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Earning Profiles for Italian Male Workers: Is there Evidence of a Premium for Education?

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Preface

This report investigates the evolution of both the education-premium and gross wage inequality in Italy in the period 1987-2006. This is a period in which many countries (particularly the US, but also the UK) experienced increases in both the skill premium and (gross) wage inequality. Both facts have been interpreted as evidence of skill-biased technological change, i.e. of changes in the relative demand for labour deriving from technological change favouring skilled workers over unskilled ones. The main factor considered to be the driver of these changes is the diffusion of ICT, as ICT complements skilled labour and is also a substitute for unskilled labour.

While the results from this study cannot be immediately generalized to other countries, the paper is particularly interesting for its methodological approach, as it uses repeated cross-sections to create pseudo panels that are then used to estimate the wage profiles of different groups of Italian male workers (according to their age and education) and wage inequality in the relevant period. As such, this report is relevant for the labour market (and related policies) aspects of the Innovation Policies and the Digital Agenda research lines, carried out by the Information Society (IS) Unit at JRC-IPTS in the context of the IDEA Action during the last two years.

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1. Introduction

Are younger generations better off than older ones? Can younger cohorts starting with lower real wages catch up with previous generations? Are young or old generations becoming more unequal? What is the role played by education in shaping wage inequality over the life-cycle?

In the last fifteen years these questions, of great interest for the policy maker, have motivated a considerable amount of research on changes in the wage structure. While some authors have documented an increase in inequality, however measured, which cannot be accounted for by observables like education, experience, gender, and age, others have concentrated their attention on how the earnings distribution (captured by its central location or other statistics) has changed through time.

In our work, we concentrate on the study of inter-generational and intra-generational patterns of earnings for Italian male employees for the period 1987-2006. Using data from the Bank of Italy's Survey of Household Income and Wealth, we construct cohort specific age profiles for mean wages (the measure of central location here adopted) and for the 90-10 percentile differential (the inequality measure); we estimate the age profiles for various group of workers, which differ for educational attainment and for region of residence; we verify how different cohorts have been doing comparatively and finally we test whether, with time, the (mean) returns to experience and education have increased. Moreover we verify how the inequality measure has changed with time and across cohorts.

Our results indicate that for the two education groups considered each successive generation, with the exception of those with high education that entered the labour market in the years 1998-2002, have benefited from higher entry wages. At the same time we find that the wage age-profiles for both groups have become flatter so that we cannot conclude that more recent cohorts are better off than their immediate predecessors. When looking at the return to education, we find scant evidence of across-cohort variation, while there is clear evidence that the education premium rises with age. Finally we find that inequality tends to increase both across-cohorts and along the life-cycle.

Our work is relevant under various aspects. On the one hand it provides a clear framework in which between and within cohorts comparisons are meaningful and easily interpretable. Moreover it allows us to relate our results to those obtained by MaCurdy and Mroz (1995) and Beaudry and Green (2000), in their study of the earning patterns of, respectively, American and Canadian workers. Finally we notice that our effort has implications that go beyond the characterization of wage patterns per se, since changes in (mean) returns to education, captured by changes in the life-cycle profiles for (mean) wages, can have relevant consequences on consumption, saving, capital accumulation and growth.[1]

The report proceeds as follows. In Section 2 we describe the methodology used. In Section 3 we present the data and clarify our cohort approach. In Section 4 we derive and discuss the results from our regressions using mean wages. Section 5 presents the results on wage inequality and Section 6 concludes our work.

1 The knowledge of the life-cycle profiles for earnings gives us information indirectly useful for estimating the effects of fiscal policy. Given the importance of overlapping generations model for fiscal policy and given that those model are generally based on the life-cycle hypothesis, knowing the changes in the life-cycle wage profiles can be useful in identifying the effects on consumption and saving of changes in life-cycle based tax-transfer programs, like Social Security. See Biagi (2000).

2. Methodological issues

During the last fifteen years, a considerable effort has been made in the study of the wage structure and its changes though time. The emphasis has been mainly on the U.S. but there have been numerous studies on the experience of other OECD countries as well (see, among others, Brunello et al., 2000; Katz et al., 1995). The results of this line of research, which started by the earlier contributions of Bound and Johnson (1992) and Juhn et al. (1993), are well described in Acemoglu (2002) and can be summarized as follows: 1) returns to education in the U.S. fell during the 1970's but they rose sharply during the 1980's; 2) overall wage inequality has risen considerably, starting in the 1970's and much of this rise is due to an increase in overall inequality; 3) average wages have stagnated and wages of low skilled workers have been falling since the late 1970's. While these can be considered stylized facts for the U.S., and hence the interest is on their causal interpretation (see Di Nardo et al.,1995; Acemoglu, 2002), for Italy we still need to draw a clear picture of what has happened in the late 1980's, in the 1990's and in the first decade of the new century. Our work is a step towards this goal, and our objective is to identify the changes through time (or across cohorts) and age of two simple and intuitive statistics, the mean wage and the 90-10 percentile wage difference.[2] The first is of particular interest because it allows us to characterize the shape of the age profile for earnings and its changes through time[3] (and hence across cohorts), while the second one captures the time evolution of inequality.

In spite of the apparent simplicity of such a task, there are some serious identification issues that make our work complex. Individuals accumulate experience as they age and this is normally assumed to improve their marginal productivity (at least up to a certain age), which gets reflected in rising (up to a certain age) wages. Such a relationship between earning and age (experience), usually referred to as the age-profile for wages, could be affected by many factors. For instance, it could be that the returns to age/experience do not change with time (so that the shape of the age profile is common across cohorts), but some generations are more fortunate than others (for instance because they did not have to go to war). This type of variation would lead to across-

2 This choice is mainly motivated by the objective of comparing our results to those of MaCurdy and Mroz (1995) and Beaudry and Green (2000).

3 The age profile could be affected by changes in training policies, while its position could depend on changes in education policies or in the relative size of the various cohorts.

cohort changes in the position of the age profile, which would show up in the estimation as significant cohort effects. Alternatively, a macroeconomic shock affecting all workers in the same way would imply that the position and, possibly, the shape of the age profile change across cohorts, simply because some individuals are affected by such a shock at the beginning and others at the end of their working life. We would like to identify the driving cause in the various cases, since the policy implications are different. Unfortunately there is a general identification issue related to the fact that we cannot separately identify age, cohort and time effects because the three are perfectly collinear (see Heckman and Robb, 1985).

This conclusion has relevant implications for the amount of information we can extract from our data, depending on the form it comes into. Suppose that we have a single cross-section and that we are interested in estimating the earnings age-profile. Since we would be observing individuals with different ages that belong to different cohorts, we would not be able to separately identify the shape of the age profile from its position (the cohort effects). In other words, if we observe that an older individual has a higher wage compared to a younger worker, we would not know whether such a difference is due to ageing itself or to the fact that the older individual belongs to a cohort that benefits from true cohort effects.

For instance, suppose that the "true" age profile is quite concave and does not change across cohorts, but suppose also that more recent cohorts benefit from positive cohort effects so that their age profile is shifted upward.[4] If we focused on a single cross section we would be estimating an age profile much less concave than the actual one, because age and cohort effects would be mixed together. On the other hand, we could have longitudinal data. In this case we would not know whether the changes observed across time for the wage of the same individual are due to ageing or to true time effects (calendar time is the sum of the birth cohort and age). Finally, we could have a repeated series of cross-sections. In this case we do not follow the same individual through time but we can go around this problem assuming that individuals belonging to the same cohort and that are identical under some aspects that do not depend upon

[4] This might happen if we have a positive shift in the demand for educated workers. Since education occurs at the earlier stage of one's life, we would observe that the wages received by younger cohorts of educated workers at each age are higher than those received by the older cohorts belonging to the same skill/education group.

time nor age (for instance education, region of residence and gender), differ on all the other aspects just because of individual idiosyncratic shocks. For instance, the wages of College Graduates belonging to the same cohort (typically defined in terms of 5 or 10 years interval) might differ for many reasons. If we assume that individual observations differ from the mean because of idiosyncratic shocks that are not correlated and that have expected value equal to zero, by taking the mean wage in a given year we can characterize the average (and representative) behaviour of this group. With the advantage that, in the following year, while we are not able to observe the same individuals (because it is a new and different cross-section) we can still follow the same average individual. At the price of averaging out individual differences we buy the possibility of exploiting variation through time. At that stage, the same identification problems encountered with true panel data appear for this synthetic panel. To solve them one needs to make identification assumptions. Ours is that the only time effects are business-cycle effects, so that the differences across cohorts can be interpreted as true cohort effects. This is an assumption and, as such, cannot be tested. The interesting consequence of such an assumption is that we can estimate cohort-specific age profiles.

Our work follows a methodology very close to the one used in MaCurdy and Mroz (1995) and Beaudry and Green (2000), in which the labour market conditions of different generations of, respectively, American and Canadian workers are considered. This allows for a comparison of the experience of Italian workers with that one of their North-American counterparts.[5]

[5] An analysis of life-cycle wage profiles for Italian workers was previously done by Lucifora and Rapelli (1995), who used individual longitudinal data from the National Pension Institute (INPS). Our data come from a different source, they cover a different time period and the methodology we use is different. We discuss their results in Section 4.

3. Data description

Our data come from the Bank of Italy's Survey of Household Income and Wealth, which reports information on individual and household variables. Data on individual labour income, defined as annual labour income net of taxes and contributions to the Social Security system, are the main concern for this work.

These data have been collected since 1965, but only for the period after 1984 are we able to have information on the age of individuals, because the age variable prior to 1984 has been recorded only in classes of ten-year intervals. Moreover, to increase data comparability we choose to focus only on data from the 1987 Survey onwards. Hence we use data from the 1987, 1989, 1991, 1993, 1995, 1998, 2000, 2002, 2004 and 2006 Survey. The data have been collected by different agencies in the different years and hence the sampling techniques and the definitions of the variables do not always coincide. We have tried as much as possible to create comparable variables when this was necessary.[6]

Given the sample provided by the Bank of Italy, we focus on a restricted sub-sample, formed by male employees in the private and public sectors. We choose to exclude self-employed workers mainly because individual income for this category of workers is under-reported. We also exclude workers from the agricultural sector.

We then split the sample by two education groups and by three macro-areas. As for education, we distinguish between those with less than or completed Junior High School (the mandatory school level in Italy) and those with completed High School or more (including those who completed a Bachelor degree or postgraduate education). As for the geographic areas, we distinguish between North, Centre and South (including Islands). For all groups, we focus only on agents (potentially) permanently attached to the labour market and hence only on individuals that, in every given year, are older than 20[7] and younger than 60 (the mandatory retirement age for Old Age Pensions in the private sector prior to the 1995 reform). When the highest bound of the age interval upon which the cohort is built is greater than 60 we drop the cohort. We also drop cohorts for which the mean values are computed using less than 20 observations.

[6] For a description and analysis of the sampling procedure see Brandolini and Cannari (1994).

[7] These values are slightly higher than the average starting age obtained from the sample but we wanted to avoid including individuals that are only temporarily attached to the labour market.

Then, for each age-region-education cell, we compute the average value and the 90-10 percentile differential for (gross) real wages, under the assumption that all the other individual characteristics are basically just error terms that are identically and independently distributed. In order to obtain a sufficient number of observations we construct cohorts that have a five year interval (the oldest one is the cohort indexed by 1, made up by those who are between age 50 and 54 in 1987[8] and hence that were between age 20 and age 24 in 1957).

A problem arises from the fact that the Bank of Italy's Survey of Household Income and Wealth reports information on annual labour income net of taxes and contributions to the Social Security system, while we are interested in gross weekly labour income. The tax structure would not matter so much if it were proportional. But this is not the case, since the Italian income tax schedule is highly progressive, so that the average tax rate is not independent from the (observed) net wage. Hence, we had to do generate gross labour income.

To assign individuals to their actual income tax bracket, for every year and every individual, we start from the reported net income and assign the individual to the tax bracket that would be appropriate if net and gross income coincided. Then, using the information on the household, we compute the resulting due tax and net income. If net income resulting from this computation is different from the observed net income, we reassign the individual to a higher tax bracket. This goes on until the computed gross income is consistent with both the observed net income and the tax schedule. Finally, once we have gross annual income we obtain gross annual labour income applying the average tax rate to the observed net labour income and taking into account Social Security taxes. Then we divide annual gross labour income by the number of weeks worked and we obtain gross weekly labour income. Given our focus on full time employees, we have excluded part-time workers or individuals employed for less than 12 months.

Once we have constructed gross nominal weekly wages for each individual we get real wages using macro-region specific CPI indexes, with base year 1995. These indexes have

[8] We dropped from the estimation the cohort made up by those who are between 55 and 59 in 1987 because we have only two useable observations for them (those from the 1987 and from the 1989 surveys),

been created by us under the assumption that in 1987 all the macro-regions considered (North, Centre, South) share the same price index, which is then allowed to vary across macro-regions in the following years.

4. Estimating life-cycle profiles for wages

Before presenting our results is important to discuss the relevance of the age-cohort interaction term, and the amount of information that we can extract from its estimated coefficient. We discuss separately the issues of within and across-group comparisons (where a group is defined by macro-region of residence and education).

First we look at within-group comparisons. Suppose that we find evidence of significant cohort effects but not of significant age-cohort interaction. Then we can conclude that all cohorts within a given regional-education group share the same age-profile, while they differ with respect to the position of such a profile. If we interpret the position of the age-profile as the relative (to the reference cohort) wage at the entrance in the labour market, the first type of information that we can get out of this exercise has to do with comparing entry wages across cohorts[9] belonging to the same group. On the other hand, if we find evidence of significant age-cohort interaction, then simple across-cohort comparisons are less obvious. For instance, for the same group, we can have some cohorts entering with higher wages but experiencing lower returns to age or, on the contrary, cohorts experiencing both higher entry wages and higher returns to experience.

Things are even more complex when we consider across-group comparisons of the age-profiles. In fact, for each group we can identify the age-profile for a generic cohort and then compare the degree of concavity/convexity of the age-profile across groups, but this comparison would be meaningful only if we could exclude significant age-cohort interaction. This point can be better appreciated if we assume that the wage profiles originate from a simple demand and supply model according to which output Y_t is given by:

$$Y_t = F(L_{1t}, L_{2t}, t) \qquad [1]$$

Where L_{it} , i=1,2, refers to the quantity of effective labour of skill group i at time t (the model[10] is developed by Beaudry and Green, 2000).

The quantity of effective labour for a particular skill group i is given by:

[9] For each sector-education group, the reference cohort is the oldest one.

[10] We allow for two types of workers given that we have two education group. Notice that we have made the production function dependent on time, hence allowing for changes in technology.

$$L_{it} = \sum_{j \in J} [\![g^i \ (a_{j,t}]\!], t) l_{i,j,t}$$ [2]

where j indexes cohorts, $a_{j,t}$ is the age of cohort j at time t, $l_{i,j,t}$ represents the level of actual employment (number of workers) in skill group i of cohort j at time t, and $g^i(a_{j,t}, t)$ are the effective units of labour of a worker of age $a_{j,t}$ in cohort j at time t belonging to skill group i (notice that productivity is time dependent).

Assume that workers are paid their marginal contribution to the aggregate production function[11] and hence that the natural logarithm of the wage is equal to:[12]

$$lnw_{i,j,t} = ln\left[\frac{\partial F(L_{1,t}, L_{2,t}, t)}{\partial L_{i,t}}\right] + lng^i(a_{j,t}, t)$$ [3]

This implies that log wages can be decomposed into a time effect $ln\left[\frac{\partial F(L_{1,t}, L_{2,t}, t)}{\partial L_{i,t}}\right]$, which is group specific but not dependent upon age, and a time-dependent age effect $lng^i(a_{j,t}, t)$, which can vary across groups.

The observed time effects depend on the factors underlying supply and demand. Given our assumptions, time effects really capture the factors affecting production and hence labour demand. If we have Hicks neutral technological change[13] we should observe positive time effects for all groups. If we have both Hicks neutral and skill/education specific technological changes, then the overall effect depends on the interaction of the two forces[14] and can be quantified only on the empirical ground.

This is clearly not the only possible structural representation for the wage process, but it has the advantage of having the following simple parameterization:

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[11] By assuming that workers just offer their effort at the level demanded by firms we make such a model depend purely on labour demand.

[12] We just derived the aggregate production function with respect to $l_{i,j,t}$.

[13] We should be aware that we could have also effects coming from changes in the education composition of the work force, which would affect labour supply. On this, see Card and Lemieux (2001) and Biagi and Lucifora (2008).

[14] Beaudry and Green (2000) propose a particular interpretation of skill-biased technological change, according to which, over time: a) the productivity of unskilled workers $\frac{\partial F(L_{1,t}, L_{2,t}, t)}{\partial L_{1,t}}$ decreases with time; b) the productivity of skilled workers $\frac{\partial F(L_{1,t}, L_{2,t}, t)}{\partial L_{2,t}}$ increases with time and c) the return to experience $\frac{\partial g^i(a_{j,t}, t)}{\partial a_{j,t}}$ increases with time for both groups.

$$lnw_{i,j,t} = \beta_{i,0} + \beta_{i,1} * t + \beta_{i,2} * a_{j,t} + \beta_{i,3} * a_{j,t}^2 + \beta_{i,4} * a_{j,t}^3 + \beta_{i,5} * a_{j,t} * t + \eta_{i,j,t} \qquad [4]$$

where *j* indexes the cohort, *t* indexes the year and $a_{j,t}$ is the age of cohort *j* in year *t*, while $a_{j,t}^2$ and $a_{j,t}^3$ capture non linearities in age. Notice that, under this representation, $\beta_{i,1}$ measures how the value of skill *j* changes with time, $\beta_{i,2}$, $\beta_{i,3}$, $\beta_{i,4}$ measure how log wages change with age and $\beta_{i,5}$ captures how the value of experience (the age profiles[15]) changes with time.

However, when trying to estimate this simple model we have an identification problem since we cannot separate age, cohort and time effects. This problem originates from the fact that calendar time *t* is the sum of the year of birth *j* of each cohort and its age $a_{j,t}$.

This amounts to saying that an equivalent representation for the wage process described in [4], obtained using $t = j + a_{j,t}$, is the following

$$lnw_{i,j,t} = \gamma_{i,0} + \gamma_{i,1} * j + \gamma_{i,2} * a_{j,t} + \gamma_{i,3} * a_{j,t}^2 + \gamma_{i,4} * a_{j,t}^3 + \gamma_{i,5} * a_{j,t} * j + \eta_{i,j,t} \qquad [5]$$

In this framework $\gamma_{i,0} + \gamma_{i,1}$ captures the relative position of the various cohorts at the moment of entry in the labour market, while $\gamma_{i,2}$, $\gamma_{i,3}$, and $\gamma_{i,4}$ capture the age profile and $\gamma_{i,5}$ measures how the age-profile changes across cohorts.[16] The error term $\eta_{i,j,t}$ is modelled as the sum of a cohort specific term (ε_i), an across-cohorts common time-specific term (v_t) and a truly idiosyncratic term ($\psi_{i,j,t}$), with mean zero and standard deviation equal to 1.

In our work we have performed various exercises. First we have estimated model [5] for each education group separately, including area-specific dummy variables (so that we allow the intercept -but not the slope- of the age profile to vary across macro-regions). Second, for each macro-region, we have generated a cohort specific education premium, given by the area and cohort-specific ratio of the mean wage for high and low education

[15] We use age as a proxy for experience.

[16] For instance the skill-biased technological change hypothesis proposed by Beaudry and Green implies that $\gamma_{1,1} < 0$, $\gamma_{2,1} > 0$ and $\gamma_{i,5} > 0$ for *i*=1,2, which amounts to saying that we should observe rising intercepts and steeper slopes for younger cohorts of skilled workers and dropping intercepts and rising slopes for younger cohorts of unskilled workers. Notice that a Hicks-neutral technological change would affects across-cohorts but not across-skills comparisons.

workers. We have then regressed the log of such ratio on the same regressors as in [5] to study how the education premium changes across cohorts and along the life-cycle. Finally, we have looked at within-group inequality, as measured by the 90-10 percentile ratio, and we have estimated how such a variable changes through age and cohorts for the two education groups. In all our exercises we have included also a control for common across-cohorts business-cycle fluctuations[17] (the OECD measure of the gap between actual and potential output as a percentage of potential output).

The precision of the estimation of the coefficients in [5] depends on the strength of the underlying factors. To clarify, assume that there are no cyclical effects and consider the following "true" profiles for two successive cohorts: the younger cohort has higher entry wages but shows lower wage growth along the life-cycle, so that the age profile is flatter. If these effects are strong enough then we would estimate significant cohort effects (a rising cohort-effects profile) and a significantly negative age-cohort interaction term (we are considering the oldest cohort as the reference one). If we excluded the age-cohort interaction term (either because it is not very strong and hence not significant or simply because we choose to do so) we force a common age-profile on the data (capturing the shapes of both actual age profiles), which affects the estimated cohort effects as well. In the example at hand it would push the cohort effects closer, because the coefficients on the cohort dummies would now take care of the different age-profiles as well. In our work we have estimated both unrestricted and a restricted models, and we have performed Wald tests on the estimated coefficients to select the most appropriate ones.

4.1 Within-group comparisons: estimating cohort-specific life-cycle profiles for gross weekly wages

High Education Group

When we estimate a cubic in age not allowing for age-cohort interaction, we find that the age profile is almost linear (we cannot reject the hypothesis that both coefficients on age cube and age squared are zero) and that there is evidence of significant cohort effects (see Table 1, col. 1). It is interesting to note that these effects would give rise to negatively sloped cohort profiles for entry wages. Given that - by assumption - we have

[17] The assumption that the only relevant time effects are cyclical effects allows us to interpret the other potential time effects (the trend) as cohort effects.

excluded age-cohort interaction, this conclusion would imply that each cohort has been doing worse than its immediate antecedents with the same education level. This counter-intuitive result is due to the assumption of an across-cohort common age-profile. In fact, when we estimate a model that allows for interaction between the cohort dummies and age, we find that we can reject the hypothesis that all the age-cohort interaction terms are zero, so that the unrestricted model is preferable (see Table 2, col. 1). Under such a model we find evidence of rising cohort effects for all cohorts. Moreover, we estimate a concave age profile, whose slope tends to become flatter for more recent cohorts. Overall the results for this group show that younger cohorts enter with higher entry wages, but, compared to their immediate antecedents, they also experience lower wage growth along the life-cycle.

Low Education Groups

For this group we get results that are quite similar to those obtained for the group with High education. When we estimate a cubic in age, excluding age-cohort interaction terms, we find negative and significant cohort effects (see Tab. 1, col. 2). On the other hand, when we allow for interaction between age and the cohort effects (we can reject the hypothesis that all the age-cohort interaction terms are zero) we find rising coefficients (with the exception of cohort 10, for which the coefficient is not significant) on the cohort dummies (see Table 2, col. 2), a concave age-profile and declining coefficients on the cohort-age interaction terms (with the exception of cohort 10), indicating that also this group is characterized by age-profiles that get flatter as younger cohorts enter the labour market. For this group as well the restricted model is soundly rejected by a Wald test on the joint significance of the estimates for the age-cohort interactions.

Overall these results indicate that younger cohorts, in both education groups, are doing better than their immediate predecessors when entering the labour market, but are also experiencing lower wage growth along the life-cycle. This result is difficult to reconcile with theories that predict that returns to skill have increased in the last 15 to 20 years, since an implication of such a theory is that - for a given education level - experience has become more and more valuable as new cohorts enter the labour market. A corollary of this (in perfectly competitive markets) is that the return to experience should become higher (i.e. the age profile should become steeper) for younger cohorts. We have showed that this is not the case. A second interesting piece of information is the one coming from the analysis of relative wages. This will allow us to test whether more recent cohorts -on average- have experienced higher returns to education.

4.2 Across-group comparisons: estimating cohort-specific life-cycle profiles for gross weekly relative wages

In this part of the research we investigate changes in returns to education as captured by across-group comparisons. For each geographical area and cohort we have generated the ratio between the mean wage of those with high education and the mean wage of those with low education (as previously defined). This is equivalent to creating an area-cohort-year specific "skilled-unskilled" relative wage, whose properties we have further analysed. Specifically, we have regressed the log of this ratio (i.e. the difference in the logs of real gross weekly wages) on a cubic in age, cohort dummies and the same variable capturing the economic cycle used in previous regressions. Notice that the possibility of generating such a relative wage arises naturally in our quasi-panel approach, in which we focus on the behaviour of representative individuals, characterized by their education level, their cohort of birth and their macro-region of residence. When we do not allow for age-cohort interaction (Table 3, col. 1), we find no evidence that (mean) education premium has increased as new cohorts have entered the labour market (with the exception of cohort 2, for which we have some positive evidence). As for the effect of age, our cubic signals that there is tendency for the education premium to increase along the life-cycle. When we allow for age-cohort interaction (Table 3, col. 2), we basically confirm this evidence: more recent cohorts tend to show higher entry-level education premium but this evidence is never statistically significant (actually for cohort 10 - the only one for which cohort effects are significant- we get a negative coefficient) while the slope on the first order term of the age-profile tends to become flatter (but again this evidence is not statistically significant). Overall, we read these results as showing that in Italy we do not find clear evidence in favour of across-cohort increasing returns to education. However we have some evidence that education and experience interact in such a way that the age-profile for more educated workers tends to be relatively steeper (but this effects does not vary significantly across generations).

4.3 Discussion

It is interesting to compare our result with those obtained by MaCurdy and Mroz (1995), who, using data from the CPS for the period 1977-1994, characterize the wage profiles for four groups of U.S. workers: high school dropouts, high school graduates, persons with some college education and college graduates. They find that real wages are monotonically increasing in educational attainment and that real wages were higher in 1980 than in 1990 for all groups, a part from College Graduates. Moreover, they cannot reject what they name the uniform-growth model for median wages, according to which, for each education group, cohorts share the same age profile, whose position though differs across cohorts. As for the shape of the age-profiles, the authors find that all education groups exhibit concave profiles (with the exception of the group with some college education, for which the profile is almost linear) and that those with higher education have higher wage growth at young ages, while wage growth stops at around age 45.

As for the position of the age profile (corresponding to the concept of entry wages), the evidence obtained by MaCurdy and Mroz points towards a dramatic drop for all groups except for College Graduates (this group experience a decrease from the years 1976 to 1980, then a raise, up to year 1989, and then a further drop). Moreover, they find that the drop is higher for the group with the lowest educational attainment. The overall evidence hence points towards a worsening of the relative position of the group with low education and a substantially unchanged position for the group of College Graduates. According to these results, the entry-wage college premium (which corresponds to the ratio of entry wages of college graduates over those of high school dropouts) has risen in the U.S. because the position of the group with low education has significantly worsened.

Beaudry and Green, using data from the Survey of Consumer Finances across the period 1971-1993, within a setup close to ours, look at the experience of only two groups: those with some or completed high school and college graduates. The results for mean wages are someway different from those of Mroz and MaCurdy. From the various models estimated, Beaudry and Green gather the following picture: on the one hand we have the group of those with some or completed high school, for which entry wages have been rising up to the 1978 cohort and then falling thereafter. For this group the two authors consistently find that the cohort-age interaction term has a negative coefficient, implying that more recent cohorts have been facing flatter age-profiles. The evidence that, past the 1978 cohort, entry wages for more recent cohorts are declining and that their age profiles are flatter suggests that it is quite unlikely that they will be able to catch up with the older cohorts. As for the group of college graduates, the evidence shows that more recent cohorts consistently start from lower wages and experience flatter age profiles.

When comparing the experience of Canadian and U.S. workers, we find that College Graduates have done better in the U.S. since, for the time horizon considered, they have not been experiencing the loss in real wages that their Canadian counterpart have. As for the groups with lower education, the two studies are not immediately comparable because the definitions for these groups do not coincide, but it appears that, after 1978, the experience of Canadian workers is not much better than that of their American counterparts. The formers have been experiencing dropping entry wages and lower wage growth, while the latter have been experiencing only dropping entry wages.

How are Italian workers doing when compared to workers from the US and Canada? The evidence for the age profiles of Italian workers obtained when we assume no age-cohort interaction (which corresponds to the model estimated by Mroz and MaCurdy) shows some similarities with that of analogously educated US workers as far as the age profiles are concerned, while it differs substantially with respect to the relative position of the various cohorts within the groups (declining cohort profiles irrespective of education). However, for Italy we cannot accept the uniform-growth model (i.e. the restricted model that imposes no age-cohort interaction), and our preferred estimation shows that each cohort -irrespective of education (a part from cohort 10 for the group with low education)- has been experiencing higher entry wages and flatter age profiles, when compared to its immediate predecessor. As in the US, in Italy as well when compared to workers with lower education, more educated workers tend to have higher entry wages and more concave age-profiles, hence experiencing higher wage growth in the first part of their life cycle (but younger cohorts are also facing flatter age profiles, for both education groups). When we compare the experience of Italian workers with High-education with those of U.S. College or High School Graduates we find that this group of Italian workers has been doing quite well. While in the U.S. High School

Graduates have been experiencing dropping entry wages and only College Graduates have been able to keep their relative position, for Italy we find quite different results (higher entry wages and flatter age-profiles). For the group with lower education, which we can compare to U.S. and Canadian High School dropouts, again we find that the experience of Italian workers differs substantially from that of their North American counterparts. In Italy we do not observe the dramatic drop in entry real wages that is observed for this group in the U.S. along the entire period considered by MaCurdy and Mroz and documented by Beaudry and Green for the post-1978 cohorts of Canadian low-education workers. On the contrary, we find rising entry wages together with flatter age profiles, so that, while we cannot conclude that younger generations of Italian Low-education workers are better off than older ones over the entire life-cycle, we can at least conclude that in Italy wages for the low-skilled group have not been dropping in the period here considered.

A previous study on Italian wages that uses longitudinal data is Lucifora and Rapelli (1995). There are some basic differences between their and our study. They use longitudinal data on individual observations for the period 1974-1988, coming from the National Institute for Social Security (INPS). They can follow the same individual through time and can control for more variables, among which sector, firm size and skill level. The more interesting models estimated by Lucifora and Rapelli are a cohort fixed effect model and a random effect model. In the first case they control for cohort dummies and cyclical time effects (hence similarly to us), while in the second case, besides cohort dummies, they allow for an error term that captures both an individual and a time stochastic factor.

Their results show that the cohort effects are robust to the introduction of a more complex error term structure and that the age profiles differ markedly from those that would be estimated with a single cross-section. Finally, they find that the degree of concavity of the age-profiles decreases as the estimated model becomes more complex.

Comparing these results to ours, we notice that the evidence of rising cohort effects is common in both studies, while the basic difference is in terms of age profiles, which, in the study of Lucifora and Rapelli, tend to be more linear for the individuals with lower education.

5. What about within-cohort inequality?

One of the main findings of the literature that has studied wage inequality is that residual inequality (defined as the inequality of the residual from a typical Mincerian wage equation) in the last 15-20 years has increased substantially (see Acemoglu, 2002). This has been interpreted either as evidence of skill-biased technological change or as a "measure of our ignorance". While residual inequality is an interesting subject on its own, here we are interested in verifying how overall wage inequality has changed across and within cohorts. We focus on a simple measure of inequality (the 90-10 percentile differential) and we verify how it varies both along the life-cycle (the age profile for wage inequality) and across-cohorts.[18] As usual we have an identification problem, and the solution to this problem is the same we proposed for the mean: we assume that the only time effects are cyclical effects, and we characterize both the age and the cohort profiles for the dependent variable.

High education

For this group we find that there is relevant across-cohort and life-cycle variation. In fact, a restricted model in which we do not allow for age-cohort interaction and age enters only with a first order term, shows that younger cohorts -especially cohort 6 to 9 (see Table 4, col.1)- have been facing more inequality and that the latter rises (linearly) with age. These results are not totally confirmed when we allow for age-cohort interaction (Table 5, col. 1). In this case, with a cubic model in age we find negative and declining (rising in absolute values) cohort effects (but never significant at customary confidence levels) up to cohort 7, followed by rising effects (but again never significant). We also find that the coefficients on the age-cohort dummies interaction terms are positive and rising in value up to cohort 7, signalling that the age profile for absolute inequality is getting steeper for younger cohorts. However these effects are significant only for cohort 6 and 7.

[18] The 90-10 percentile differential is a measure of absolute wage inequality, since it just captures how far apart are the 90th and the 10th percentiles. Such a measure is not affected by changes in the central locations (the mean or the median) of the distribution. On the contrary, if we considered the differential in the logs of the 90th and 10th percentiles, we would be looking at relative changes. It is easy to see that changes in the central locations of the distribution that do not affect the 90-10 percentile difference (and hence would lead us to conclude that there have been no changes in absolute inequality) would lead to variations in the difference between the logs of the 90th and 10th percentiles (hence pointing towards an increase in relative inequality).

To reconcile these apparently opposite results (declining versus rising cohort effect) we have to realize that, when we allow for full cohort-age interaction, we permit the cohort profiles to be more flexible, and, particularly, we allow them to cross. If for instance the data point towards dropping cohort effects and positive and increasing coefficients on age-cohort interaction, we could observe some crossing of the life-cycle profiles for inequality, showing that younger generations start with lower wage inequality, which then increases with age. If we restricted the functional form to exclude those age-cohort interaction terms we would be forcing the data to exhibit rising cohort effects, in order to capture those crossings that the data actually show. We expect that the stronger and more significant are those excluded cohort-age interaction terms, the less significant are the cohort effects that we estimate in the restricted model. In the case of High Education workers the evidence shows that those age-cohort interaction terms are not very significant and hence the cohort effects estimated in the restricted model are quite significant.[19] In fact, when performing a Wald test on the joint significance of the estimates for the parameters on the age-cohort interactions we find that we cannot reject the Null hypothesis that all the parameters are jointly equal to zero, so that the restricted model appears more appropriate.

Low education

For this group, the restricted model with no age-cohort interaction and with age entering linearly shows clear evidence of positive cohort and age profiles (i.e. inequality rises as younger cohorts enter in the labour market and as workers become older). The unrestricted model, with age-cohort interaction terms, shows similar results: cohort effects are declining only for the first three cohorts while they rise thereafter (they are negative but their absolute value becomes smaller past cohort 3). Moreover the estimates for the age-cohort interaction coefficients are positive, rising and significant (with the exception of cohort 2). For this group both the restricted and the unrestricted model show consistent evidence that younger cohorts of workers with low-education have been facing more inequality at the entrance in the labour market and the effect of age on inequality has been rising as well. When performing a Wald test on the estimates for the age-cohort interaction terms we find that we can reject the Null, so that the unrestricted model appears more appropriate.

[19] This is just the mirror image of what happens when estimating the profiles for mean wages for this group.

Overall it appears that, for both education groups, inequality increases along the life-cycle, as predicted by models in which ability is revealed with experience. We have sufficient evidence that younger cohorts face higher inequality even at the entrance in the labour market, and -for the group with lower education- we also find that the age profile for inequality has become steeper for more recent generations (but this evidence is not statistically significant).

Once again it is interesting to compare the experience of Italian workers with that of their North American counterparts. The work by MaCurdy and Mroz (1995) for the U.S. finds that within each education group there is evidence of an increase in the 90-10 percentile difference along the life cycle. At the same time they find that with time (and hence across cohorts), the 90-10 percentile difference has been shrinking for the group with the lowest education (high school dropouts), it has remained roughly constant for the groups with the average level of education and it has increased slightly for the youngest generations of College Graduates. Overall they conclude that, within each education group, real absolute dispersion (within-group inequality across cohorts) has not increased much, while there is strong evidence of a widening of the wage distribution across education groups. But this is due to a widening of the mean and median education wage premium. Hence they argue that "the location of the wage distribution for each education group shifted homogeneously across time and all ages, and the real absolute dispersion about the central tendency remained roughly constant". This, together with the evidence that for all groups, with the exclusion of College Graduates, median "entry" wages have been falling across cohorts, leads to the conclusion that what is driving the observed increase in the skill-premium for the U.S. is really the fall in the real wages of less educated workers.[20]

Beaudry and Green (2000) looking at the performance of the 90-10 percentile differential for various education groups of Canadian workers, find significant evidence that absolute inequality increases along the life-cycle (similarly to the findings of MaCurdy and Mroz and consistently with the human capital model for wages). They also find that Canadian cohorts experience different values for the 90-10 percentile differential. Specifically, they show that for both groups considered (workers with some

[20] Note that these findings are consistent with an increase in relative inequality, which would be driven by the variation in the median wage for each group.

or completed High school and College Graduates), absolute within-cohort wage inequality increases across successive cohorts up to the cohort that entered the labour market in 1984 after which it basically stopped. Moreover they find that the coefficient on the age-interaction term is negative, so that as they age, more recent cohorts experience lower increase in inequality.

Our results indicate that, as far as inequality in concerned, the experience of Italian workers is only partially similar to that found by Mroz and MaCurdy for the U.S. or Beaudry and Green for Canada. Similarities refer to the fact that we find that wage inequality increases over the life-cycle. The main difference refers to the fact that we consistently find evidence -stronger for the group with lower education- that the cohort profiles for wage inequality are positive across education groups.

6. Conclusions

Within a framework in which inter and intra-generational comparisons of labour market performance are well defined, we have characterized the wage patterns for various cohorts of Italian full time employees. Our results show that –over the period 1987-2006- Italian workers have had an overall better labour market experience than their North American counterparts. Previous studies by Mroz and MaCurdy for the U.S. and Beaudry and Green for Canada have in fact documented the strong decline with time in the relative position of workers with low education, when compared to College Graduates, clarifying how such a change is if fact the result of a drop in real wages for low education workers together with almost constant real wages for College Graduates. On the contrary, for Italy we find that both education group considered (High vs. Low Education) share similar patterns: younger generations have been doing better than previous ones at the entry in the labour market, but the age profiles of more recent generations are becoming flatter. Along the life-cycle this could offset the benefits coming from higher entry wages, so that we cannot conclude that more recent generations are overall better off, but we can safely conclude that Italian fully-employed workers with low education have had a better performance in comparisons with their North American counterparts. What are left to be explained are the reasons for such a different outcomes. One possibility is that the forces at play are different. For instance we could argue that the U.S. and Canada in the late 1970s and early 1980s experienced a technological revolution that favoured skilled over unskilled workers, while Italy did not. The problem with this simple "demand driven" interpretation is that it does not appear to be consistent with the data. In fact, if we do not consider the supply side of the story, a skilled-biased technological change should lead to an increase in the education premium, due to the fact that educated workers become absolutely better off while low skill workers more or less keep the same real wage. However, what we observe in the U.S. and Canada is something different: younger cohorts of college workers barely kept their position while younger generations of low-education workers are strictly worse off. Hence a pure labour demand interpretation of the phenomenon is not appropriate for North America as well. Returns to skill and education have increased in North America, together with an increase in the literacy rate. A skill-biased technological change hypothesis would be consistent with the data only as long as we allow for (skill/education dependent) labour supply adjustment. But the latter is also potentially affected by the secular changes observed in the female participation rate, which could have affected the education premium in a way consistent with the data as long as the labour force participation rate in recent generations is higher among women with low education. Finally it is possible that the different outcome in Italy is due to the successful effort of Unions directed to the compression of the earnings distribution. If these efforts are successful in a situation where we observe a shock on the demand side favouring skilled labour, then, in an Inside-Outside framework, we would observe that the unemployment rate has increased more for younger generations of unskilled workers. While this study, belonging to the class of reduced form estimation, has just characterized the wage patterns for Italian male employees, future research should try to disentangle the wage and the unemployment effects and quantify their relative importance.

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Annex – Tables

Table 1: Log of Gross Wages-Synthetic Cohorts: no Age-Cohort interaction

	High Education (Secondary,Tertiary and Post-Tertiary Education)	Low Education (Primary Education or less)
Age	-0.0069 (0.0049)	-0.0184** (0.0045)
Cohort 2	-0.0616 (0.0640)	-0.0778** (0.0277)
Cohort 3	-0.1646** (0.0706)	-0.1366** (0.0506)
Cohort 4	-0.3140** (0.0892)	-0.2422** (0.0750)
Cohort 5	-0.4466** (0.1133)	-0.3943** (0.0939)
Cohort 6	-0.6181** (0.1326)	-0.5445** (0.1189)
Cohort 7	-0.7701** (0.1467)	-0.6986** (0.1312)
Cohort 8	-1.0057** (0.1599)	-0.9069** (0.1456)
Cohort 9	-1.2670** (0.2066)	-1.1563** (0.1663)
Cohort 10	-1.7336** (0.2073)	-1.8853** (0.1595)
Centre	-0.1242** (0.0376)	-0.0791** (0.0340)
South	-0.1352** (0.0392)	-0.1484 ** (0.0313)
Output gap	-0.0289** (0.0079)	-0.0125** (0.0062)
Intercept	3.8443** (0.2654)	3.8877** (0.2439)
Adj. R2	0.68	0.52
Number of Obs.	175	181
Dependent Variable	Log of Gross (Weekly) Wages	Log of Gross (Weekly) Wages

Note: Standard Errors are in parenthesis.
** 95% of significance.
* 90% of significance.

Table 2: Log of Gross Wages: Synthetic Cohorts with Age-Cohort interaction

	High Education (Secondary, Tertiary and Post-Tertiary Education)	Low Education (Primary Education or less)
Age	0.9028** (0.1927)	0.6291** (0.2035)
Age Square	-0.0103** (0.0048)	-0.0040 (0.0050)
Age Cube	0.0000 (0.0000)	-0.0000 (0.0000)
Cohort 2	2.4401 (1.8165)	2.3201** (0.9723)
Cohort 3	5.4937** (1.9652)	5.0037** (1.2577)
Cohort 4	8.4909** (2.2542)	7.8598** (1.6000)
Cohort 5	11.0107** (2.4943)	10.4688** (1.7889)
Cohort 6	13.3238** (2.6295)	12.7162** (1.9419)
Cohort 7	15.2732** (2.7241)	14.2433** (2.0183)
Cohort 8	16.8799** (2.8182)	15.3328** (2.1543)
Cohort 9	20.4859** (3.0799)	17.6323** (2.3231)
Cohort 10	29.2581** (2.9394)	-21.0931** (5.8630)
Age*Cohort 2	-0.0442 (0.0340)	-0.0439** (0.0181)
Age*Cohort 3	-0.1055** (0.0372)	-0.0972** (0.0241)
Age*Cohort 4	-0.1731** (0.0439)	-0.1609** (0.0320)
Age*Cohort 5	-0.2370** (0.0502)	-0.2270** (0.0367)
Age*Cohort 6	-0.3048** (0.0546)	-0.2926** (0.0419)
Age*Cohort 7	-0.3712** (0.0589)	-0.3455** (0.0455)
Age*Cohort 8	-0.4392** (0.0642)	-0.3938** (0.0535)
Age*Cohort 9	-0.5976** (0.0812)	-0.5005** (0.0642)
Age*Cohort 10	-1.0310** (0.0787)	1.2254** (0.2592)
Centre	-0.1224** (0.0309)	-0.0825** (0.0278)
South	-0.1432** (0.0331)	-0.1522** (0.0273)
Output gap	0.0101 (0.0097)	0.0179** (0.0076)
Intercept	-19.6651** (3.4128)	-15.7227** (3.1262)
Adj. R2	0.81	0.70
Number of Obs.	175	181
Dependent Variable	Log of Gross (Weekly) Wages	Log of Gross (Weekly) Wages

Note: Standard Errors are in parenthesis.
** 95% of significance. * 90% of significance.

Table 3: High/Low Education Difference in log of Gross Wages: Synthetic Cohorts

	Without Age- Cohort Interaction	With Age- Cohort Interaction
Age	0.1460** (0.0569)	0.1059 (0.1255)
Age Square	-0.0038** (0.0014)	-0.0026 (0.0032)
Age Cube	0.0000** (0.0000)	0.0000 (0.0000)
Cohort 2	0.0797 (0.0552)	0.6112 (1.2064)
Cohort 3	0.0268 (0.0523)	1.0002 (1.1990)
Cohort 4	0.0213 (0.0652)	0.9302 (1.4645)
Cohort 5	0.0251 (0.0677)	0.6177 (1.5828)
Cohort 6	-0.0301 (0.0670)	0.5497 (1.6112)
Cohort 7	-0.0241 (0.0711)	0.5014 (1.6357)
Cohort 8	-0.0447 (0.0750)	0.4259 (1.7081)
Cohort 9	-0.0202 (0.0829)	0.3493 (1.7678)
Cohort 10	0.0010 (0.1084)	-5.8262** (1.9455)
Age*Cohort 2	n.a.	-0.0095 (0.0226)
Age*Cohort 3	n.a.	-0.0183 (0.0224)
Age*Cohort 4	n.a.	-0.0172 (0.0285)
Age*Cohort 5	n.a.	-0.0097 (0.0317)
Age*Cohort 6	n.a.	-0.0091 (0.0327)
Age*Cohort 7	n.a.	-0.0075 (0.0339)
Age*Cohort 8	n.a.	-0.0055 (0.0379)
Age*Cohort 9	n.a.	-0.0016 (0.0430)
Age*Cohort 10	n.a.	0.2764** (0.0605)
Centre	-0.0417** (0.0165)	-0.0449** (0.0171)
South	0.0326* (0.0197)	0.0287 (0.0198)
Output gap	-0.0197** (0.0054)	-0.0186** (0.0063)
Intercept	-1.6308** (0.7160)	-1.5446 (2.0988)
Adj. R2	0.75	0.76
Number of Obs.	175	175
Dependent Variable	Ratio of log of Gross (Weekly) Wages	Log of Gross (Weekly) Wages

Note: Standard Errors are in parenthesis.

** 95% of significance.

* 90% of significance.

Table 4: P90-P10 for Gross Wages-Synthetic Cohorts: no Age-Cohort interaction

	High Education (Secondary-Tertiary and Post-Tertiary Education)	Low Education (Primary Education or less)
Age	0.0468** (0.0059)	0.0297** (0.0047)
Cohort 2	0.1879 (0.2116)	0.1376 (0.1115)
Cohort 3	0.2038 (0.1918)	0.2301** (0.1007)
Cohort 4	0.2146 (0.2062)	0.3223** (0.1221)
Cohort 5	0.4062* (0.2088)	0.5170** (0.1253)
Cohort 6	0.4220* (0.2305)	0.6340** (0.1352)
Cohort 7	0.5915** (0.2446)	0.8620** (0.1851)
Cohort 8	0.5722** (0.2593)	1.0714** (0.2194)
Cohort 9	0.9302** (0.4157)	1.3745** (0.3727)
Cohort 10	0.6919** (0.3425)	2.2090** (0.9709)
Centre	0.0193 (0.0681)	0.0331 (0.0444)
South	0.1010 (0.0702)	0.5223** (0.0624)
Output gap	-0.0319* (0.0178)	-0.0262 (0.0167)
Intercept	0.3953 (0.3815)	0.2778 (0.2826)
Adj. R2	0.39	0.44
Number of Obs.	175	181
Dependent Variable	P90- P10 for Gross (Weekly) Wages	P90-P10 for Gross (Weekly) Wages

Note: Standard Errors are in parenthesis.
** 95% of significance.
* 90% of significance.

Table 5: P90 - P10 for Gross Wages-Synthetic Cohorts: with Age-Cohort interaction

	High Education (Secondary-Tertiary and Post-Tertiary Education)	Low Education (Primary Education or less)
Age	-0.0664 (0.2684)	0.2159 (0.3046)
Age Square	-0.0076 (0.0072)	-0.0058 (0.0075)
Age Cube	0.0001 (0.0000)	0.0000 (0.0000)
Cohort 2	-3.5597 (4.8355)	-4.5064** (2.1477)
Cohort 3	-7.4768 (4.7017)	-6.0097** (2.0176)
Cohort 4	-9.6086* (5.2580)	-4.4131* (2.4494)
Cohort 5	-10.7736* (5.5005)	-4.5573* (2.6913)
Cohort 6	-12.8763** (5.6878)	-3.5935 (2.8677)
Cohort 7	-13.2225** (5.7406)	-2.4329 (2.9894)
Cohort 8	-13.0805** (5.8114)	-2.1768 (3.1737)
Cohort 9	-8.7991 (7.2229)	0.0936 (4.4252)
Cohort 10	2.9408 (6.4707)	543.9628** (12.8258)
Age*Cohort 2	0.0680 (0.0891)	0.0850** (0.0405)
Age*Cohort 3	0.1456* (0.0866)	0.1180** (0.0379)
Age*Cohort 4	0.1923* (0.0992)	0.0858* (0.0475)
Age*Cohort 5	0.2245** (0.1056)	0.0944* (0.0537)
Age*Cohort 6	0.2820** (0.1117)	0.0721 (0.0594)
Age*Cohort 7	0.2998** (0.1147)	0.0419 (0.0657)
Age*Cohort 8	0.2950** (0.1186)	0.0394 (0.0787)
Age*Cohort 9	0.1400 (0.2035)	-0.0410 (0.1470)
Age*Cohort 10	-0.4193** (0.1873)	-24.8765** (0.5810)
Centre	0.0348 (0.0661)	0.0295 (0.0429)
South	0.1127 (0.0702)	0.5123** (0.0618)
Output gap	-0.0524** (0.0202)	-0.0237 (0.0180)
Intercept	12.6865** (5.9662)	0.9519 (4.5866)
Adj. R2	0.45	0.51
Number of Obs.	175	181
Dependent Variable	P90-P10 for Gross (Weekly) Wages	P90-P10 for Gross (Weekly) Wages

Note: Standard Errors are in parenthesis.
** 95% of significance.
* 90% of significance.

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Abstract
Are younger generations better off than older ones? Can younger cohorts starting with lower real wages catch up with previous generations? Are young or old generations becoming more unequal? In this study we concentrate on the study of inter-generational and intra-generational patterns of earnings for Italian male dependent workers for the period 1987-2006. Using data from the Bank of Italy's Survey of Household Income and Wealth, we construct cohort-education-(macro) region-specific age profiles for mean real wages (the measure of central location here adopted) and for the 90-10 percentile differential (the inequality measure), allowing for region-specific price indexes. We verify how different cohorts have been doing comparatively and finally we test whether, with time, the (mean) returns to experience and education have increased.
Our results indicate that, for the two education groups considered, each successive generation has benefited from higher entry wages. At the same time, we find that the wage age-profiles for both education groups have become flatter so that we cannot conclude that more recent cohorts are better off than their immediate predecessors. When looking at high/low education relative wages, we find that there is only scant evidence of positive cohort profiles (i.e. that the education premium has been rising across cohorts), while we notice that the relative wage tends to increase over the life-cycle. Finally, we find that inequality tends to increase with age, while we also find evidence of across-cohort variation, in the direction of increasing inequality.
Our work is relevant under various aspects. On the one hand, it provides a clear framework in which between and within cohort comparisons are meaningful and easily interpretable. Moreover, it allows us to relate our results to those obtained by MaCurdy and Mroz (1995) and Beaudry and Green (2000) in their studies of the earning patterns of, respectively, American and Canadian workers.

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