribution; the Variance of Logarithms attaches more importance to income transfers at the lower end of the distribution, whilst the Gini coefficient is most sensitive to income differences about the middle (more precisely, the mode). Table 3 reports the temporal values of three indices along with their bootstrap standard errors, which provide some indication of the variability of those estimated inequality values. The impression that earnings inequality has been increasing over the period considered is confirmed by each of the three measures computed. The rise slows down after 1991, but the level in 1996 is still about 12% higher than in 1985 according to the Gini coefficient and almost 32% higher if the variance of logs is used instead. Interestingly, standard errors appear to be rather small and that increases our confidence in the statistical validity of our conclusions about the inequality trends discussed.[11]

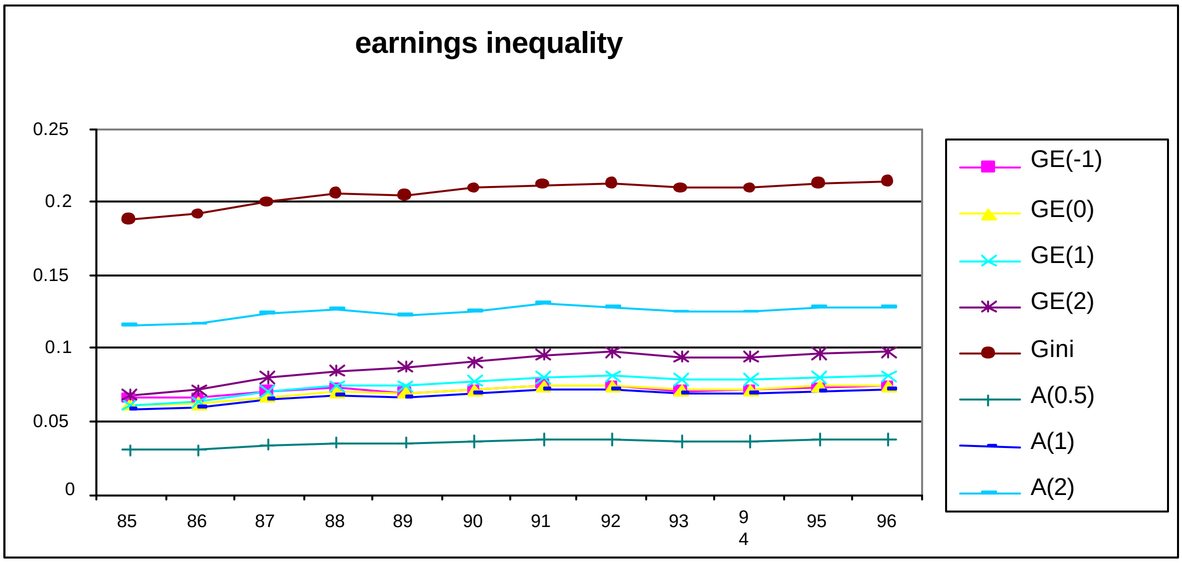
Table 3: Trends in earnings inequality, 1985-1996

Year	***Inequality measure***		
	Gini	**Theil**	**Var-logs**
1985	189	62	122
	(0.0006)	(0.0004)	(0.0008)
1986	192	64	123
	(0.0006)	(0.0004)	(0.0007)
1987	200	70	130
	(0.0006)	(0.0005)	(0.0007)
1988	206	74	135
	(0.0006)	(0.0005)	(0.0007)
1989	206	75	129
	(0.0006)	(0.0005)	(0.0007)
1990	210	77	134
	(0.0007)	(0.0005)	(0.0008)
1991	213	80	138
	(0.0007)	(0.0005)	(0.0008)
1992	213	81	136
	(0.0007)	(0.0006)	(0.0008)
1993	209	79	131
	(0.0006)	(0.0005)	(0.0007)
1994	210	79	132
	(0.0006)	(0.0005)	(0.0007)
1995	213	81	136
	(0.0006)	(0.0005)	(0.0007)
1996	214	81	137
	(0.0007)	(0.0005)	(0.0008)
% change 1985-96	12.7	30.45	11.48

Notes: The values of the indices have been multiplied by 1000. Bootstrap standard errors in brackets (1000 replications).

[11] In principle, one may use these standard errors to statistically test the hypothesis that inequality in one year is statistically different than inequality in another. There are however some theoretical and practical complications in doing so, due the panel nature of our data (see for instance Biewen, 2001).

Figure 3 Trends in earnings inequality, 1985-1986



Notes: see Box 2 for the formulae.

Box 2 **Empirical measures of inequality**

The indexes reported in the paragraph are widely used in the literature on inequality measurement (for instance, Cowell, 1995). In this appendix we just present their formulae. Consider a population of persons, $i = 1,...,n$, with income y_i. Denote the arithmetic mean with m.

The first indicator is the *variance of logarithms*, defined as:

$$I_{\text{varlogs}} = \frac{1}{n}\sum_{i=1}^{n}(\log y_i - \log m)^2$$

Higher values imply higher inequality.

The Gini's coefficient can be interpreted as the expected income gap (in percentage terms) between two individuals randomly selected from the population and is defined as:

$$I_{Gini} = \frac{2}{n^2 m}\sum_{i=1}^{n} i(y_i - m)$$

where incomes y_i are ordered in ascending order. The index varies between 0 (*maximum equality*) and 1 (*maximum inequality*).

The Atkinson index can be thought as an index constructed on the basis of a social welfare function such that ε represents the degree of (social) aversion to inequality:

$$A(e) = 1 - \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i}{m} \right)^{(1-e)} \right)^{1/(1-e)}$$

The index varies between 0 (*maximum equality*) and 1 (*maximum inequality*).

The Generalized Entropy class of inequality indices is given by

$$\text{GE(a)}= \frac{1}{a(a-1)} \left\{ \left[\sum_{i=1}^{n} f_i \left(\frac{y_i}{m} \right)^{a} \right] - 1 \right\}, \qquad a \neq 1,\ a \neq 0$$

$$\text{GE(1)}= \sum_{i=1}^{n} f_i \left(\frac{y_i}{m} \right) \log \left(\frac{y_i}{m} \right), \qquad a = 1,$$

$$\text{GE(0)}= \sum_{i=1}^{n} f_i \log \left(\frac{m}{y_i} \right), \qquad a = 0 \quad .$$

The inequality indices differ in their sensitivities to income differences in different parts of the distribution. The more positive a is, the more sensitive $GE(a)$ is to income differences at the top of the distribution; the more negative a is, the more sensitive it is to differences at the bottom of the distribution. $GE(0)$ is the *mean logarithmic deviation* (*MLD*), $GE(1)$ is the *Theil index*, and $GE(2)$ is half the square of the coefficient of variation. The more positive $\varepsilon>0$ (the 'inequality aversion parameter') is, the more sensitive $A(\varepsilon)$ is to income differences at the bottom of the distribution. The Gini coefficient is most sensitive to income differences about the mode.

It is not easy to explain why earnings inequality has increased, as a variety of changes in the economy, such as changes in the industrial structure, increased foreign trade, increased immigration, skill-based technical change and the decline in institutions that limit the market (e.g., fall in the minimum wage and the decline in unionization) are consistent with the observation that wage differentials have enlarged. The interaction of these factors and others more specific to the Italian macroeconomic and institutional context adds further elements of complexity to the business of disentangling the causes of the widening earnings distribution. In Italy some studies have highlighted the role played by the abolition of automatic cost-of-living indexation (*scala mobile*) and the ending of synchronized wage bargaining across different sectors (Erickson and Ichino, 1995; Bank of Italy, 1995). While these factors are likely to have had a widening impact on the earnings distribution, the “stability pact” signed between unions and the government in 1992 might be invoked as a potential effect in the opposite direction.

In principle, the impact of business cycle on inequality is unclear, crucially depending on the pattern of growth in different subgroups of the distribution. If earnings everywhere increase by the same proportion, relative inequality measures (like the ones we have used) do not change. On the other hand, overall growth is inequality enhancing when it implies disproportional gains (losses) for those at the top (bottom) of the earnings scale. A compression of the wage differentials may for example occur if, on the face of an economic downturn, labor market institutions concentrate their efforts in the employment and wage protection of those at the bottom of the distribution. Lower inequality may also be the outcome of an economic slowdown where most lay-offs are concentrated amongst low-paid low-skill jobs (for example, very young workers), so that the distribution gets 'censored from below'. However, OECD (1996) reports that "no uniform picture emerges either across countries or over time of a cyclical pattern in the dispersion of wages", (p.63).[12] In the case of Italy, we find only weak evidence that inequality is higher when average income grows and tends to lower during the recession years.[13]

Section 3 further moves in the direction of explaining the observed trends in earnings inequality, by studying how earnings changed within and between different subgroups of the population.

3. What accounts for changes in the earnings distribution.

Breakdowns by population subgroups are a useful tool often employed by researchers to help disentangle between (some of) the many influences that may be at play in explaining the observed changes in the Italian earnings distribution. Underlying these decompositions is the basic intuition that some causal factors affect the earnings distribution by changing, in various combinations, three basic ingredients: the number of persons in each subgroups, the mean earnings in these subgroups, and finally the dispersion within each subgroup. The methodology is explained in Box 3. Table 8 contains the results of this decomposition exercise and, in its footnotes, presents an illustrative example too.

An inequality index is decomposable by population subgroups when it satisfies the requirement that total inequality be expressed only as a function of the subgroup inequalities, mean incomes and population shares. Three of the indices considered so far are *exactly* decomposable, in that total inequality is the sum of a within-group component (an average of the subgroup inequalities, weighted by the subgroup share), plus a between-group component (the amount of inequality that would remain if there was no inequality within any sub-group). The three indices are *MLD*, the Theil index and $GE(2)$, which are all special cases of the so-called Generalized Entropy class.

Box 3 **Decomposition methodology used in Table 8**

Suppose there is an exhaustive partition of the population into mutually-exclusive subgroups $k = 1,...,K$.

Inequality indices in the generalised entropy family are the ones with the most desirable decomposability properties (see for example, Cowell, 1995). Each $GE(a)$ index can be additively decomposed as

$$GE(a) = GE_W(a) + GE_B(a)$$

[12] However, Burtless (1990) found that inequality in annual earnings of all workers in the United States tended to rise during a recession.

[13] A 12-observation regression of each of the inequality indices shown in Table 3 on a deterministic time trend, average earnings and its growth rate displayed positive but not statistically significant coefficients.

where $GE_W(a)$ is *Within-group inequality* and $GE_B(a)$ is *Between-Group inequality.*

It can be shown that:

$$GE_W(a) = \sum_{k=1}^{K} (v_k)^{1-a} (s_k)^a GE_k(a)$$

where $v_k = N_k/N$ is the number of persons in subgroup k divided by the total number of persons (subgroup population share), and s_k is the share of total income held by k's members (subgroup income share). $GE_k(a)$, inequality for subgroup k, is calculated as if the subgroup were a separate population, and $GE_B(a)$ is derived assuming every person within a given subgroup k received k's mean income, m_k .

3.1 Earnings trends by activity sectors

A first exercise we consider is to separately investigate earnings trends for workers belonging to the three activity sectors - constructions, manufacturing and services – in which the totality of jobs has been partitioned. In principle, modifications occurred to the Italian industrial structure in the 1980s and 1990s may well be responsible for an important part of the economic growth performance and the distributional changes discussed so far. Table 4 displays the time series of mean earnings and three percentiles for jobs held in each of the three sectors.

One can soon notice a confirmation to the general pattern found for the whole distribution: mean earnings grew in constructions and services until 1992 (1993 for manufacturing) and then they decreased. When we look at the p10, p50 and p90 earnings percentiles, the story is not very different: the path is a growing one during the first eight/nine years, becoming more stable or even decreasing during the last three/four years. Note that, while p10 starts declining only after 1993, there is a tendency of p90 to get dragged down more promptly by the economic slowdown. In constructions and services, in effect, p90 starts declining in 1992.

More revealing is a direct comparison of the three sectors performance between the first and the last year in our sample. Overall growth was very low for construction (a 0.3% change during the period) and much higher in manufacturing (7.1%) and services (10.3%). In 1985, mean earnings were highest in constructions, followed by services and manufacturing. In the following years services emerge as the sector that pays better on average, 6% more than manufacturing and 10% more than constructions in 1996. Interestingly, however, construction is the sector that guarantees better pay for employees at the bottom (p10) and at the median of the distribution[14], followed by manufacturing. This ranking is completely reversed when we look at p90, which explains why the mean in service is higher than in the two other sectors.

[14] These results consider only regular jobs, while in the construction sector irregular jobs are easily diffused and, usually, they are low-paid jobs.

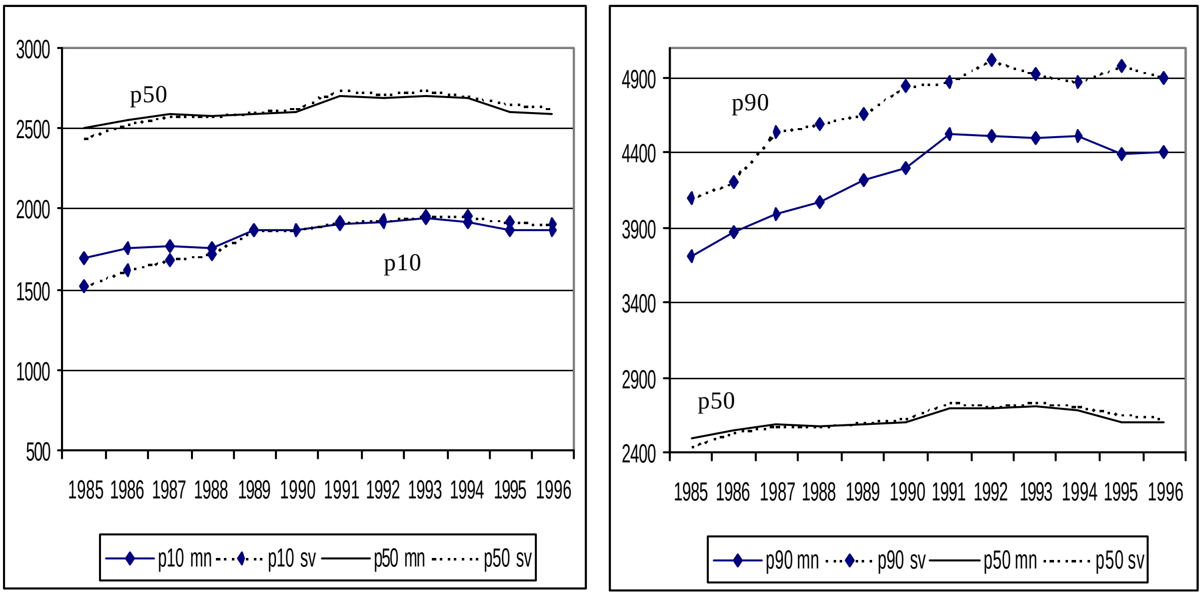
Table 4
Manufacturing, Constructions and Services

	Mean			p10			p50			p90		
	Manuf.	**Constr.**	**Service**	**Manuf.**	**Constr.**	**Service**	**Manuf.**	**Constr.**	**Service**	**Manuf.**	**Constr.**	**Service**
1985	2653	2722	2694	1699	1776	1523	2499	2752	2439	3708	3465	4103
1986	2730	2770	2808	1762	1863	1614	2547	2760	2530	3869	3518	4207
1987	2787	2785	2926	1773	1903	1682	2586	2772	2571	3984	3512	4538
1988	2797	2822	2956	1759	1894	1723	2573	2801	2577	4067	3608	4591
1989	2871	2839	3023	1862	1975	1866	2591	2759	2602	4224	3647	4656
1990	2898	2909	3086	1872	1961	1871	2604	2832	2627	4298	3788	4847
1991	3013	2988	3174	1908	1971	1920	2697	2901	2737	4520	3928	4871
1992	3022	2991	3194	1919	1983	1933	2693	2913	2713	4515	3881	5026
1993	3030	2943	3179	1938	1999	1960	2706	2845	2735	4498	3784	4920
1994	3013	2923	3150	1916	1991	1952	2685	2829	2705	4506	3774	4876
1995	2928	2810	3120	1864	1915	1920	2607	2687	2650	4390	3682	4977
1996	2925	2778	3098	1874	1923	1906	2594	2641	2628	4407	3650	4902
% change 1985-96	7.1	0.3	10.3	6.4	3.2	18.1	1.8	-4.3	3.9	13.9	3.8	16.5

Note: Values are expressed in thousands of Italian liras. *Source*: INPS panel data.

The trends described above are better visualized with the help of figure 4, which focus on the two biggest sectors – manufacturing and services.

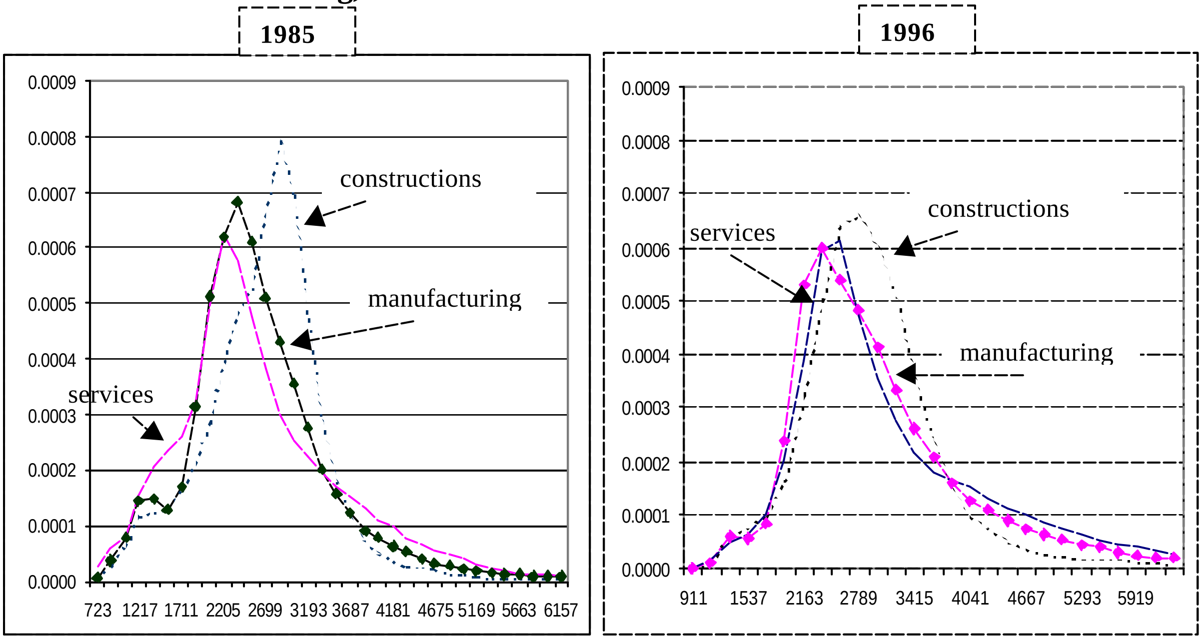
Figure 4
P10, P50 and P90 in Manufacturing and Services



Source: INPS panel data. The letter "m" refers to manufacturing, while "sw" indicates percentiles that refer to services.

Percentiles historical series suggest that earnings inequality in services is larger than in manufacturing. However, focusing only on few points of the distribution can be misleading when gauging inequality. To get a more complete picture of the distributional changes occurred within and between the three activity sectors we first display the estimates of the density functions and next turn to the decomposition of total inequality in its within-group and between-group components. The ingredients of such an exercise are collected in Table 8. In the interest of brevity, both the density functions and the figures reported in Table 8 refer to a direct comparison only of the first and the last years in our sample. Given that observed trends during the whole period manifest a generally increasing path, this choice does not seem to significantly distort the overall picture.

Figure 5
Frequency Density Function:
Manufacturing, Construction and Services in 1985 and 1996



Source: INPS panel data, 1985 and 1996.

The estimates of the density functions in 1985 and 1996 for these three sectors are revealing of important changes occurred in the Italian industrial structure during the 1980s and 1990s (see Figure 5). Mean earnings increased in all three sectors, but perhaps more striking is the augmented thickness of the right tails of the three densities portrayed by figure 5. Workers in the service distribution continue to display a right tail that is thicker than in the other sectors in both years. Note also how the density function of manufacturing features a "bump" in its left tail in 1985 - which is somewhat reduced in 1996 – while services and constructions present more regular curves. Overall the distributional changes occurred within and between sector are such that their density functions look much more the same in 1996 than they were in 1985.

The horizontal Panel F of Table 8 offers additional ingredients for a better understanding of the modifications that concerned the Italian industrial structure. As shown by column 5, manufacturing's share was 57% in 1985 but declined to 52% in 1996. Constructions too shrunk, from a share of 13% in 1985 to a tinier 10% at the end of the period. On the other hand, workers employed in the service sector witnessed a sizeable expansion from a share of 30% to 38% in 1996. The relative decline of manufacturing and constructions is also substantiated by the changes in average earnings. Manufacturing had the lowest relative mean earnings in 1985 (column 7 in

Table 8) and lost some additional grounds in 1996. Even more visible is the reduction of relative mean earnings experienced by the construction sector: mean monthly earnings increased from 2.722 million Italian liras in 1985 to 2.778 in 1996, but - relative to the population mean – this is equivalent to a mean earnings drop from 1.02 to 0.93. The relative mean of the service sector, instead, increased from 1.01 to 1.04.

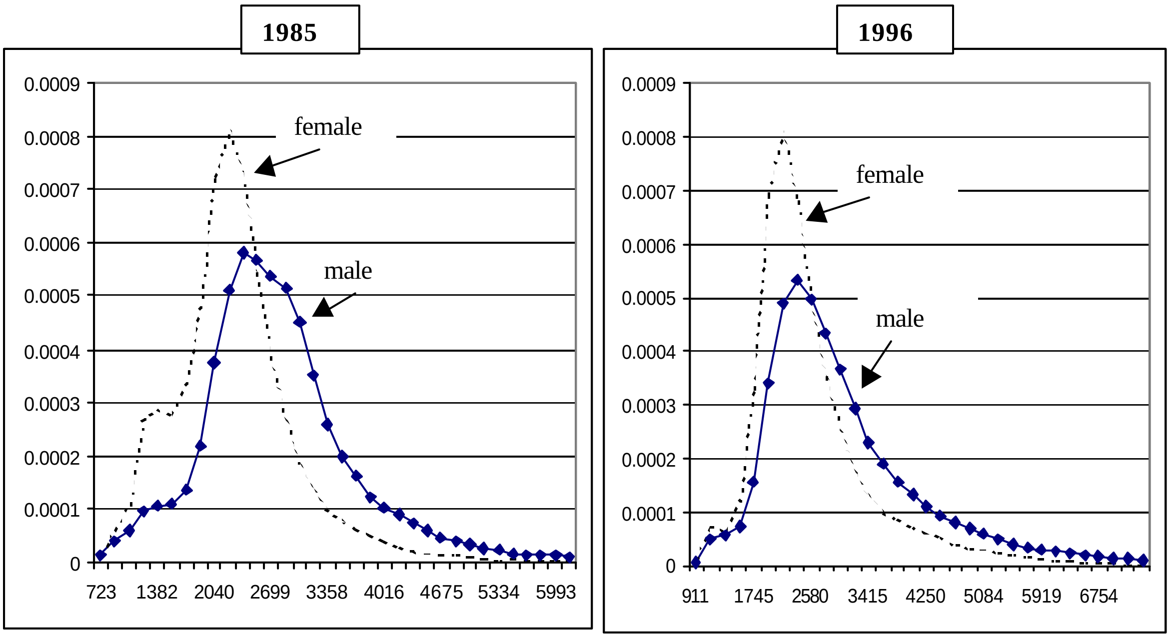
When we turn to earnings inequality other interesting results emerge. According to the three measures reported in columns 2, 3 and 4 of Table 8, services is the sector with highest inequality levels in both 1985 and 1996, followed by manufacturing and constructions. However, in terms of inequality growth, earnings differentials opened faster in manufacturing, followed by constructions and services.

Interestingly, virtually all observed inequality is accounted for by the within-group component. Though of a negligible entity, note how the between-group component has slightly increased in 1996.

3.2 Earnings trends by gender

We now disaggregate the sample according to gender. It is well known that the participation of women to the Italian labor market has been increasing over time, and in fact female employees had a share of 30% in 1985 and of 33% in 1996 (see Table 8, column 5, panel B).

Figure 6
Frequency Density Function by Sex in 1985 and 1996.



Note: we showed two representative years in order to have extremes of the sample.
Source: INPS panel data, 1985 and 1996.

The distribution for women appears to be characterized by smaller modal earnings than for men (Figure 6). It is also evident how the female's distribution is much more concentrated around its mode than the men's. Moreover, the men's distribution presents a ticker right tail that is considerably flatter than women's, providing hints that earnings are more dispersed for men than for women.

Also worrying is the larger proportion of women that receive pays at the bottom of the earnings scale compared to men, as implied by the "fatter" tail that the female distribution displays on the left. In effect, there is a "bump" in the left tail of the distributions in 1985, which seems to be more accentuated for women. In 1996 the female distribution moved to the right, somewhat getting closer to the shape of men's. Yet, notable differences persist both in the extent of concentration around the mode and in the amount of right-tail skewness.

A more detailed numerical assessment of these differences can be drawn from the figures collected in Table 5.

Table 5
Men and Women

(a) percentile levels

	Mean		p10		p50		p90		Male / Female			
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**mean**	**p10**	**p50**	**P90**
1985	2839	2289	1841	1387	2682	2222	4010	3129	1.24	1.33	1.21	1.28
1986	2929	2346	1898	1457	2741	2252	4177	3253	1.25	1.30	1.22	1.28
1987	3002	2426	1922	1505	2776	2282	4364	3402	1.24	1.28	1.22	1.28
1988	3030	2434	1905	1539	2789	2268	4462	3448	1.24	1.24	1.23	1.29
1989	3095	2515	1967	1740	2799	2294	4598	3553	1.23	1.13	1.22	1.29
1990	3146	2545	1970	1744	2831	2306	4729	3648	1.24	1.13	1.23	1.30
1991	3251	2650	2008	1799	2918	2412	4876	3781	1.23	1.12	1.21	1.29
1992	3263	2668	2012	1835	2912	2411	4939	3826	1.22	1.10	1.21	1.29
1993	3251	2687	2037	1844	2901	2429	4885	3844	1.21	1.10	1.19	1.27
1994	3234	2670	2020	1832	2880	2410	4877	3841	1.21	1.10	1.19	1.27
1995	3162	2627	1953	1798	2795	2359	4845	3813	1.20	1.09	1.18	1.27
1996	3151	2623	1958	1804	2772	2349	4836	3832	1.20	1.09	1.18	1.26
% change 1985-96	11.0	14.6	6.3	30.1	3.4	5.7	20.6	22.5	-3.1	-18.2	-2.2	-1.5

(b) percentile ratios

	p90/p50		p50/p10		p90/p10	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
1985	1.50	1.41	1.46	1.60	2.18	2.26
1986	1.52	1.44	1.44	1.55	2.20	2.23
1987	1.57	1.49	1.44	1.52	2.27	2.26
1988	1.60	1.52	1.46	1.47	2.34	2.24
1989	1.64	1.55	1.42	1.32	2.34	2.04
1990	1.67	1.58	1.44	1.32	2.40	2.09
1991	1.67	1.57	1.45	1.34	2.43	2.10
1992	1.70	1.59	1.45	1.31	2.45	2.09
1993	1.68	1.58	1.42	1.32	2.40	2.08
1994	1.69	1.59	1.43	1.32	2.41	2.10
1995	1.73	1.62	1.43	1.31	2.48	2.12
1996	1.74	1.63	1.42	1.30	2.47	2.12
% change 1985-96	16.7	15.8	-2.8	-18.7	13.4	-5.8

Source: INPS panel data.

As one may expect, mean earnings for men are higher than for women in each year of our sample. In 1996 this difference was still about 20%. Looking at trends, the general increasing patterns found for the population as a whole are confirmed for both men and women. For men (women) the distribution mean grew until 1992 (1993), but the subsequent reduction was much more moderate for women than for men. The turning point in the levels of p10 is 1993 for both sexes, and for p50 and p90 for women. For men, instead, the decline of p90 and p50 started at least one year earlier. This circumstance may suggest that the economic slowdown was slightly more deleterious for medium/high earnings of men, or at least that it hurt them more promptly, then for women or low-paid men.

A glance at the growth rates reported in the last row of table 5(a) demonstrates that female employees have been catching up with men over the time period studied, a finding common to all OECD countries (OECD, 1996). Female's average earnings grew by almost 15% from 1985 to 1996, while men's growth was only 11%. At all percentile points, too, female employees saw their earnings expand more than men. Particularly impressive was the pay raise of the poorest female tenth, which increased by 30% compared to a much smaller 6% for men. In Italy as in other OECD countries, the gender gap is narrowed not only because of the substantial earnings rise of more qualified women, but also – and above all – because women's growth at the bottom of the distribution has been larger than for men. Note also that for both men and women the median was characterized by a much more stable path, which – coupled with the large expansion of the distribution extremes – is consistent with increased polarization.

Finally, Table 5(b) computes the percentile ratios for men and women separately and provides clues that earnings are more unequally distributed for men than for women – a result consistently found in the literature. In effect, the ratio of p90 and p50 is always higher for men, as is the ratio of p90 and p10 – with the exclusion of the two initial years. The men's ratio of p50 and p10 is instead lower than for women until 1988, after which year the situation is reversed as a reflection of the spectacular growth of women's p10. This would imply that not only inequality amongst men is greater; it is also rising faster than among women.

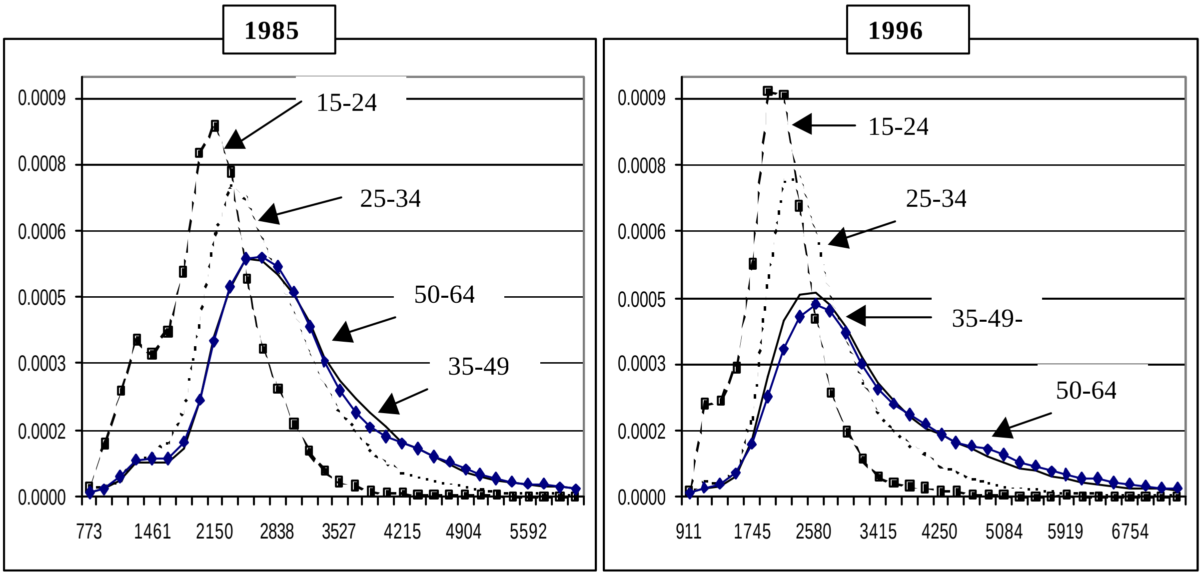
The decomposition of observed inequality into within-gender and between-gender components (Table 8, panel B) enables us to deliver a numerical assessment of the previous indications. For the three summary measures considered, inequality is higher for men than for women at the start and at the end of the sample period, and is also increasing faster. Once again, the lion's share of observed inequality is held by the within-group components, but inequality between men and women explains between four and eight percent of total inequality. Moreover, the within-group component has been expanding over time, highlighting an increasing return to observable and unobservable characteristics other than gender. On the other hand, differences between men and women as separate groups have been somewhat reduced by the economic changes that took place in the twelve years following 1985, as demonstrated by a falling between-group contribution.

3.3 Earnings trends by age groups

Next, we disaggregate our sample into four different age groups. The first comprises the youngest employees – presumably new entrants – with age between 15 and 24. The second group is made up by more experienced young employees with age between 25 and 34, while the third group consists of all those with age between 35 and 49. The most mature workers – with age between 50 and 64 – constitute the final group. As reported in Table 8 (panel E, column 5), the youngest employees had a share of about 26 per cent in 1985, which dropped at only 17% in 1996. The oldest age group shrunk too, though to a much lesser extent (from 14% in 1985 to 13% in 1996). On the other hand, those with age 25-34 considerably expanded their share, from 28 to 35 per cent, as did those with age 35-49, from 32 to 35 per cent. This modification of the age structure in our sample – which points to a significant ageing of the employee population – is likely to be at the root of important distributional changes.

Figure 7 draws the distribution density functions for the four age groups, separately. Not unexpectedly, the older the employee group the more located and skewed to the right is the corresponding density function. The empirical and theoretical literature on earnings has long documented wage profiles that are increasing (at a decreasing rate) with age and that, at the same time, features increasing variability as the cohort grows older. Young employees are less experienced and more likely to have entered the labor market in a job that does not fully rewards their unobservable skills. As time passes, they acquire knowledge and employers manage to elicit more information on the employee's skills. As a result received wages grow and become more variable across workers observationally equivalent. The two older age classes – 35-49 and 50-64 years old – have almost identical distributions, with a right tail definitely larger than the other two younger classes – 15-24 and 25-34 years old. Note also that the distribution for the youngest age group displays a bump in the left tail of the wage distribution, likely to reflect the existence of 'typical' entry wages.

Figure 7
Frequency Density Function by Age Groups in 1985 and 1996.



Source: INPS panel data.

Confronting 1985 with 1996, three main features catch the eye. Reflecting the general economic growth during the period, the density functions shifted to the right for each age cohort. Also, the heights of the curves lowered in 1996, particularly so for the two older age groups, and the right tails became thicker. One would then expect wage dispersion to have enlarged in these sub-groups.

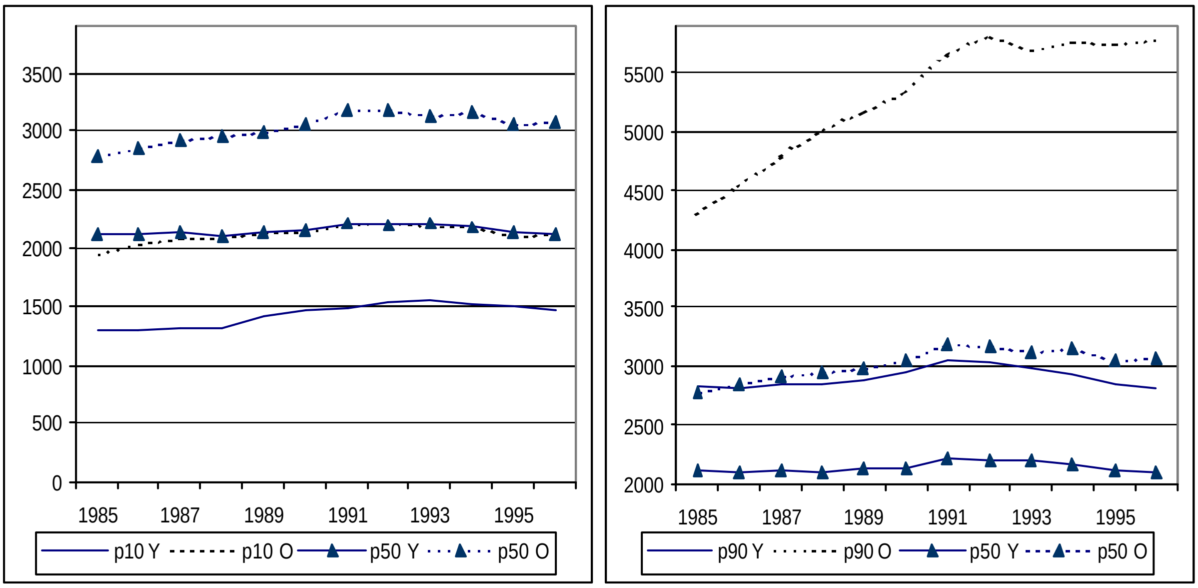
Table 6 focuses on the youngest (15-24) and the oldest (50-64). In principle, the former are the new entrants in the labor market, the latter are the almost-leavers.

Table 6
Young and Old

	Mean		**p10**		**p50**		**p90**		**Y / O**			
	Y	**O**	**Y**	**O**	**Y**	**O**	**Y**	**O**	**mean**	**p10**	**p50**	**p90**
1985	2115	2981	1292	1949	2109	2786	2838	4292	0.71	0.66	0.76	0.66
1986	2115	3110	1297	2026	2105	2857	2827	4536	0.68	0.64	0.74	0.62
1987	2136	3228	1309	2082	2121	2915	2846	4801	0.66	0.63	0.73	0.59
1988	2131	3293	1310	2072	2102	2961	2861	5006	0.65	0.63	0.71	0.57
1989	2195	3388	1420	2124	2133	2992	2892	5165	0.65	0.67	0.71	0.56
1990	2215	3479	1468	2133	2139	3057	2954	5339	0.64	0.69	0.70	0.55
1991	2281	3656	1488	2201	2217	3181	3061	5673	0.62	0.68	0.70	0.54
1992	2282	3690	1537	2206	2203	3175	3042	5823	0.62	0.70	0.69	0.52
1993	2277	3616	1555	2180	2207	3124	2992	5693	0.63	0.71	0.71	0.53
1994	2241	3661	1525	2173	2174	3160	2934	5761	0.61	0.70	0.69	0.51
1995	2189	3569	1495	2101	2123	3050	2851	5752	0.61	0.71	0.70	0.50
1996	2169	3613	1472	2104	2107	3079	2828	5784	0.60	0.70	0.68	0.49
% change 1985-96	2.6	21.2	13.9	8.0	-0.1	10.5	-0.4	34.8	-15.4	5.5	-9.6	-26.1

Note: *Y* stands for young (age 15-24) and *O* for old (age 50-64). Values in the first part of the table are expressed in thousands of Italian lire. *Source*: INPS panel data.

Figure 8
P10, P50 and P90 for Young and Old



Note: where *Y* stays for young – dotted lines -and *O* old –continuum lines. We kept a constant range of £ 4 million shifted from 0 to 2 million in the second graph. *Source*: INPS panel data.

Together with Figure 8, Table 6 documents a picture of relative stability of the wage distribution of the group of new entrants, at least when this is compared to the distribution of the almost-leavers. The result of these trends is that the gap between the very young and the oldest workers has visibly magnified over the 1980s and the 1990s. In fact, while the new-entrants mean grew by only 2.6%, the mean for the almost-leavers jumped up of about 21% over the entire time window. Mainly this is the result of the stunning growth experienced by those aged 50-64 and receiving very high wages, as shown by an almost 35% raise of p90. The same percentile for those aged 15-24 was virtually unchanged in 1996 from its value in 1985. To a lesser extent a similar discrepancy is also found for the medians of the two groups. However, at very low wages the new-entrants score a higher growth than the almost-leavers, with p10 increasing respectively of 14% and 8%. Whether this is the effect of institutional constraints (e.g., labor market legislation for young employees) or of more general market forces is hard to say within our descriptive framework. Further research is called for shedding light on this important issue.

Table 8 (panel E) makes the overall picture even clearer by comparing various inequality indicators for the first and last year in the sample period. Relatively to the population mean, the mean of the youngest cohort decreased from 0.79 to 0.73, while the reduction of the next younger group fell from about unity to 0.93. On the contrary, the two most senior groups saw their mean wages increase relative to the overall mean, suggesting that structural changes in the Italian labor market might have pushed the return to seniority and experience upwards – as has been documented in all developed countries. As about earnings inequality, the theoretical link between age and increased dispersion seems to be confirmed by the three indicators computed. The relation is not monotonic, though, with inequality in age group 25-34 being lower than in age group 15-24. When we examine trends in inequality within each subgroup, we witness to a widening of relative earnings differences in all but the youngest age group (due to the improved situation of very low wages in that group).

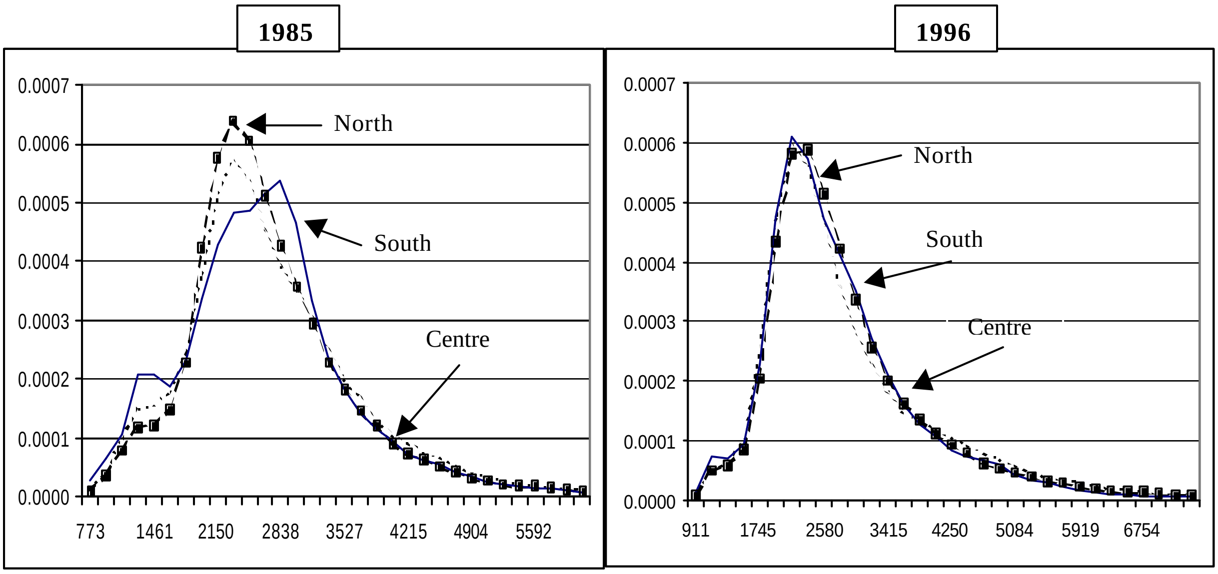
Once again the bulk of observed inequality is within-group, and this is increasing too. However, differences between age groups are important (being able to account for between 13 and 19 percent of aggregate inequality) and have exacerbated during the 1990s.

3.4 Earnings trends by region

Next, we disaggregate the sample by geographical areas. We identify three Italian macro-regions as follows:

- *North*: Piemonte, Valle d'Aosta, Lombardia, Trentino, Veneto, Liguria and Emilia Romagna.
- *Centre*: Toscana, Umbria, Marche, Lazio and Abruzzo.
- *South*: Campania, Molise, Basilicata, Puglia, Calabria, Sardegna and Sicilia.

Figure 9
Frequency Density Function by Regional Area in 1985 and 1996.



Source: INPS panel data.

With reference to their density functions the three macro-regions do not seem to differ much, particularly so in 1996 when it becomes hard to distinguish the three curves (figure 9). In 1985 the south stands out for its more pronounced bump in the left-hand tail and its tri-modality (its highest mode is larger than the modes in the remaining macro-areas). Note also that in 1985 the proportion of employees with low monthly earnings was higher in the south, followed by the center. However, these features do not seem to persist in 1996 as well.

These findings may be thought of as at variance with what one would expect in a country where, notoriously, a prosperous and economically developed north is often contrasted to a more backward south. The possibility that the wage normalization used so far - where the employee's annual remuneration is divided by the number of days s/he is recorded to have worked during the year - may hide distortions of the INPS data panel, and particularly so in the southern parts of the country, is investigated in Box 4.

BOX 4 Measuring the wage differentials between North and South

BOX 4.1 *Normalizing and measuring amount of work produced*

In every analysis in which a unit measure is needed, the reference variable must undergo a process of normalization. The study of wage differentials therefore demands a normalization of the gross earnings received by workers, in such a way to consider earnings independently of the length of time of each pay period.

The *desiderata* would be to have a measure of hourly pay so as to permit an accurate evaluation of the economic condition of each employment position. To obtain such an indicator one must know the number of hours worked per week, which is also useful in verifying that collective work contracts are respected (which set a ceiling for the number of hours worked per week for "ordinary" employment).

But INPS collects information on dependent workers only for purposes strictly related to its task of managing pensions: on one side it tracks and checks the amount a firm must pay for each employee, on the other side it measures the level of employment seniority of the worker, which is the basis on which his future pension is calculated.

In one case (payments made by employers), the necessary information is in the form of the daily wage: the firm applies a tax rate to the daily wage payments, which must be equal to or greater than a minimum established by INPS. In the second case (determination of a worker's employment seniority), the relevant information is in the form of the number of paid weeks, remembering that working one day in any given week is sufficient to consider it a paid week.

In light of the fact that one cannot rely on measures of the number of hours worked, the most natural next best measure is daily wages. Multiplying daily wage by 26, it can be considered the monthly wage.

BOX 4.2 *Paid days by geographical area*

When the distribution of the paid days[15] by geographical area is observed, it appears that in the South employees work less, especially industrial workers (table box 4.1)[16]. This data could influence the proper measuring of the wage gap between the North and South, which as shown in figure 9, is almost non-existent.

Table box 4.1

Distribution of paid days for full-time industrial workers

paid days	*North West*	*North Est*	*Centre*	*South*	*islands*
0-26	4.7	5.0	5.3	7.9	9.0
27-78	8.0	10.3	9.0	12.6	17.4
79-156	8.8	10.5	10.8	12.4	12.3
157-234	8.0	8.3	9.7	14.8	13.1
235-286	9.5	8.2	12.6	16.0	14.2
287+	**61.0**	57.6	52.6	**36.3**	34.0
absolute values	13850	10364	6366	5351	1540

Table box 4.2

Distribution of paid days for full-time industrial workers that are paid for 12 months by the same firm

paid days	*North West*	*North Est*	*Centre*	*South*	*islands*
0-26	0.0	0.0	0.0	0.0	0.0
27-78	0.0	0.0	0.1	0.2	0.3
79-156	0.2	0.2	0.7	2.5	1.5
157-234	1.2	0.8	3.1	12.2	10.0
235-286	8.5	6.2	13.5	22.6	20.5
287+	**90.1**	92.7	82.6	**62.4**	67.7
absolute values	9366	6435	4056	3109	772

[15] One speaks of paid days, some of which may not be worked days, since included under this heading are periods of paid time during which no work is done (maternity leave, sick leave, holiday…).

[16] Econometric estimates indicate, however, that in the *mezzogiorno* – ceteris paribus – the number of paid days is much lower than in the central northern area. See Contini, Filippi, Malpede (2001).

Selecting only full-time employment spells that are not interrupted during the year, in which the employee is paid by the same firm for the full 12 months, one expects that the number of paid days would not be so different between different geographical areas. In reality, differences persist (table box 4.2) and could have varying explanations. Two of these explanations seem particularly plausible:

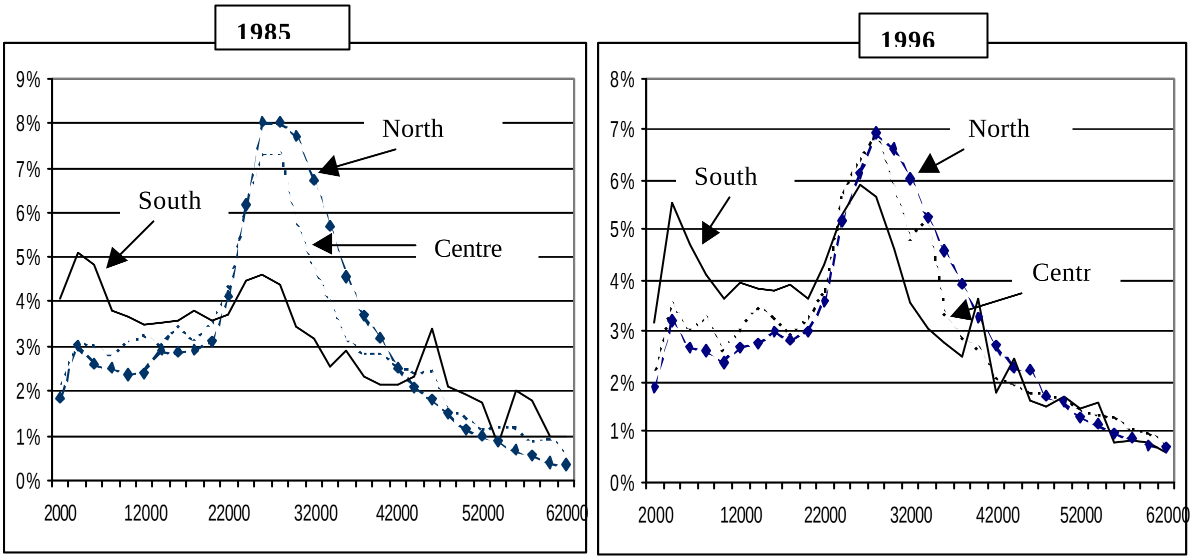
- There could be errors in the codification of the contract, such that a part-time position is considered full-time.
- The firms could have an incentive to declare fewer paid days than there really are, so that they fall into the minimum category of daily wages established by INPS.

For a more complete examination of this topic, see Contini, Filippi, Malpede (2001). Here, it is of interest to point out how in some cases it is helpful to make use of the sum total of all yearly earnings for purposes of national comparisons.

BOX 4.3 *Wage differentials using the sum of all wages gained in a year*

Figure 10/a shows the comparison using for the entire sample the yearly wage: the gap in favour of the North is certainly overestimated because there is a higher number of short term employment spells in the South, which creates a distortion in the analysis.

Figure 10a
Frequency Density Function by Regional Area in 1985 and 1996.
(Yearly Wage)

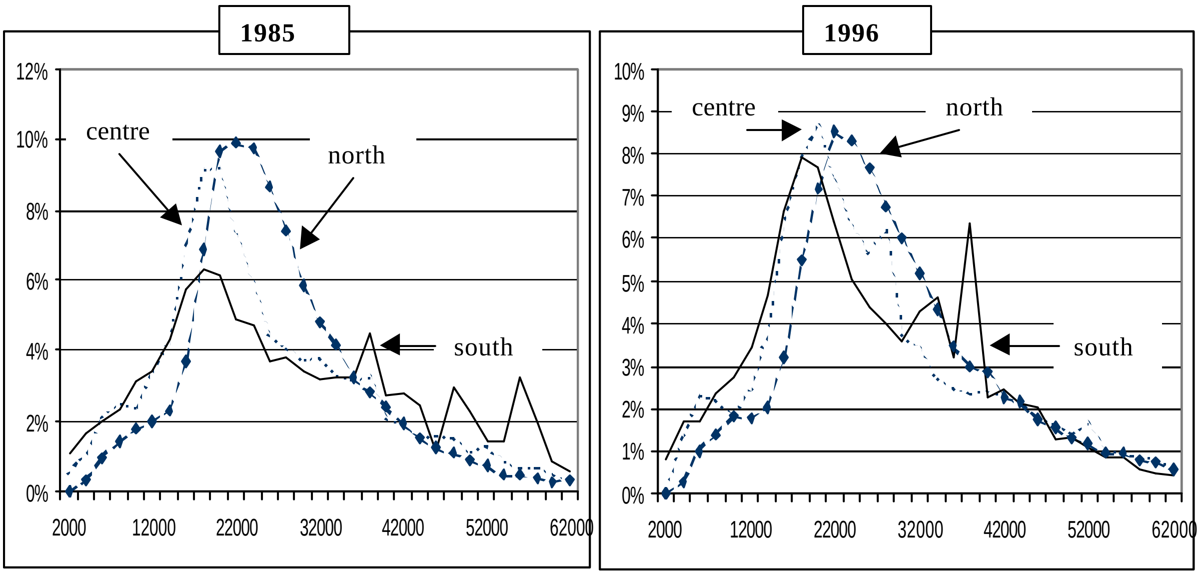


Note: Distribution of wages calculated as sum of all wages gained in a year. *Source*: INPS panel data.

Figure 10/b instead shows a comparison between groups of “similar” workers, relative to their pay period (12 months): with these figures, using the sum of all wages gained in a year, an undistorted national comparison can be made. Neither different numbers of paid days nor pay periods of differing duration distort the comparison. The difference between North and South is reduced, but remains nonetheless higher than that revealed using monthly wages, as shown in figure 10/b.

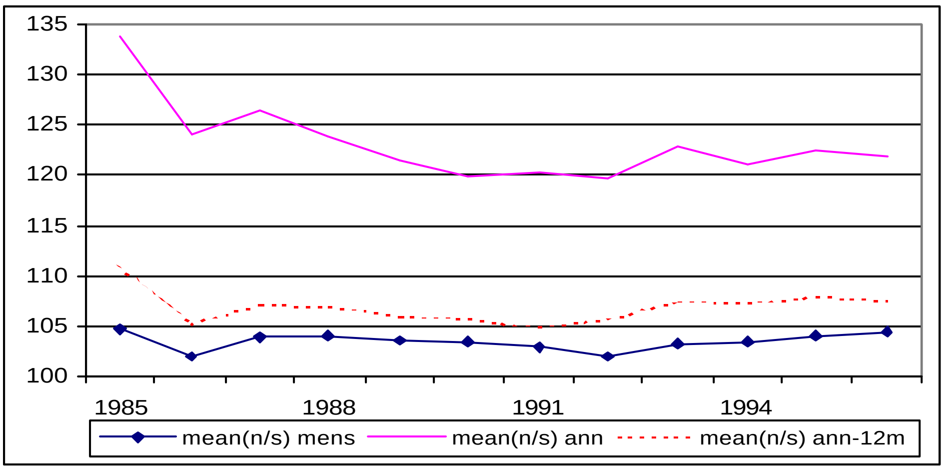
In conclusion, yearly wages can be important in analysing wage differentials in the presence of apparently distorted measures of daily wages, but it is necessary to consider homogeneous groups of workers, that is those with the same type of contract (full-time) and the same duration of the employment spell.

Figure 10b
Frequency Density Function by Regional Area in 1985 and 1996.
(Yearly Wage – 12 months workers)



Note: Distribution of yearly wages for workers who receive a wage each month of the year. *Source*: INPS panel data.

Figure 10c
Mean comparison with the three different wage normalization methods



Note: each line shows the ratio between northern and southern mean respectively with monthly wage, yearly wage and yearly wage for 12 months workers.

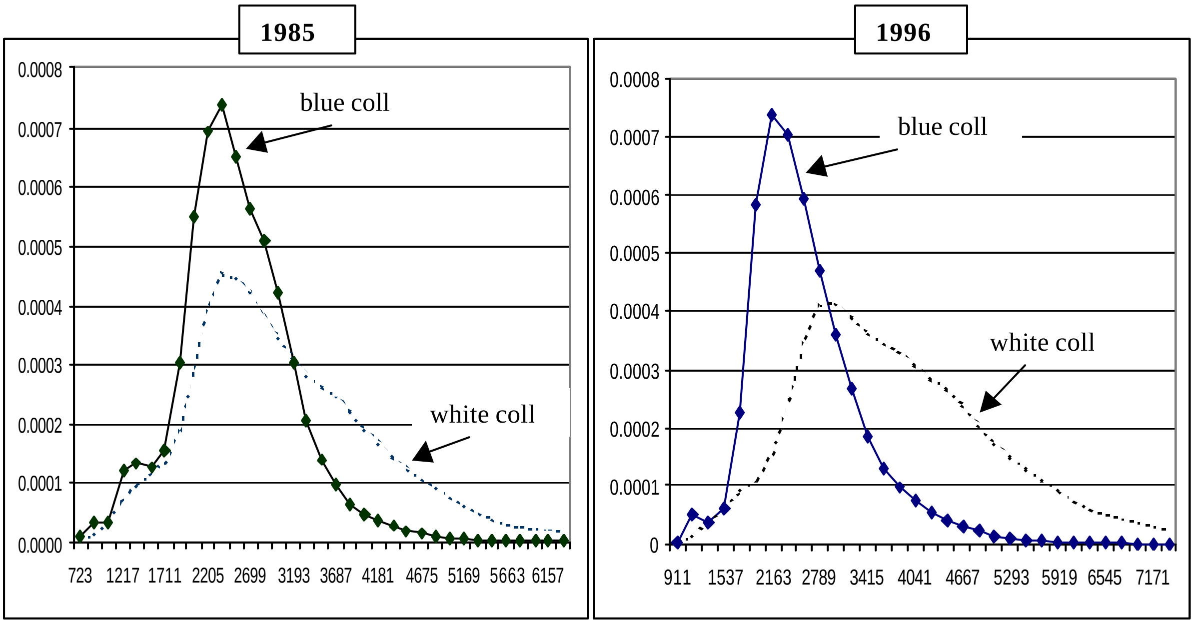
3.5 Earnings trends by occupation

Our last subgroup breakdown is by occupation type: manual (blue collar), non-manual (white collar), manager and apprentice. Needless to say, this classification is correlated with the skills possessed by each worker and required for any particular job.

The two most important groups are the blue and the white collars, having in 1985 a share of 66 and 26 percent, respectively. By comparison, in the same year the share of managers and apprentices in the population were a tiny 0.4 and 7 percent, respectively. These shares went through important structural changes during our sample period, with both white collars and managers absorbing a larger share of the Italian employees at the expenses of the other two groups (see Table 8, panel C).

Figure 11 puts under a lens the wage distributions of blue and white collars, highlighting the main differences in the shape of their density functions. Not only have white collars a wage distribution that is much less concentrated than blue collars'. Their distribution is also substantially more skewed to the right. While this pattern was already visible in 1985, it became even more so eleven years later.

Figure 11
Frequency Density Function by Occupation in 1985 and 1996.



Note: we showed two representative years in order to have extremes of the sample. *Source*: INPS panel data.

Trends of mean earnings, p10, p50 and p90 are investigated with the help of Table 7. For both blue and white-collar workers, mean earnings decreased after 1991-92, an anticipated pattern. The growth rate was higher for white collars, no matter the part of the distribution we are looking at – including the mean. Figure 12 helps visualizing the percentile patterns. See in particular how white collars' p90 (p90 W) grew more than blue collars' (p90 B), which may largely be held responsible for the differential means growth observed in the two groups. White collars show a quite strange drop after 1995 in the richest decile. If we look at table 3 in the data box (section W), we note that the number of white collars present in the panel strongly declined while the managers' number highly arose. This is because a considerable proportion of white collars after 1995 passed to the manager workers group.

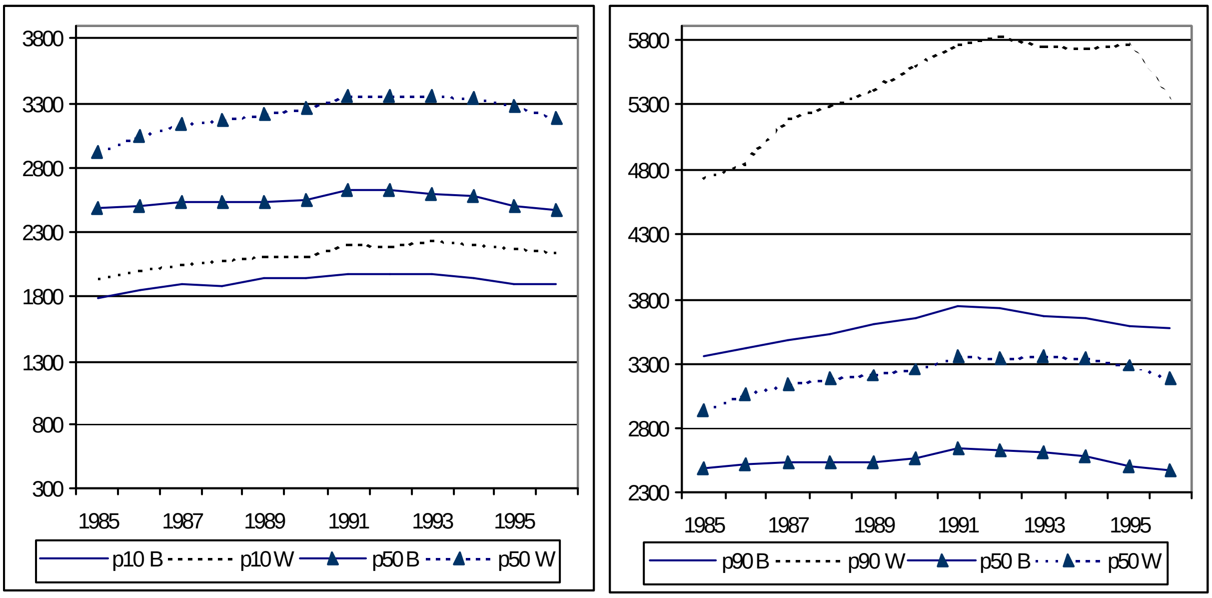
Blue collars' average wages were below the overall average in 1985 and they saw a worsening of their relative position during the next 11 years, their relative mean dropping from 0.95 to 0.88 (see Table 8). White collars kept their relative mean wages above the aggregate mean in both years and no appreciable trend can be spotted. Observe, as is obvious, how apprentices and managers have mean earnings that are, respectively, substantially lower and higher than the aggregate mean. Perhaps more surprising, is the circumstance that both groups saw their relative mean earnings decline over the sample period.

Table 7
Blue and White Collars

	Mean		**p10**		**p50**		**p90**		**B / W**			
	B	**W**	**B**	**W**	**B**	**W**	**B**	**W**	**mean**	**p10**	**p50**	**p90**
1985	2552	3175	1783	1940	2481	2927	3358	4735	0.80	0.92	0.85	0.71
1986	2595	3279	1852	2001	2509	3050	3430	4845	0.79	0.93	0.82	0.71
1987	2631	3430	1892	2057	2538	3132	3485	5190	0.77	0.92	0.81	0.67
1988	2636	3476	1885	2077	2528	3171	3523	5283	0.76	0.91	0.80	0.67
1989	2690	3543	1947	2114	2538	3211	3603	5408	0.76	0.92	0.79	0.67
1990	2712	3609	1947	2112	2555	3257	3659	5585	0.75	0.92	0.78	0.66
1991	2784	3740	1978	2213	2632	3359	3752	5766	0.74	0.89	0.78	0.65
1992	2780	3748	1978	2196	2622	3351	3731	5818	0.74	0.90	0.78	0.64
1993	2752	3743	1972	2235	2603	3358	3673	5747	0.74	0.88	0.78	0.64
1994	2727	3725	1947	2216	2576	3348	3660	5729	0.73	0.88	0.77	0.64
1995	2653	3695	1895	2173	2496	3286	3590	5763	0.72	0.87	0.76	0.62
1996	2635	3546	1895	2148	2474	3183	3571	5341	0.74	0.88	0.78	0.67
% change 1985-96	1.5	8.1	2.3	7.3	-1.4	4.4	4.1	10.2	-6.3	-5.4	-4.9	-5.6

Note: *B* stays for blue collars and *W* for white collars. *Source*: INPS panel data.

Figure 12
P10, P50 and P90 for Blue and White Collars



Note: *B* stays for blue collars and *W* for white collars. We kept a constant range of £ 3.5 million shifted from 0.3 to 2.3 million in the second graph. *Source*: INPS panel data.

Table 8 numerically assesses the general impression that white collars have the most unequal earnings distribution, according to whichever of the three indices is used and in both 1985 and 1996. Universally confirmed is also the fact that inequality within white-collar workers increased during the 1980s and 1990s. The precise ranking of the four groups in terms of their levels of inequality does however depend on the particular measures chosen. Inequality seems to have lowered for apprentices, according to the three measures, but no unambiguous statement can be made about managers and blue collars.

The within-group component certainly explains most of the observed inequality but note that for this population partition the between-group component is now able to explain as large as 36% of observed inequality. Moreover, this component has exhibited an impressive growth during the period 1985-1996, more than doubling its level. This implies that skills that we can observe and classify as above have increasingly attracted differential rate of returns in the labor market.

Table 8: Inequality decompositions by population subgroups, 1985 and 1996

	(1)	(2)		(3)		(4)		(5)		(6)		(7)	
	Sub-group Partition	1000**GE*(0)		1000**GE*(1)		1000**GE*(2)		Share (%)		mean		relative mean	
		1985	1996	1985	1996	1985	1996	1985	1996	1985	1996	1985	1996
A													
	All persons	61	74	62	81	68	97	100	100	2674	2977	100	100
B													
	Male	58	77	59	84	65	99	70	67	2839	3151	1.06	1.06
	female	51	58	52	64	57	77	30	33	2289	2623	0.86	0.88
	within-group inequality	56	71	57	78	64	94						
	between-group inequality	5	4	5	4	4	3						
C													
	blue collars	39	38	38	40	40	45	66	61	2552	2635	0.95	0.88
	White collars	68	70	68	74	73	83	26	32	3176	3553	1.19	1.19
	managers	50	33	37	32	31	32	0.4	2	6668	6983	2.49	2.35
	apprenticeship	44	32	45	35	49	40	7	5	1649	1691	0.62	0.57
	Within-group inequality	47	48	48	52	53	64						
	between-group inequality	14	26	14	29	15	34						
D													
	North	58	75	59	82	67	99	62	63	2703	2997	1.01	1.01
	Centre	63	82	64	89	71	106	18	18	2678	3022	1.00	1.02
	South	68	66	66	71	70	83	20	19	2584	2871	0.97	0.96
	within-group												

inequality	61	74	62	81	68	97						
(1)	(2)		(3)		(4)		(5)		(6)		(7)	
between-group inequality	0.2	0.2	0.2	0.2	0.2	0.2						
E												
age 15-24	46	38	45	39	47	44	26	17	2115	2169	0.79	0.73
age 25-34	43	46	43	50	45	58	28	35	2663	2759	1.00	0.93
age 35-49	59	75	60	81	67	93	32	35	3001	3372	1.12	1.13
age 50-64	61	90	62	96	69	112	14	13	2981	3613	1.11	1.21
within-group inequality	51	60	52	68	59	84						
between-group inequality	10	14	9	14	9	13						
F												
manufacturing	57	72	58	78	64	94	57	52	2653	2925	0.99	0.98
constructions	43	46	41	49	43	58	13	10	2722	2778	1.02	0.93
services	77	84	79	91	88	108	30	38	2694	3099	1.01	1.04
within-group inequality	61	74	62	81	68	97						
between-group inequality	0	1	0	1	0	1						

Notes: See box 3 for the decomposition formulae. Due to rounding, the sum of within-group and between-group inequality may not exactly add up to total inequality.
Illustrative example. Consider year 1985 and the gender decomposition (panel B in Table 8). Column 2 shows that total inequality (i.e. over all persons, in section A) is 61according to the index *GE*(0). When we disaggregate according to gender, we calculate that inequality in the same year and for the same index is 58 for men and 51 for women. The share of men and women in 1985 is 70 per cent and 30 per cent, respectively (column 5). Averaging inequality for men and for women, using these shares as weights, we obtain the within-group inequality value of 56. To compute the between-group inequality, we first eliminate inequality within men (i.e. assign to each man the men's mean earnings of reported in column 6) and inequality within women (i.e. assign to each woman the women's mean earnings reported in column 6). The between-group value of 5 obtained in 1985 is the inequality that still remains between men and women. Finally, column 7 reports the ratio of the group's mean earnings to the population mean.

Conclusions

In this paper we have studied the Italian earnings distribution over the time period 1985-1996, using administrative data from the Italian institute for social security (INPS). We have documented a slight, but not negligible, increase in earnings inequality, according to a battery of commonly used distributional indicators. Even though changes in computed inequality indices from one year to the next are small, their bootstrapped standard errors are small too, increasing our confidence in the statistical validity of the conclusions reached.

The gap between the richest tenth and the poorest tenth broadened, but by less than what happened to the distance between the richest tenth of the distribution and the median. This could be explained by observing that the poorest tenth managed to reduce over time the distance between their position and that of the person in the median position. Concomitantly, the fact that the share of total earnings accruing to the bottom tenth of the employee population has increased, implies that we cannot speak of an unambiguous increase in inequality. We can therefore predicate a rise in earnings inequality only according to a - possibly large - subset of the available inequality measures.

Decomposition of inequality indices by various population subgroups have followed, aimed at shedding light on the causes of the observed distributional changes. For all the population partitions used, inequality is mainly explained by its within-group component, which, in all cases, is increasing too.

Male’s earnings are more unequally distributed than female’s, but the two groups are getting more similar to each other over time in terms of group’s share and mean earnings. Men’s inequality, though, is still growing faster than women’s. When focusing on low-pay, we find that the female’s poorest tenth displayed an impressive growth of 30% over the time period investigated, while the corresponding figure for men is a much more modest 6%. Not surprisingly, much of the reduction in the distance between the poorest tenth and median earnings in the whole distribution can be explained by this growth in the least well-paid jobs for females.

Among occupations, white collars have the most unequal earnings distribution, with inequality growing fastest too, during the 1980s and 1990s. Inequality seems to have lowered for apprentices, but no unambiguous statement could be made about managers and blue collars. The between-group component was able to explain up to 36% of the observed inequality value. Moreover, this component has exhibited an impressive growth during the period 1985-1996, more than doubling its level. This may be seen as implying that the skills correlated with our occupation classification - e.g. education, which is not observable in our dataset - have increasingly attracted differential rate of returns in the labour market.

The classic wage-age profile is found in our data, with monthly wages increasing as the employees grow older. The same pattern is revealed with respect to wage variability. Relative to the population mean, the mean of the youngest age group fell while for more senior employees the situation is reversed, suggesting that structural changes in the Italian labor market may have pushed the return to seniority and experience upwards. When we examine trends in inequality within each age subgroup, we witness to a widening of relative earnings differences in all but the youngest age group (due to the improved situation of very low wages in that group). Differences between age groups were able to account for between 13 and 19 percent of observed total inequality, and have exacerbated during the 1990s.

Modifications of the Italian industrial structure also contributed to the increase in earnings inequality. The share of manufacturing and constructions declined during the 1980s and 1990s, while the share of employees in the services sector expanded. Manufacturing had the lowest relative mean earnings in 1985 and lost some additional grounds in 1996. Even more conspicuous was the reduction of relative mean earnings experienced by constructions, while the relative mean in services increased. The service sector was also found to be the one with higher inequality levels in both 1985 and 1996, followed by manufacturing and constructions. However, in terms of inequality growth, earnings differentials opened up faster in manufacturing, followed by constructions and services. Virtually all observed inequality was accounted for by the within-group component, with the between-group component that slightly increased its importance over time.

Our decomposition by geographical areas pointed to a substantial uniformity in the distributions of monthly wages in the north, centre and south. It was noted that this result might be spurious, and mainly arising from the (mis)practice of southern firms to underreport the number of days worked by their employees. When focusing on annual earnings for year-round workers, differences between the geographical areas of the countries re-emerge as expected, with the earnings distribution of the north lying almost everywhere to the right of those of the centre and the south. Differences are even more pronounced when considering annual earnings for all workers (year-round or not), with the greater concentration of low remuneration in the south of the country than in the north increasing correspondingly. As this latter measure of earnings conflates both wage variability and quantity of labor variability, the larger gap between the north and the south it produces is not surprising, simply reflecting the different labor market conditions and overall job precariousness in the two areas.

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