The best youth:
evidence from Italy

Paolo Naticchioni[♥], Michele Raitano[♦] and Claudia Vittori[♠]

VERY PRELIMINARY VERSION: PLEASE DO NO QUOTE OR CIRCULATE

21 June 2013

Abstract

This paper documents the evolution of the young seniority-earnings profiles in Italy across four birth cohorts (1960-1964, 1965-1969, 1970-1974, 1975-1979), followed along the first ten years of their working career over the period 1975-2009. We explore the average trends and also how the patterns vary across the distribution, looking at the bottom and top percentiles, disentangling the differences by educational attainments. Results suggest that most recent cohorts have been penalized in terms of entry earnings and in terms of seniority profile. We also show that the group that has been more penalized is that of graduates, which should instead represent the best youth of a country.

1. Introduction

The economic situation of young workers has been lively debated at the European level in the last years. Due to economic crisis, the unemployment rate for young workers increased massively, reaching almost 25% at the EU level, and 40% at the Italian level. Also for earnings, there is evidence that most recent cohorts that entered the labour market display lower entry wages with respect to previous cohorts.

For the UK, Gosling et all (2000) explore how education differentials along with cohort effects explain a big portion (two thirds) of the overall increase in wage dispersion (1966-1994). Successive new generations of workers who entered the labour market have shown more and more dispersed wages which have persisted over time to create more unequal wages. Similar findings are derived for Canada by Beaudry and Green (2000) and Beach and Finnie (2004) who find a declining entry wage for those entered in the labour market during the '90s. Also for the US Card and Lemieux (2001) show that increase in inequality might be at least partially explained by a cohort effect.

[♥] University of Cassino and Southern Lazio, IZA
[♦] Sapienza University of Rome and Giacomo Brodolini Foundation
[♠] Sapienza University of Rome

As for Italy, some papers have investigated the generational gaps along the career path using INPS or SHIW data up to 2004 (e.g. Rosolia and Torrini 2007; Sartor, Schizzerotto and Trivellato 2011). Rosolia and Torrini (2007) provide some first evidence on the Italian labour market focusing on administrative data, that, however do not record individual education. To overcome this issue they proxy the educational achievement by the observed entry age, assuming that workers who entered the labour market at age 21-22 are very likely to have completed secondary education and workers entered at age 25-26 hold a college degree. To deal further with education issues they use Bank of Italy SHIW data, so loosing the longitudinal dimension.

This paper contributes to this literature for the Italian case. With respect to Rosolia and Torrini (2007) we make use of a new database, the AD-SILC, which merges information from the Italian sample of the Survey on Income and Living Condition (SILC) for 2005 and all administrative archives managed by the Italian Social Security Institute (INPS), which allows reconstructing the whole working history of the individual observed in the SILC sample. As, papers considering INPS data cannot control for education, that, as known, is instead a crucial determinant of earnings. In our case, this limitation has been overcome through the merge with the IT-SILC survey, that record the value at 2005 of dozens of individuals' and households' characteristics. Moreover, with respect to Rosolia and Torrini (2007), the time span is updated, and it covers the period 1975-2009. Another additional advantage of this dataset is that, differently from the other datasets based on INPS data that only include private employees and some groups of self-employed, AD-SILC also includes information coming from Workers and Retired Registers, so allowing to observe the whole working careers of each type of worker.

Our main focus in the paper is on cohort effects. For such a reason, we group individuals according to their birth year in 4 cohorts – 1960-1964, 1965-1969 , 1970-1974 and 1975-1979 – and we follow their working careers since the year of entry on the labour market up to their 11th year of labour market experience.

Apart from a descriptive analysis, we estimate a simple model in order to identify the components of wage dynamics that are cohort specific and seniority specific and, at the same time, to control for business cycle (proxied by GDP growth and regional unemployment rates) and basic individual characteristics such as gender, part time contracts, education. The dependent variable is the yearly gross private employees earnings.

Our results clearly shows that the entry earnings substantially decrease, i.e. around 10%, from the oldest to the newest cohort. When focusing on individuals with tertiary education the entry earnings gap is just lower, around 5%. When taking the seniority patterns, it comes out that graduates of the youngest cohort experience a wage growth which is much reduced with respect to the oldest cohorts. Overall, graduates are the group of individuals that worsen the most across cohorts.

Similar results are derived when using weekly wages instead of yearly wages, and when controlling in the set of covariates for the earnings of prime age workers, in order to investigate the relative position of young with respect to prime age.

We then move to investigate whether the deterioration of the most recent cohorts observed for average wages is uniform along the wage distribution, or on the contrary whether it refers more to skilled or unskilled workers. We make use of unconditional quantile regressions, proposed by Firpo, Fortin, Lemieux (2009). By using this methodology it is possible to estimate a given unconditional percentile of a distribution as function of a set of covariates, in such a way doing something very similar to what we did for average wages.

Interestingly, for the 10th and the 25th percentiles of the distribution, the entry level of yearly earnings increases across cohorts. The patterns in the first 11 years of seniority point out a clear catching up of the 60-64 cohort which is the one that increases the most, showing the highest level after 11 years. From the median there is no longer evidence of a gain of the most recent cohort: at the 50th, 75th, 90th percentile the curve of the most recent cohort is always the lowest along the 11 years time seniority span, and differences with the other cohorts become wider moving from the median to the 90th percentile.

Results are much stronger when carrying out the same exercise for the group of graduates. Also in this case from the median to the 90th percentile the entry earnings of the two most recent cohorts are lower than those of the oldest ones. And also in a seniority dimension, earnings of the most recent cohorts are also always lower than those of the oldest one. The finding for the 90th percentile is impressive: entry earnings are not much far away across cohorts (the lowest is anyway the most recent), while the dynamics over time is such that for the youngest cohort the dynamics is basically flat, i.e. earnings do not increase over time.

So findings of this paper clearly show that the Italian "best youth" – the graduates –, have suffered a much stronger earnings penalty with respect to the other educational groups. The Italian "best youth" has then been massively hit even before the rise of the crisis.

In detail the paper is organized as follows: next section will briefly review the related literature, especially as regards the Italian case. In section 3 the characteristics and the main pros of the AD-SILC dataset will be discussed and in section 4 the structure of the estimated models will be presented. The following sections will show the main results of the empirical analyses coming out from the descriptive evidence (section 5), the OLS estimates (section 6) and the unconditional quintile regressions (section 7). Final, some remarks about the determinants of the results found in our analyses will be discussed in the conclusive section.

2. Related literature

To be added

3. Dataset

Long panel datasets or homogenous repeated cross-sectional surveys are needed to analyze the time trend of earnings. In Italy the evolution of wage inequality is usually studied using microdata provided by the Survey on Household Income and Wealth, which is carried out every two years by the Bank of Italy (Brandolini et al., 2001), while the time span covered by surveys homogeneous at the EU level is still limited (the ECHP covers the period 1994-2001, while the EU-SILC for now refers to the period 2004-2011).

In this paper we use a panel on individual working histories, called AD-SILC, recently built merging the IT-SILC 2005 survey sample (i.e. the Italian version of EU-SILC 2005, carried out by ISTAT) with the administrative records on individual working histories since their entry in the labour market up to 2009 that are collected in all administrative files managed by the Italian National Social Security Institute (INPS).

AD-SILC is the first panel available for Italy that allows to observe a large part of individual working histories and collects detailed information on individual gross earnings, working statuses and characteristics (e.g. education).

Actually, a great deal of longitudinal data is collected in the administrative archives managed by INPS (the Italian Social Security Institute), which, among the others, record, on a yearly base, for each working episode gross earnings and the number of working weeks related to these earnings[1]. However, these archives record only the information needed for administrative purposes. In particular the INPS files do not record individuals' education, that, as known, is instead a crucial determinant of earnings. This limitation has been overcome through the merge with the IT-SILC survey, that record the value at 2005 of dozens of individuals' and households' characteristics.

Therefore AD-SILC is a retrospective panel – being the reference population that surveyed by ISTAT in 2005 – and is composed of about 1.2 million observations concerning 43,388 individuals recorded at least once in administrative files.

Furthermore, differently from the other datasets based on INPS data (e.g. the WHIP and the CLAP datasets) that only includes private employees and some groups of self-employed (i.e. craftsmen, dealers, farmers and parasubordinate workers), AD-SILC also includes information coming from Workers and Retired Registers (*Casellario degli Attivi e dei Pensionati*), so allowing to observe also whole working careers of public employees and professionals[2].

Hence, the administrative sources allow to exactly reconstruct for each individual the time of entry in the labour market, actual experience and annual earnings (earnings are considered in Euros, converted to 2010 constant prices using the price index consumption)[3]. These sources allow to include further individual controls, as the Region where the individual works, his gender, age, actual experience and the contractual arrangement (i.e. part-time versus full-time)[4]. The matching with the survey data allows to add information on educational attainment, that in this paper has been codified through by three dummies about the highest degree achieved: at most lower secondary (ISCED 1-2), upper secondary (ISCED 3) and tertiary or post-secondary (ISCED 4-5). Being available in EU-SILC the information about the year when the highest degree was attained, we

[1] Administrative data are much less plagued by measurement errors than survey data. By their nature, administrative archives are not balanced – because individuals are followed for a different number of years since the moment they start to work – and not plagued by attrition: if someone disappears from the archives it means that he/she has stopped to work or has gone to work abroad.

[2] Moreover, these other longitudinal datasets do not follow individuals since their entry in the labour market, but since a given date (e.g. from 1985), hence preventing from identifying the working histories before that date.

[3] For reducing the impact of outliers we dropped, in each year, the top 1% and those earning less than 1,000 Euros (at 2010 prices).

[4] The distinction between open-ended and fixed-term contract is instead available since 1998 only. Employers' characteristics (e.g. firm's size and sector) are recorded since 1987 only.

consider the educational level held in that year (around 10% of Italian workers start to work before completing the educational process).

The retrospective panel AD-SILC is based on the representativeness of the Italian population in 2005. Its cross-sections (before and after 2005) can be used to obtain reliable estimates for aggregates whose sampling distribution (e.g. by age) is similar to that of the population. For this reason, the analysis is carried out not taking into account the immigrant population (they are under-represented in the retrospective panel because of their greater mobility in and out of Italy) and the active population aged over 45 years (for the construction of the dataset, which refers to individuals interviewed in 2005, the sample representativeness of older workers in the early years of observation in AD-SILC, as the '70s is not sufficient).

Taking into consideration these caveats, we proceed to assess the evolution of the earnings distribution in the beginning phase of working careers. More in detail we group individuals according to their birth year in 4 cohorts – 1960-1964, 1965-1969 , 1970-1974 and 1975-1979 – and we follow their working careers since the year of entry on the labour market[5] up to their 11th year of labour market experience (as employees or self-employed).

We observe the earnings path in the period 1975-2009. Years prior 1975 are not used because the variable collecting earnings is not reliable before that date (so we cannot extend our analysis to those born before 1960).

We follow all types of workers (i.e. public and private employees and self-employed), so as to precisely identify the year of entry in the labour market and the actual experience[6]. However, as regards earnings, in this paper we refer to private employees only, because self-employed incomes are plagued by huge problems of underreporting and truncation and public employees, professionals and parasubordinates' earnings are available since 1996. Then the main variable of interest of our analyses is the annual gross income from private employment (i.e. including personal income taxes and employees' social insurance contributions).

Due to these restrictions, the final sample used in this paper is composed by 84,099 observations concerning 9,822 individuals born in the period 1960-1979.

4. Empirical strategy

As said, the aim of this paper is comparing the earnings path in the first phase of the working life by individuals belonging to four birth cohorts and distinguishing them by educational attainments.

This comparison is carried out through three methodologies[7]: i) showing sample means and percentiles (section 5); ii) estimating mean earnings profiles through OLS regressions (section 6); iii) estimating the trends of different points in the earnings distribution using unconditional quantile regressions (section 7).

---

[5] We dropped from the sample those aged at the entry year on the labour market more than 35.

[6] The entry year is identified as the first year with a working episode lasting at least 13 weeks and an age no lower than 15.

[7] The analyses of the following sections have been carried out using the sample weights provided in IT-SILC 2005.

Results are presented through figures where descriptive and estimated trends in the first 10 years of labour market experience following the entry year[8] are shown.

The descriptive evidence refers to sample means and percentiles (P25 and P75) of the gross annual earnings from private employment distribution computed for the four birth cohorts in each of the ten working years following the entry one and also distinguishing workers according to their education.

However, descriptive plots are to be taken with caution because they do not take into account individual characteristics and business cycle effects on the patterns characterizing different cohorts at different seniorities. Thus, in the second step of our empirical analysis, we move to estimate through OLS average earnings profiles that isolate these effects.

In order to estimate mean earnings along the career, the baseline Model 1 considers as dependent variables individual earnings w_{ijt} (where *i* is the individual, *j* the birth cohort and *t* the year) and includes as covariates the four birth cohorts, to allow for different intercepts[9], and the interaction terms between the four cohort dummies and the labour market experience. In order to capture possible non linearities we interact experience with birth cohorts up to the third degree. Further a set of control variables X_{it} is included: individual characteristics – gender, education, a dummy on part-time arrangement and regional dummies – and proxies of the business cycle, i.e. the GDP real growth rate in the previous year and the current regional unemployment rates, both included through a third order polynomial (see equation 1)[10].

$$w_{ijt} = \beta_j * cohort_j + \gamma_j * seniority_{ijt} * cohort_j + \delta_j * seniority_{ijt} \text{^} 2 * cohort_j$$
$$+ \eta_j * seniority_{ijt} \text{^} 3 * cohort_j + X'_{ijt}\gamma + \varepsilon_{ijt} \qquad (1)$$

Therefore, estimated mean earnings along the first ten years of the working life are computed adding the values of the estimated interactions between the cohort and the experience to the cohort specific β_j coefficient.

Afterwards we investigate if results are affected by the diffusion of unemployment spells during the year (Model 2), considering as dependent variables weekly wages (computed dividing annual earnings and the number of worked weeks during the year).

Then, we extend Model 1 including among the covariates the mean annual earnings of prime-age private employees (i.e. those aged 35-44 in the full AD-SILC sample), in order to further depurate patterns specific to the beginning phase of the career from trends common to all employees (Model 3).

Finally we aim at investigating the patterns of different percentiles of the wage distribution over time in a cohort dimension making use of unconditional quantile regressions, proposed by Firpo, Fortin and Lemieux (2009). By using this methodology it is possible to estimate a given percentile of a distribution as function of a set of covariates, in

[8] Annual earnings in the entry year are not considered because their values are clearly much lower than those of the following years being the individuals employed only for some month in the starting year. Therefore, in the figures presented in this paper the experience 1 refers to the working year following the entry one.

[9] In order to estimates absolute values for each cohort the model does not include the intercept.

[10] In the following sections these models are also run splitting individuals by education.

such a way doing something very similar to what we do for average wages. The goal of this final step is to investigate estimated patterns are uniform along the wage distribution.

The basic idea behind the unconditional quantile regressions is to estimate a linear regression where the dependent variable Y is replaced by the recentered influence function (RIF) of the distributional parameter ν, $RIF(y;\nu)$. The RIF is obtained by adding the distributional parameter of interest to the influence function $IF(y;\nu)$[11].

An useful property of the $RIF(y;\nu)$ is that its expected value is the statistic of interest. Hence, using the law of iterated expectations, it is possible to write:

$$\nu = E[RIF(Y;\nu)] = E_X\{E[RIF(Y;\nu)|X]\} \tag{2}$$

In its simplest form, the conditional expectation of the $RIF(y;\nu)$ can be written as a linear function of the covariates, yielding the RIF regression (Firpo et al, 2009):

$$E[RIF(Y;\nu)|X] = X\gamma^{\nu} \tag{3}$$

where the parameters γ_t^{ν} can be estimated by OLS. The parameter ν can be whatever distributional parameters, such as the Gini index, the variance or the percentiles of the wage distribution. The extension to the percentiles of the wage distribution has been proposed by Firpo, Fortin, Lemieux (2009). In such a way we can write the percentile of the distribution as a function of the set of covariates ($\nu = E[RIF(Y;\nu)] = E_X\{E[RIF(Y;\nu)|X]\}$), and so doing isolating the contribution of the variables we are interested in (cohort and seniority), as we did for average wages.

It is worth stressing the importance of using unconditional quantile regressions instead of the standard conditional quantile regressions (Koenker and Basset, 1978). Conditional quantile regressions provide the contribution of the set of covariates on the conditional distribution of wages. More specifically, when using conditional quantile regressions computed for instance at the median the estimates refer to the median of the 'error term', whereas using median unconditional quantile regressions it is possible to recover the impact of the covariates on the median of the unconditional distribution, that is what we are interested in.

From a practical point of view, we estimate by OLS the recentered influence function for the 10th, 25th, 50th, 75th, 90th percentiles of the yearly employees earnings on the same set of covariates used in Model 1 when estimating average earnings. In such a way we can isolate the contribution of the different cohorts and of seniority in the first 10 years of workers' career.

---

[11] The influence function (Hampel 1974) is a statistical tool, used to assess the robustness of a distributional statistic to the presence of outliers, which detects the contribution (also defined as *influence*) of each observation to the distributional parameter of interest. As an example, the influence function of the variance is $(y-\mu)^2 - \sigma^2$, and the RIF is $\sigma^2 + [(y-\mu)^2 - \sigma^2] = (y-\mu)^2$. Hence, each observation is replaced by its squared difference from the mean. For instance, for the influence function of the Gini coefficient see Monti (1981).

5. Descriptive Evidence

In this section we offer a descriptive picture of the average "raw" age-earnings profiles (Figure 1A) and then, since age-earnings profiles are likely to be different for different segments of the labour market, we disentangle the pattern by educational attainment (Figures 1B-1D), taking advantage of the richness of the AD-SILC data.

We indeed show the generational gap in earnings for those with at most a lower secondary degree (Figure 1B), with an upper secondary degree (Figure 1C), and with a tertiary degree (Figure 1D). Furthermore, Figure 2 to 3 show how the picture changes as we look at the bottom 25th and the top 75th percentiles for those holding a tertiary degree.

Two facts are immediately apparent from Figure 1A: different cohorts experience substantially different earnings profile as they age and the age-earnings profiles have been deteriorating for more recent cohorts in comparison with older ones. At almost all level of seniority, the different cohorts keep a clear ordering: the older cohorts earn more and the later cohorts earn less. In particular the most recent cohort, those born in the period 1975-1979, shows an entry earnings that is approximately five percent less than the 1960-1964 cohort. The generation 1965-1969 is that performing best. By the end of the observed working career (after ten years of seniority), the gap between the youngest generation and the other ones widens, with a slope of the earnings profile that becomes almost flat for the former. Indeed, as also documented by Rosolia and Torrini (2007) new cohorts experience a permanent loss in their working life earning, due to a lower entry wage which is not offset by a faster career.

The picture becomes worrisome when we explore the differences in the generational gaps by educational attainments (Figures 1B-1D). The youngest generation (i.e those born during the period 1975-1979) shows the worst earnings profile especially amongst the highly educated ("the best youth"). From Figure 1D we can clearly see that young people with an upper secondary degree show a pattern which is almost consistently lower and less steep all over the career compared with the other generations. In particular we observe a strong gap between the generation 1975-1979 and those born in the 1965-1969 window. The latter generation has an entry wage which is roughly 15 percent more than the former and this gap increases by the 9th year of seniority where the earnings differential between these two generations reaches a level of twenty percent.

The story changes as we look at the low educated group (those with at most a lower secondary degree, Figure 2). The most recent generation belonging to this group appears to be less disadvantaged over the working career than the same generation holding a tertiary degree. Despite showing one of the lowest initial entry wage, the youngest generation tends to catch up, surprisingly reaching the highest pay by the end of the observed working career (in correspondence of 10 years of seniority).

Figures 2 and 3 show the age-earnings profiles for the low paid (25th percentile) and the high paid (75th percentile) and once again confirms what we have already found looking at the profiles by education. The youngest generation is the most disadvantaged especially among the high paid (75th percentile).

We do not expect the scenario for the "best youth" to improve once we also include incomes from parasubordinate jobs. This is because most of the highly skilled people are employed with these contracts at least at the beginning of their career. This can partially explain the lack of growth of the skill premium which is observed from 1996 in Raitano (2012).

6. OLS estimates

Figures 4, 5 and 6 show the estimated trends relative only to the cohort and seniority variables, obtained respectively from Model 1, 2 and 3 on the whole sample and by educational attainment. For ease of comparison, all the values are expressed relative to the oldest cohort earnings (1964-1964) for the first year of seniority.

A preliminary look at the graphs confirms the evidence of the descriptive analysis: most recent generations are worse off and this is particularly evident amongst the high skilled. From Figure 4A we can see that, once controlling for macroeconomic conditions and individual characteristics, the entry earnings of the youngest cohort (1975-1979) is almost six percent less than the same for the oldest cohort (1960-1964). Moreover, the situation does get worse by the end of the observed working career (10^{th} year of seniority): the youngest cohort earnings are found to be ten percent lower than the oldest cohort earnings. The picture is almost the same when we extend Model 1 to further depurate patterns specific to the beginning phase of the career from trends common to all employees, (Model 3, Figure 6A). As far as wages are concerned (Model 2, Figure 5A), the generation gap is still pretty evident although the seniority-earnings profiles for all generations show a less steep pattern.

We now focus the attention on the highly educated (Figures 4D, 5D and 6D). Although "the best youth", those belonging to the latest cohort (1975-1979), shows an entry earnings that is only five percent less than the one of the oldest generation, we observe a clear increasing gap with respect to previous generations. This is particularly striking when compared with the oldest generation. From the 6^{th} year of seniority onwards, the gap between the first (1960-1964) and last cohort (1975-1979) widens from 8 to 15 percent, in correspondence of seniority 10.

Let us stress that by the end of the observed career, the youngest generation exhibits earnings levels which are almost equivalent to the entry earnings of the oldest generation. This is fairly clear from Figure 4D. Results are robust to the three different specifications.

By contrast, the earnings gap between the oldest and youngest generations narrows down with seniority for those with at most a lower secondary degree (Figures 4B, 5B, and 6B).

7. Unconditional quantile regressions

Figure 7 includes the estimated trends of the 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} percentile of the yearly earnings distribution, trends that are associated only to the cohort and seniority variables, and not to the other covariates. Interestingly, for the 10^{th} and the 25^{th} percentiles of the distribution, the entry level of yearly earnings increases across cohorts, with the levels for cohorts of individuals born in 70-74 and 75-79 that is higher than those of individuals born in 60-64 and 65-69. The patterns in the first 11 years of seniority point a clear catching up of the 60-64 cohort which is the one that increases the most, showing the highest level after 11 years.

From the median there is no longer evidence of a gain of the most recent cohort: at the 50th, 75th, 90th percentile the curve of the most recent cohort is always the lowest along the 11 years time seniority span, and differences with the other cohorts become wider moving from the median to the 90th percentile: at the median the entry earnings difference amounts to around 1,500 Euros (with respect to the oldest cohort) and it is stable afterwards; at the 75th percentile the entry difference is around 2,200 Euros and increases slightly in seniority; at the 90th percentile the entry difference amounts to around 3,500 Euros, and increase dramatically over seniority up to 7,600 Euros. This impressive differences in patterns across cohorts at the 90th percentile is due both to a strong increase over seniority for the oldest cohort (60-64), but also to the fact that for the youngest cohort the increase in earnings over seniority is very mild. Important differences are also at work for the cohort 70-74, especially in the upper tail of the earnings distribution.

Similarly to the part on average wages, we pay special attention to the group with the highest education, the graduates. Figure 8 uses the same unconditional quantile regressions as in Figure 7, restricted to the group of graduates. It is interesting to note that for all percentiles the increase of earnings over seniority is much steeper in the two oldest cohorts with respect to the two recent ones. As for entry earnings, it is still true that at the bottom of the distribution the new cohorts display higher levels, levels that remain higher than the oldest cohort for several years of seniority (especially at the 10th and 25th percentile).

From the median to the 90th percentile we have, as in Figure 7, that the entry earnings of the two most recent cohorts are lower than those of the oldest ones. And also in a seniority dimension, earnings of the most recent cohorts are also always lower than those of the oldest one. The finding for the 90th percentile is impressive: entry earnings are not much far away across cohorts (the lowest is anyway the most recent), while the dynamics over time is such that for the most recent cohort (75-79) the dynamics is basically flat, i.e. earnings do not increase over time. Since for the cohort with the best dynamics (i.e. 65-69) earnings increased substantially, after 11 years of seniority the gap between the 60-64 cohort and the 75-79 amounts to around € 11,000, and the cumulative difference amounts to around 80,000 Euros. Just as comparison, for individuals at the 90th percentile of the whole sample (all education groups) the difference after 11 years of seniority between the best cohort (65-69) and the most recent one amounts to € 5,000, and the cumulative one amounts to around € 52,000.

This evidence clearly shows that the best graduates have suffered a much stronger earnings penalty with respect to the other education groups, i.e. the best youth has been massively hit.

8. Discussion and conclusions

To be added

References

To be added

Figures

Fig. 1A: Mean gross annual earnings in the first 10 years of working career by birth cohort.
Source: elaborations on AD-SILC data

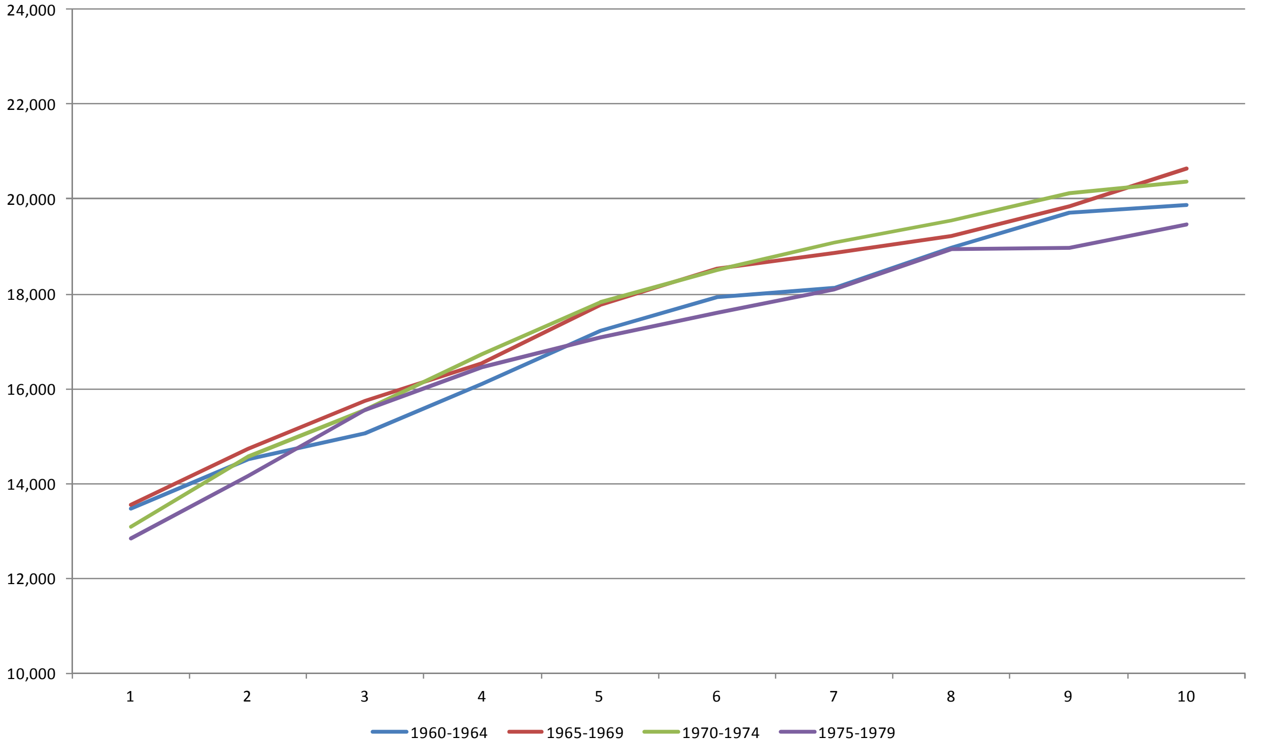
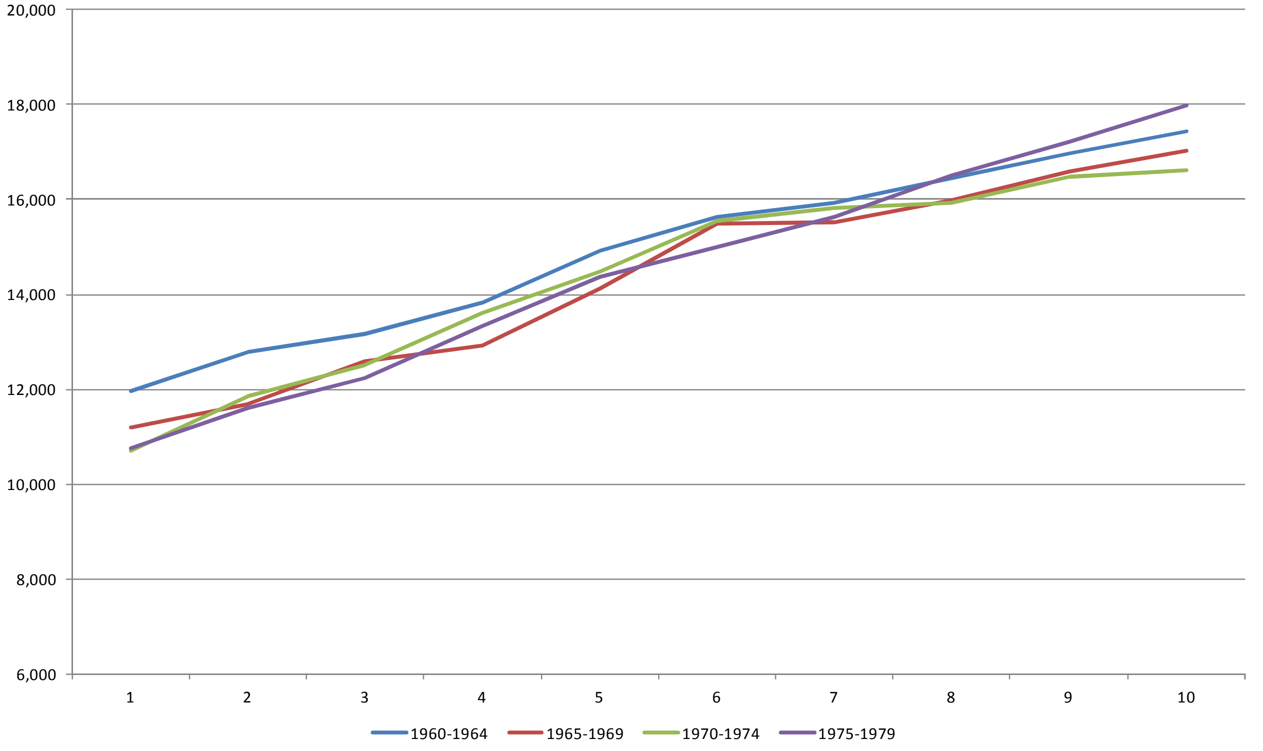


Fig. 1B: Mean gross annual earnings in the first 10 years of working career by birth cohort.
At most lower secondary educated. Source: elaborations on AD-SILC data



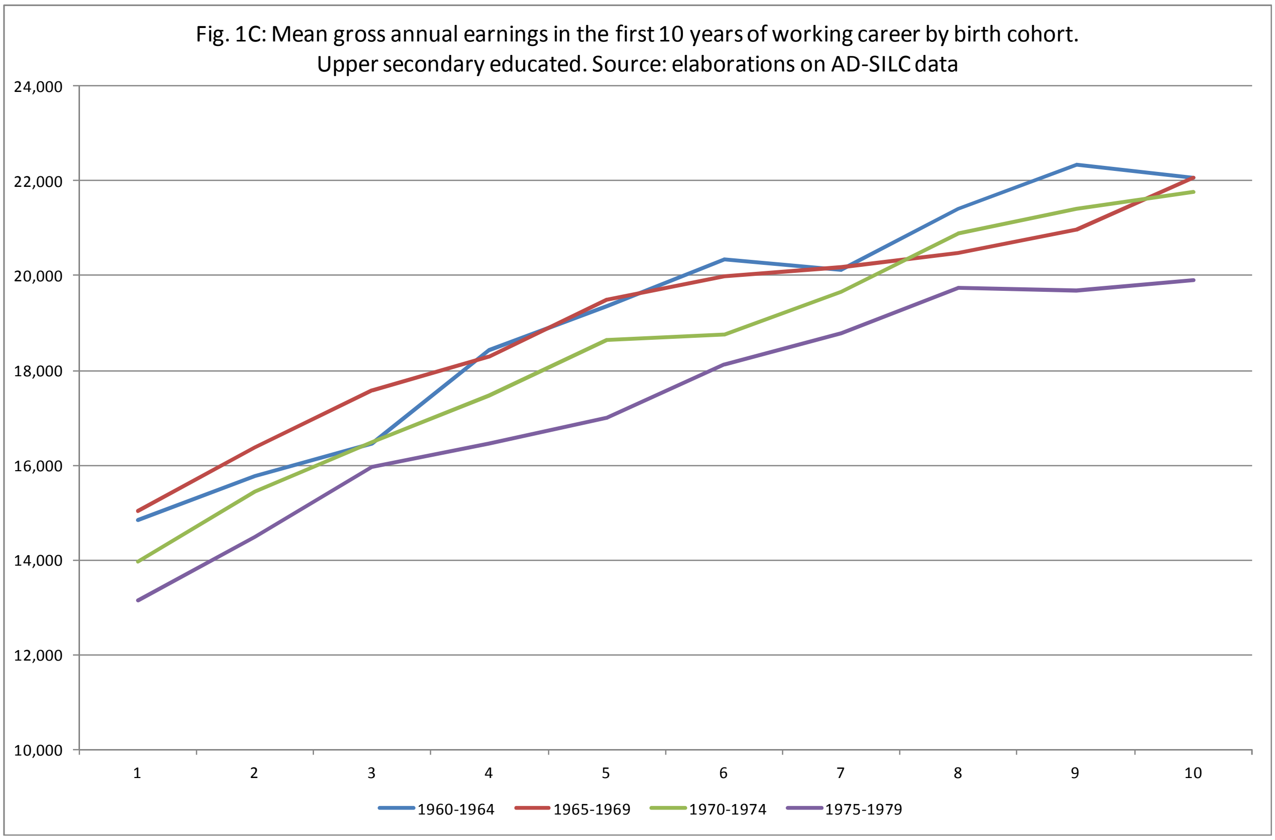


Fig. 1C: Mean gross annual earnings in the first 10 years of working career by birth cohort.
Upper secondary educated. Source: elaborations on AD-SILC data
24,000
22,000
20,000
18,000
16,000
14,000
12,000
10,000
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

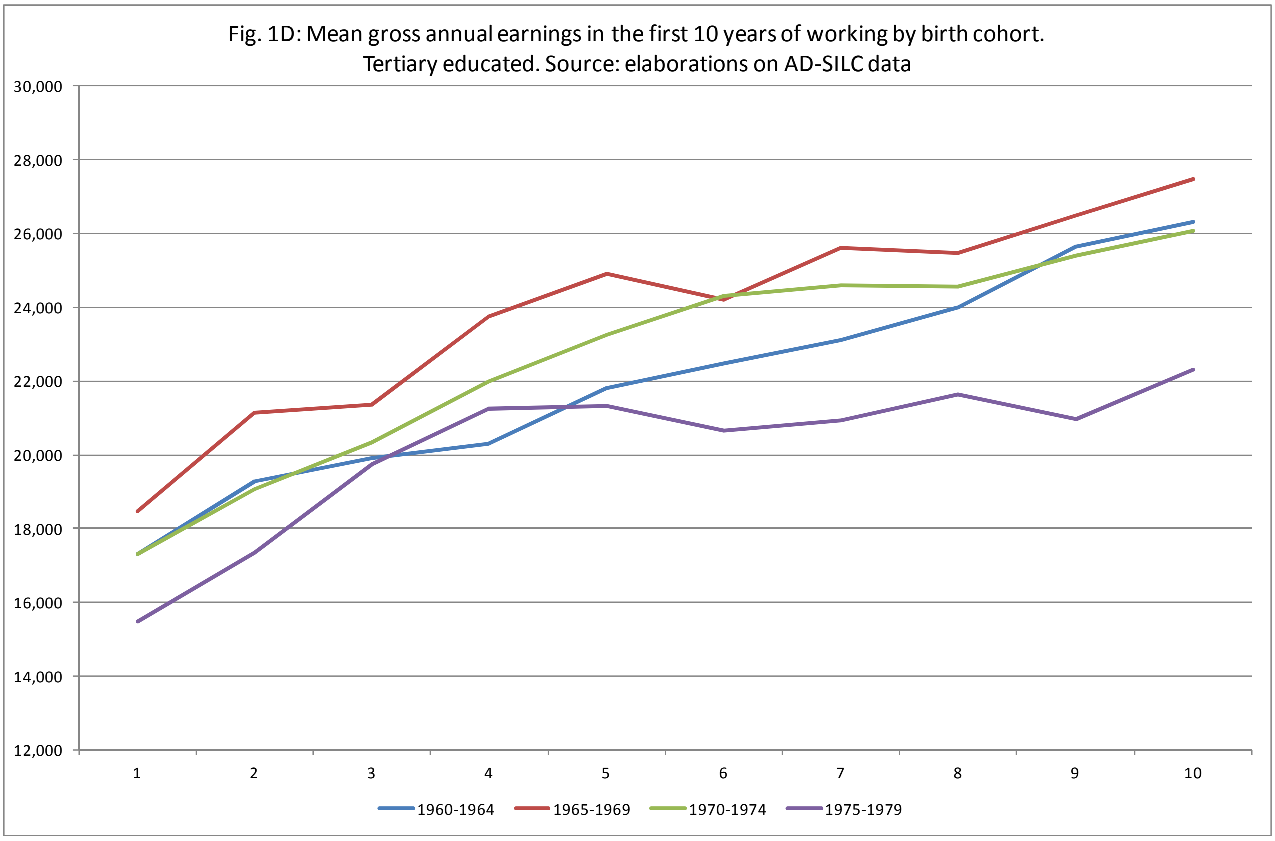


Fig. 1D: Mean gross annual earnings in the first 10 years of working by birth cohort.
Tertiary educated. Source: elaborations on AD-SILC data
30,000
28,000
26,000
24,000
22,000
20,000
18,000
16,000
14,000
12,000
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

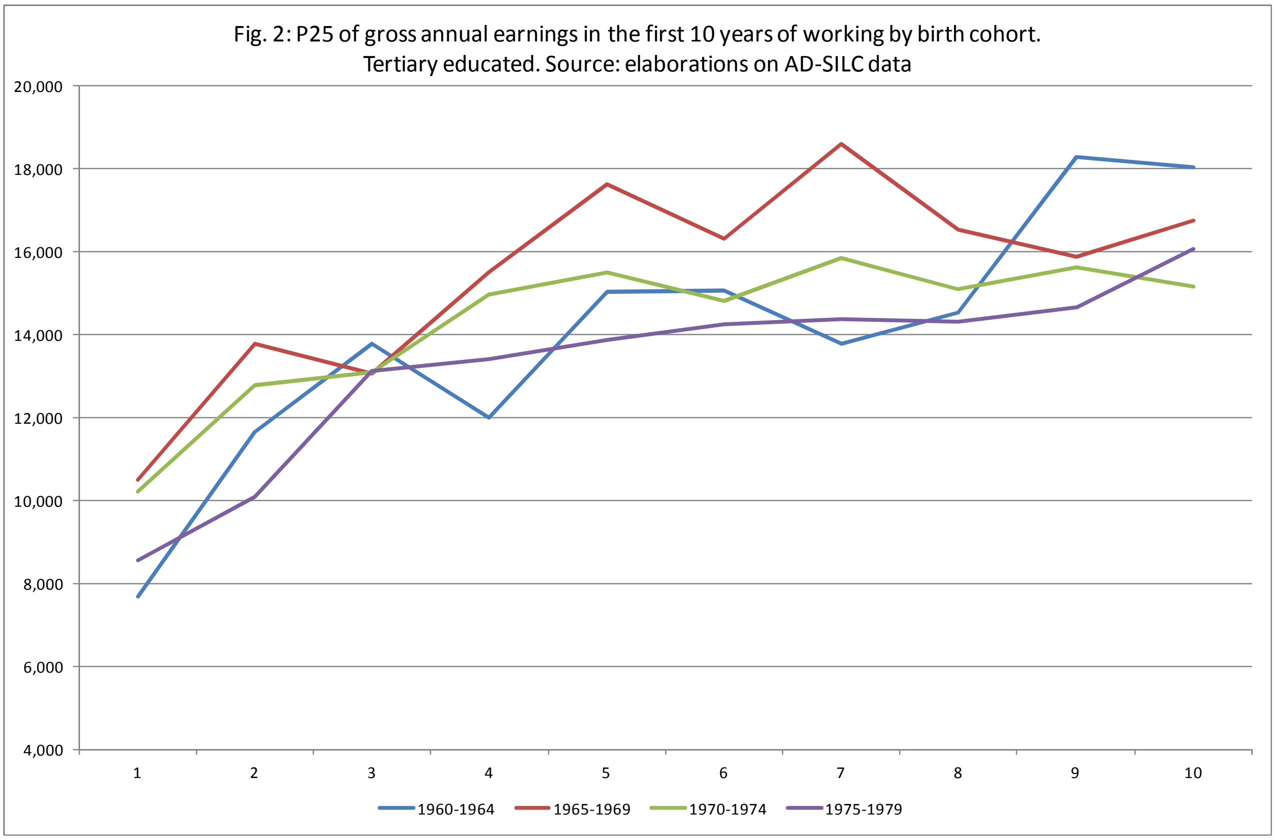


Fig. 2: P25 of gross annual earnings in the first 10 years of working by birth cohort.
Tertiary educated. Source: elaborations on AD-SILC data
20,000
18,000
16,000
14,000
12,000
10,000
8,000
6,000
4,000
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

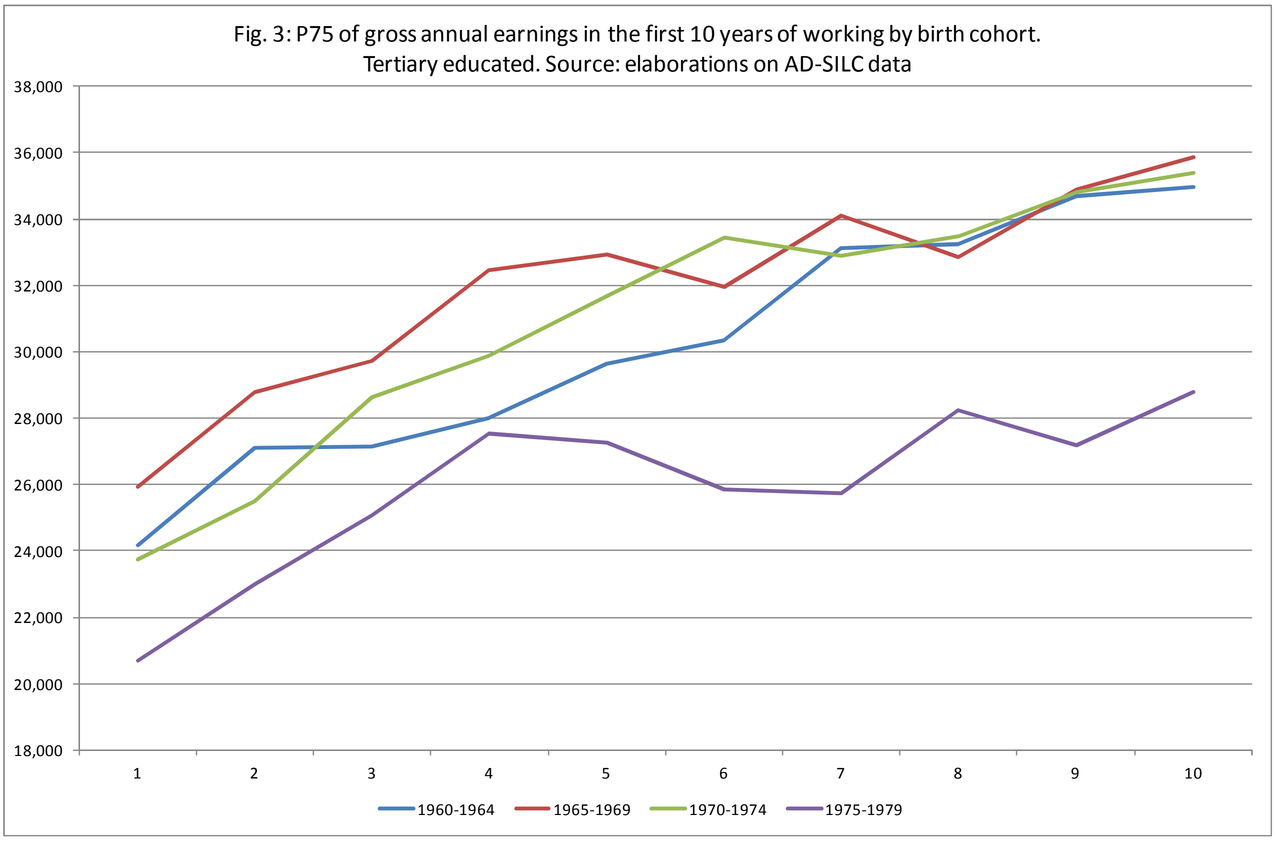


Fig. 3: P75 of gross annual earnings in the first 10 years of working by birth cohort.
Tertiary educated. Source: elaborations on AD-SILC data
38,000
36,000
34,000
32,000
30,000
28,000
26,000
24,000
22,000
20,000
18,000
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

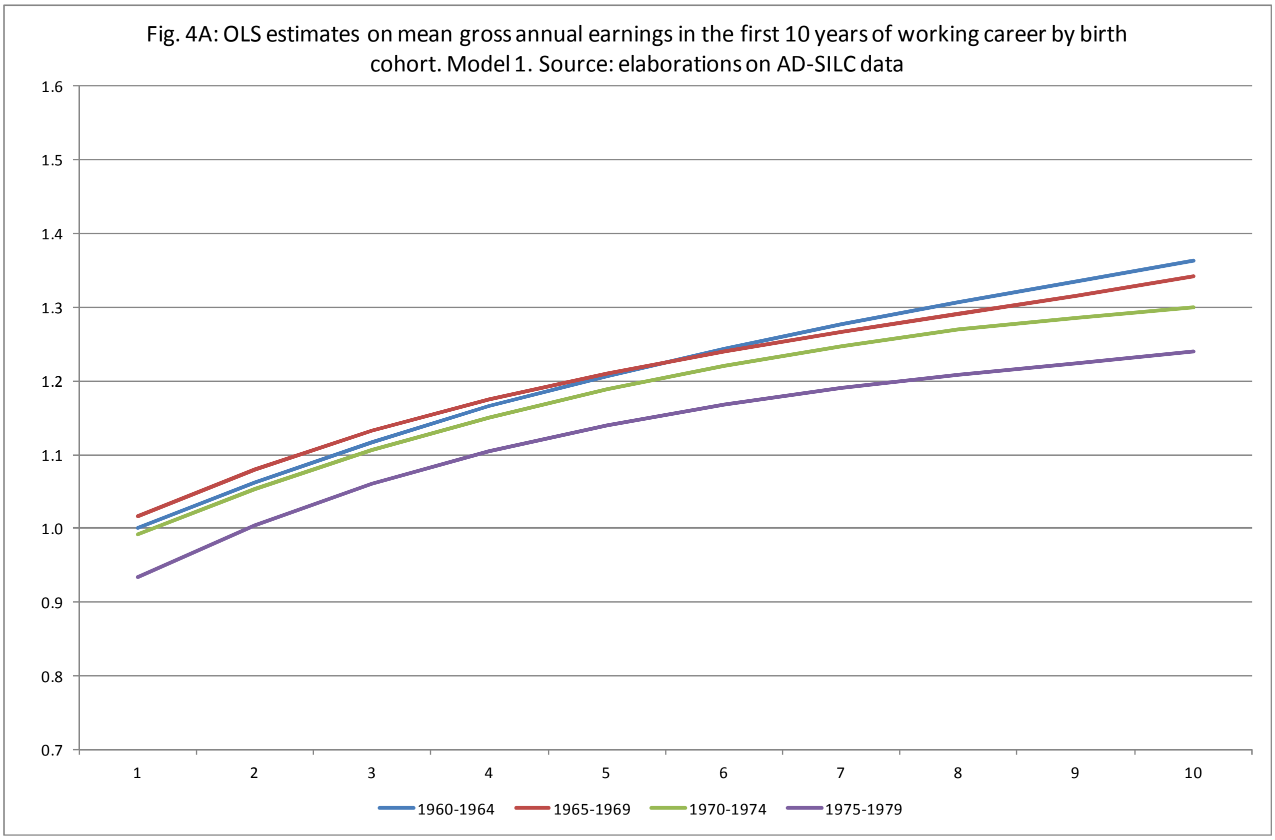


Fig. 4A: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Model 1. Source: elaborations on AD-SILC data
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

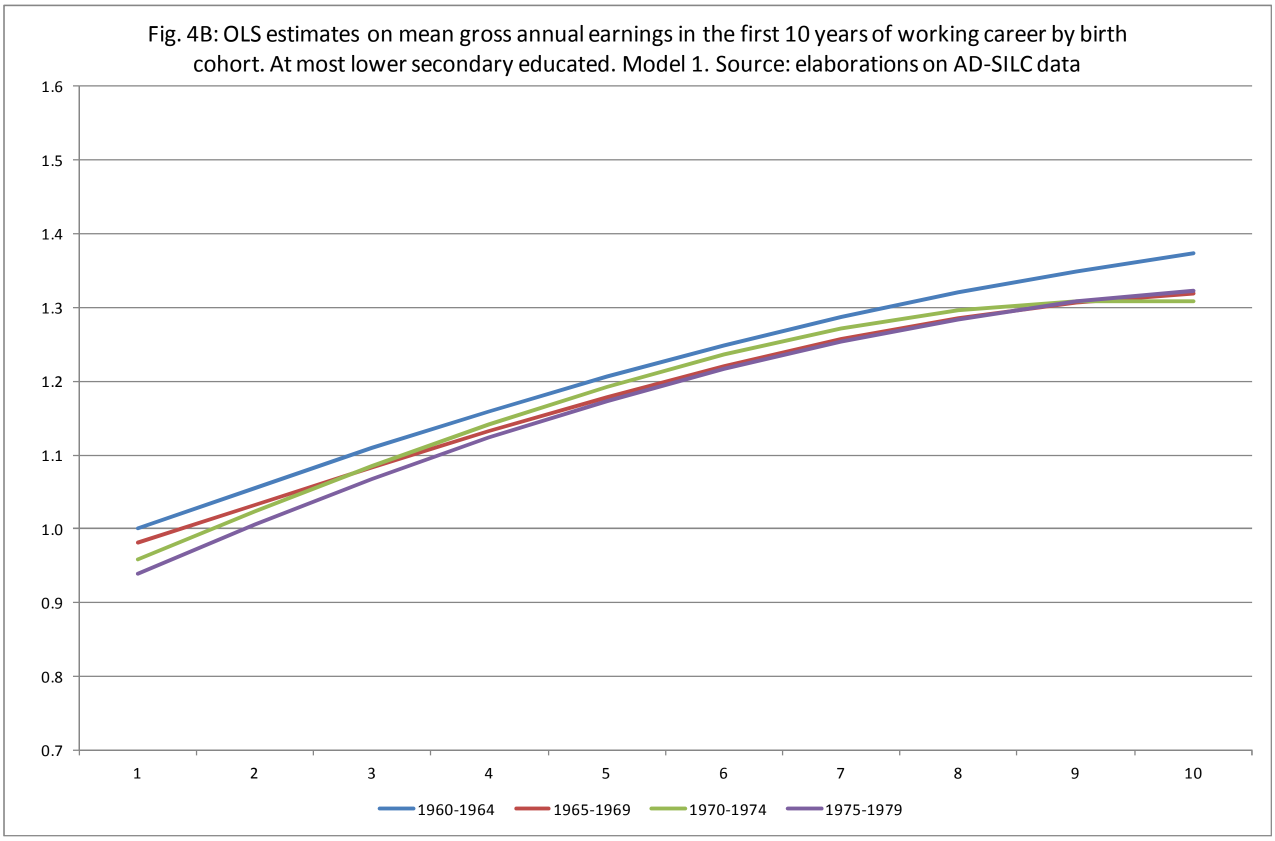


Fig. 4B: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. At most lower secondary educated. Model 1. Source: elaborations on AD-SILC data
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

Fig. 4C: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Upper secondary educated. Model 1. Source: elaborations on AD-SILC data

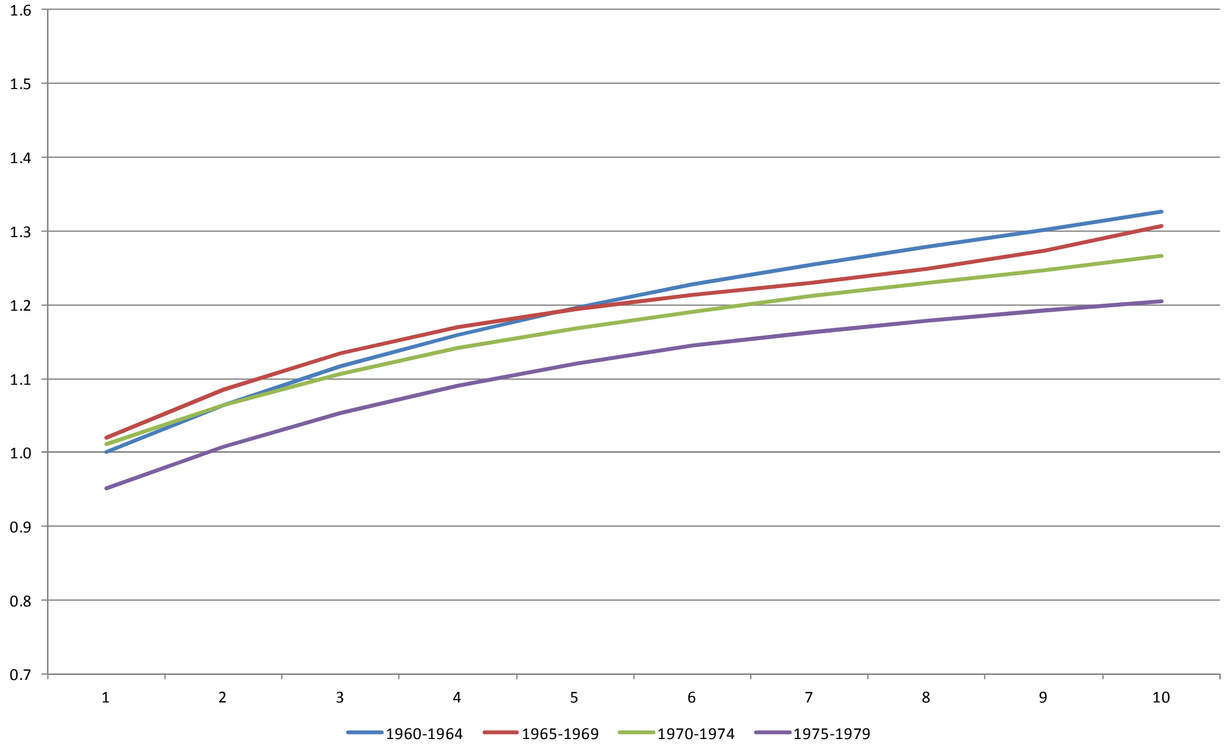


Fig. 4D: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Tertiary educated. Model 1. Source: elaborations on AD-SILC data

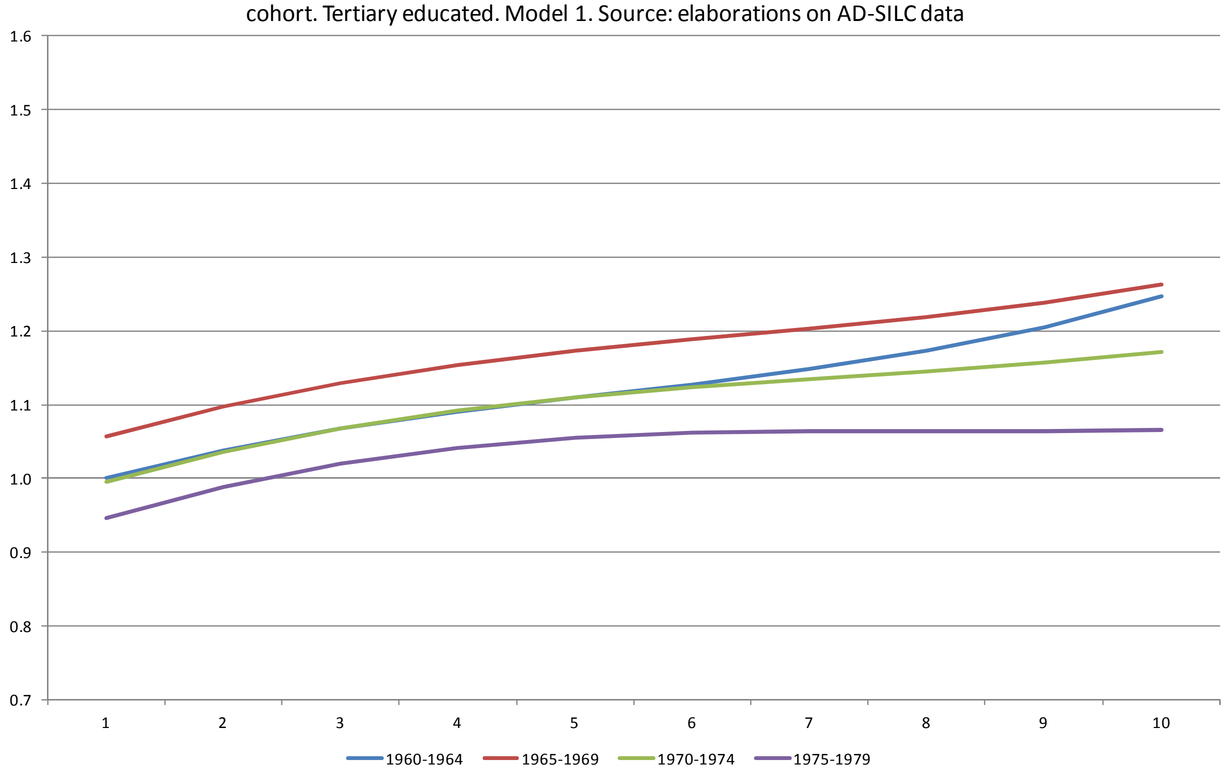


Fig. 5A: OLS estimates on mean gross weekly wages in the first 10 years of working career by birth cohort. Model 2. Source: elaborations on AD-SILC data

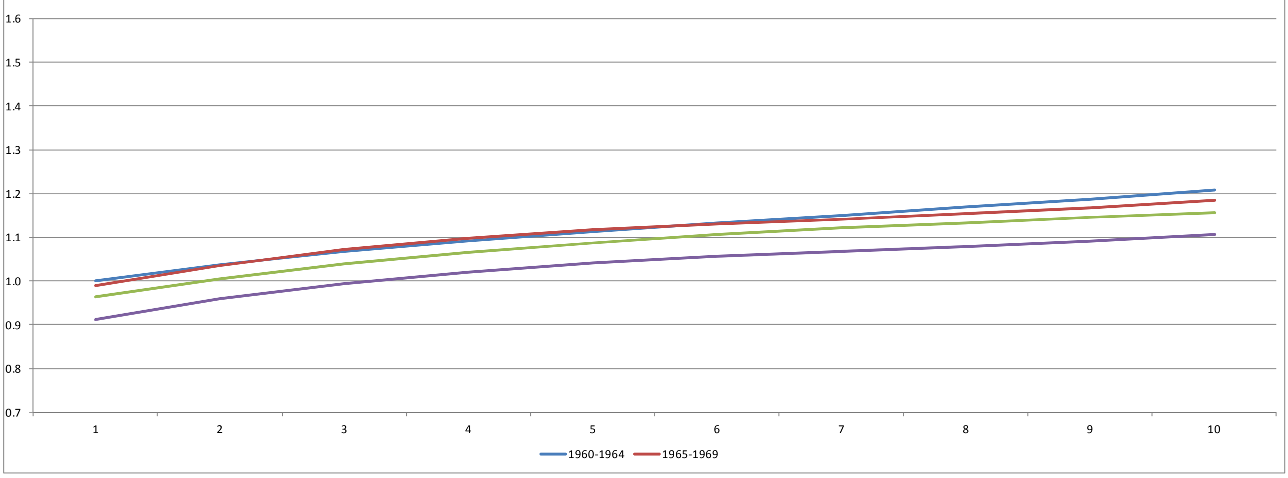


Fig. 5B: OLS estimates on mean gross weekly wages in the first 10 years of working career by birth cohort. At most lower secondary educated. Model 2. Source: elaborations on AD-SILC data

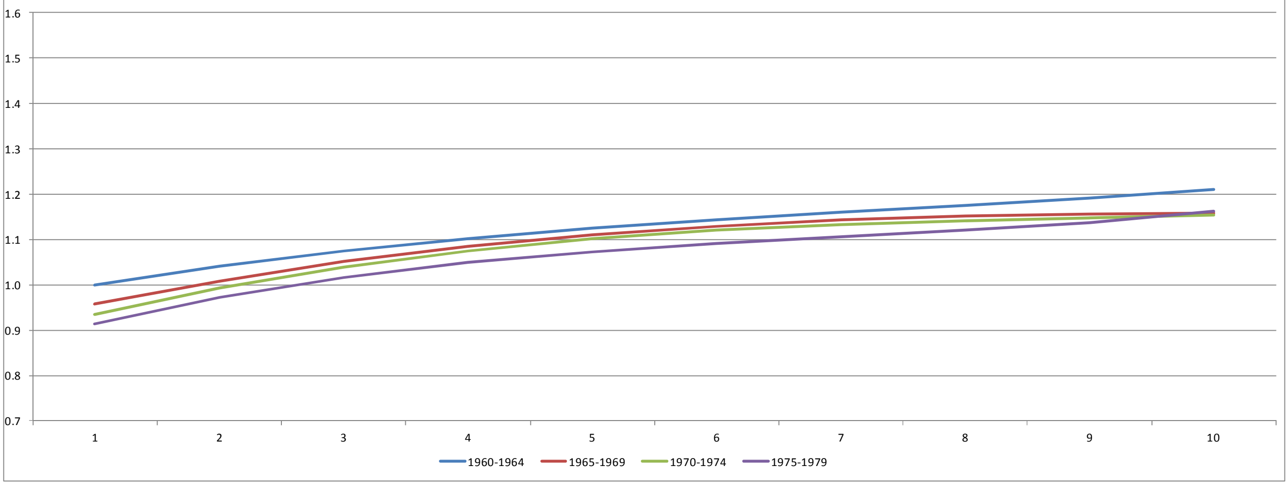


Fig. 5C: OLS estimates on mean gross weekly wages in the first 10 years of working career by birth cohort. Upper secondary educated. Model 2. Source: elaborations on AD-SILC data

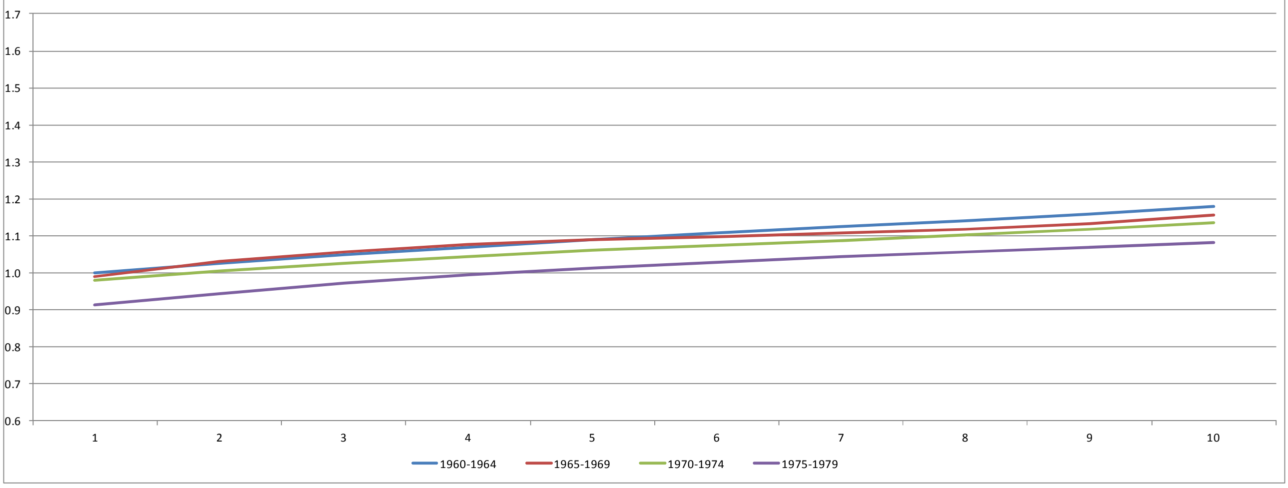
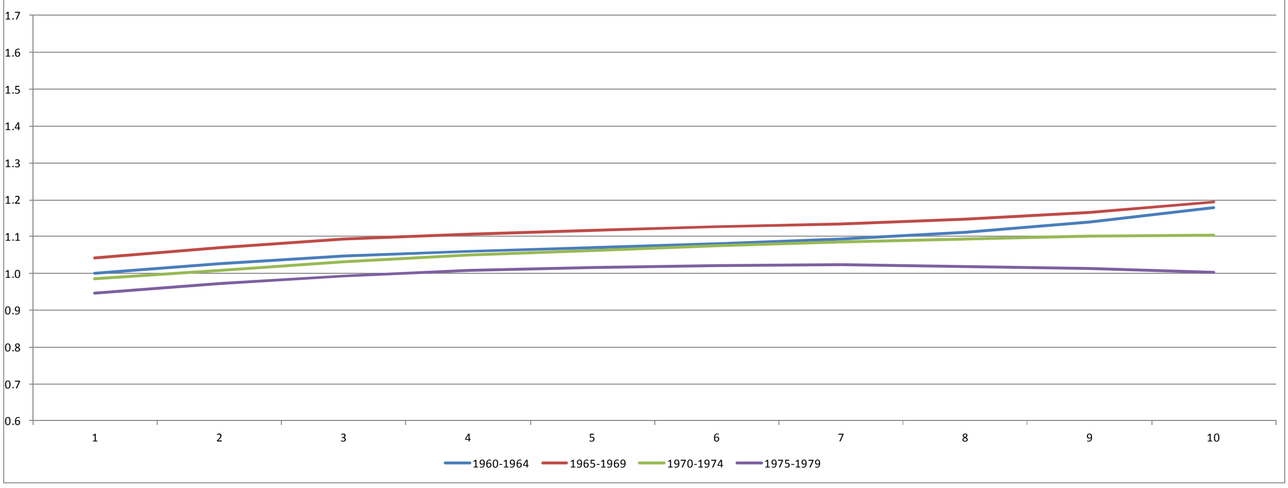


Fig. 5D: OLS estimates on mean gross weekly wages in the first 10 years of working career by birth cohort. Tertiary educated. Model 2. Source: elaborations on AD-SILC data



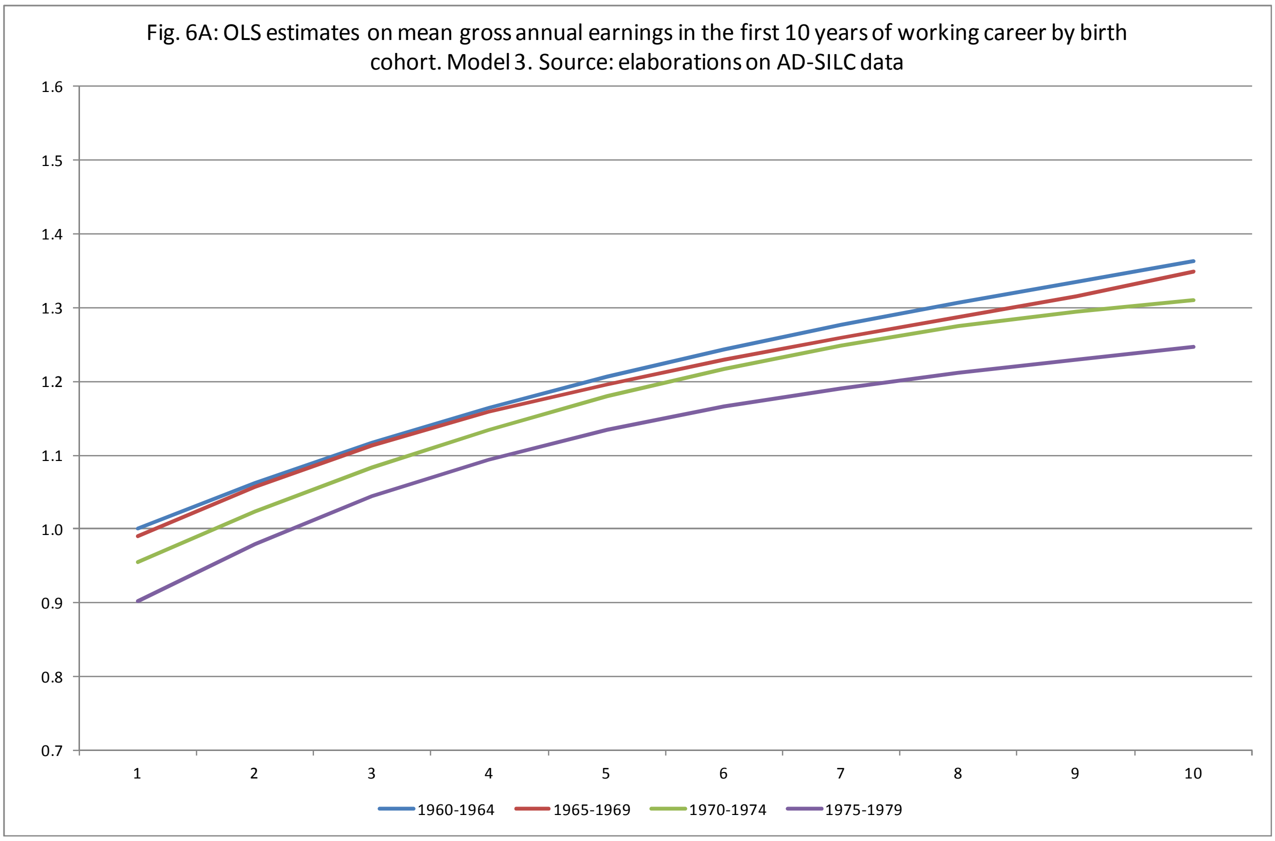


Fig. 6A: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Model 3. Source: elaborations on AD-SILC data
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

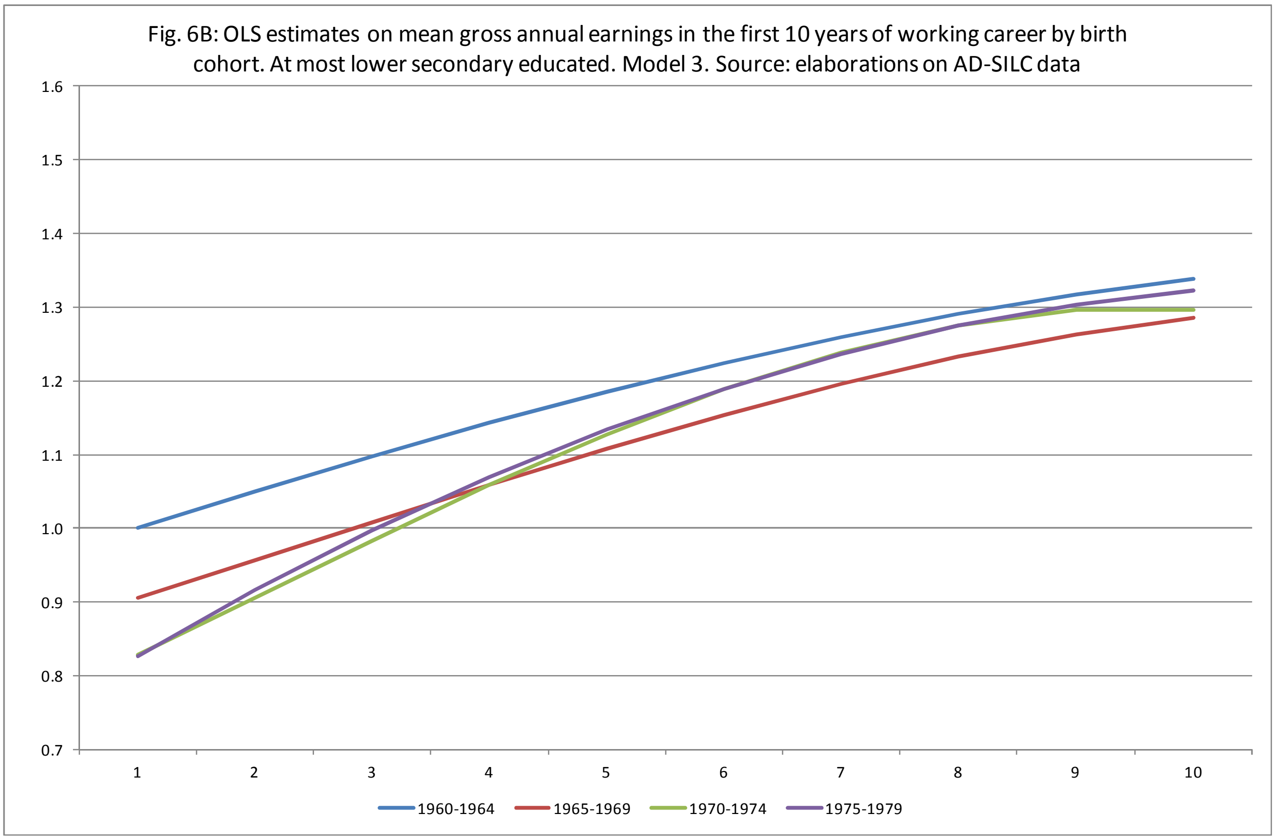


Fig. 6B: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. At most lower secondary educated. Model 3. Source: elaborations on AD-SILC data
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
1
2
3
4
5
6
7
8
9
10
1960-1964
1965-1969
1970-1974
1975-1979

Fig. 6C: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Upper secondary educated. Model 3. Source: elaborations on AD-SILC data

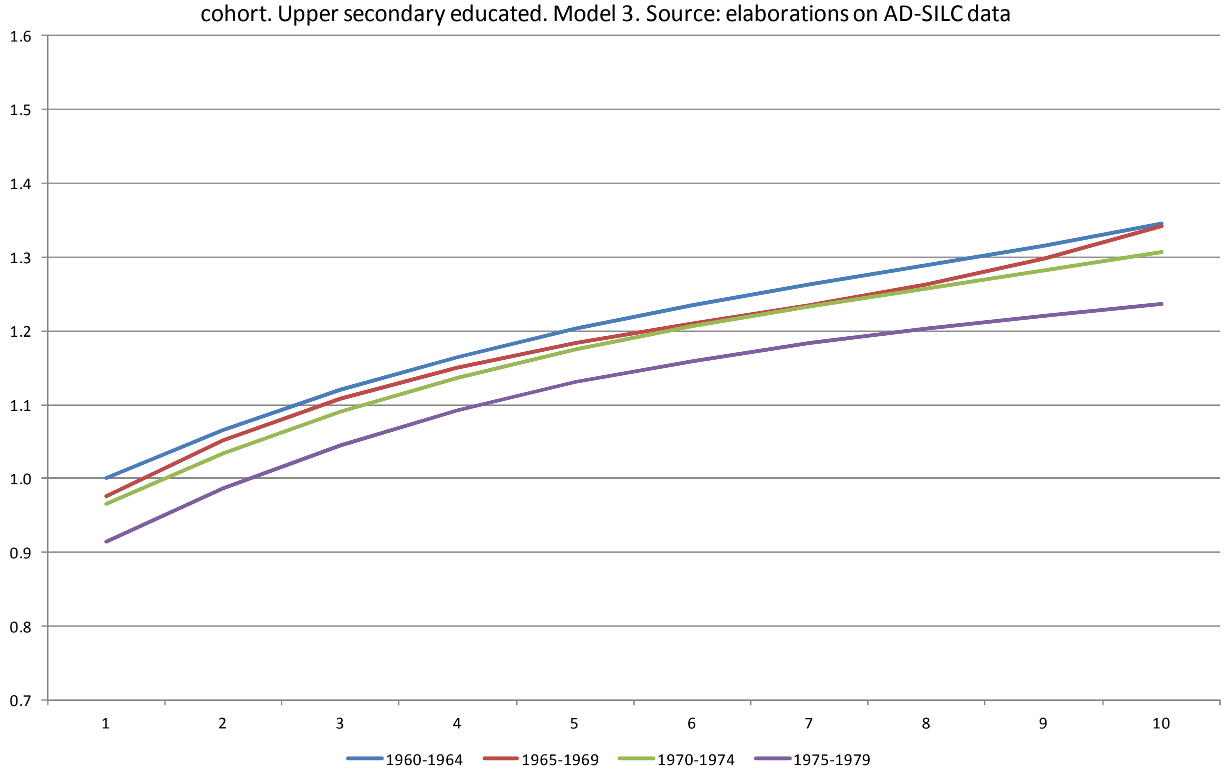
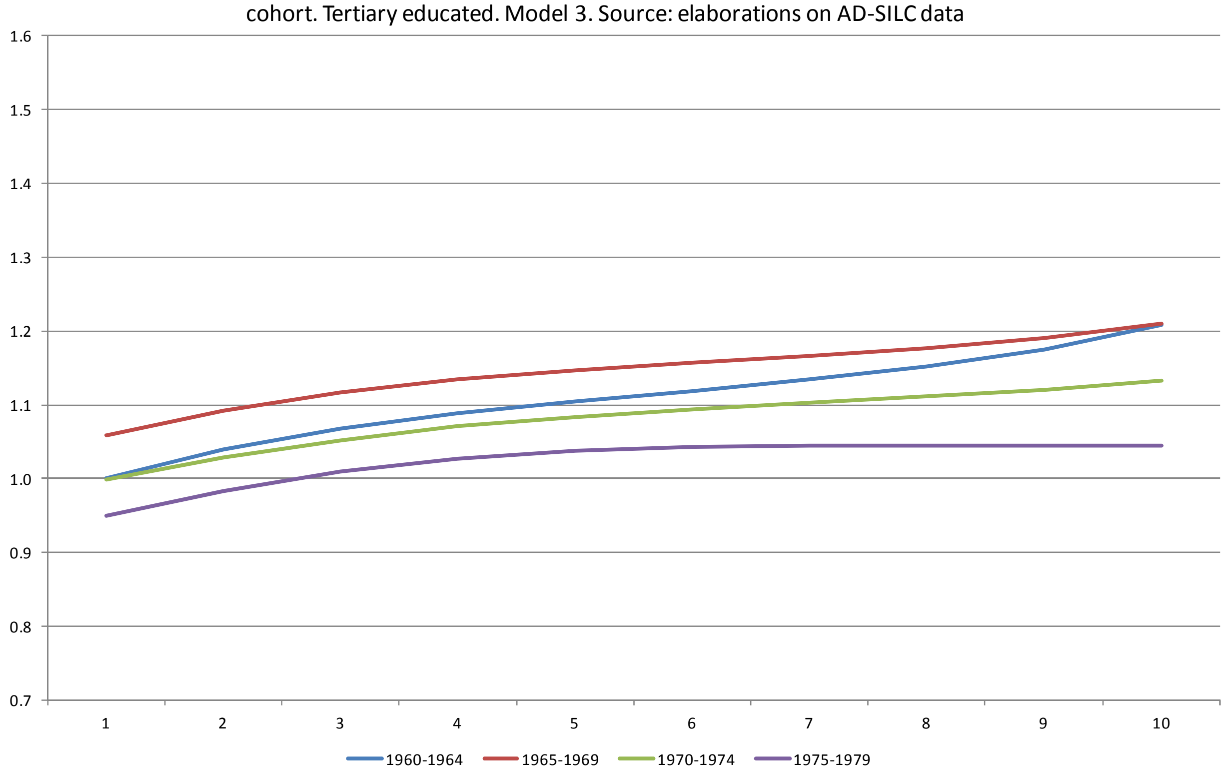


Fig. 6D: OLS estimates on mean gross annual earnings in the first 10 years of working career by birth cohort. Tertiary educated. Model 3. Source: elaborations on AD-SILC data



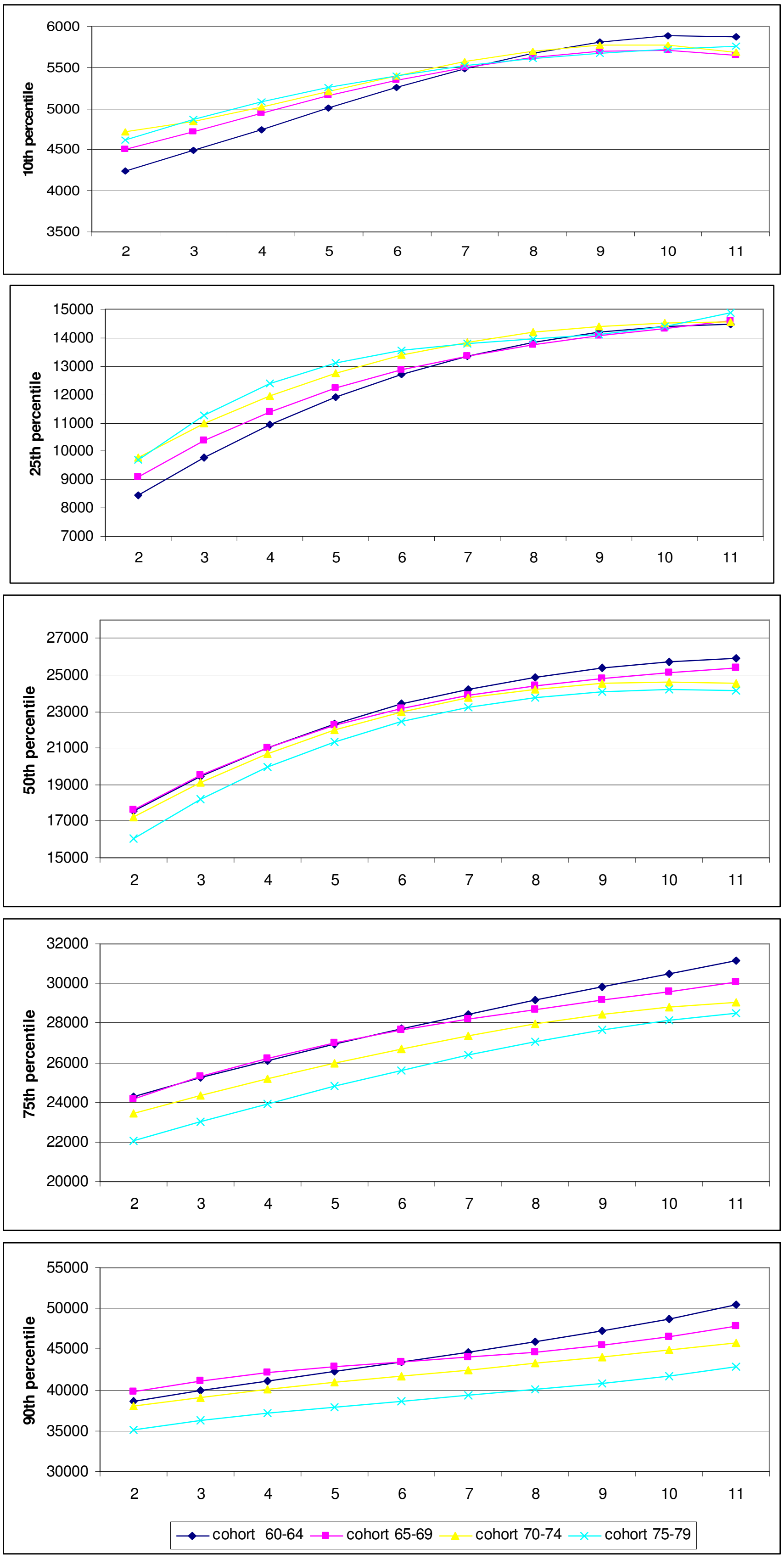


Figure 7: Estimated dynamics of the 10th, 25th, 50th, 75th, 90th percentiles by cohort

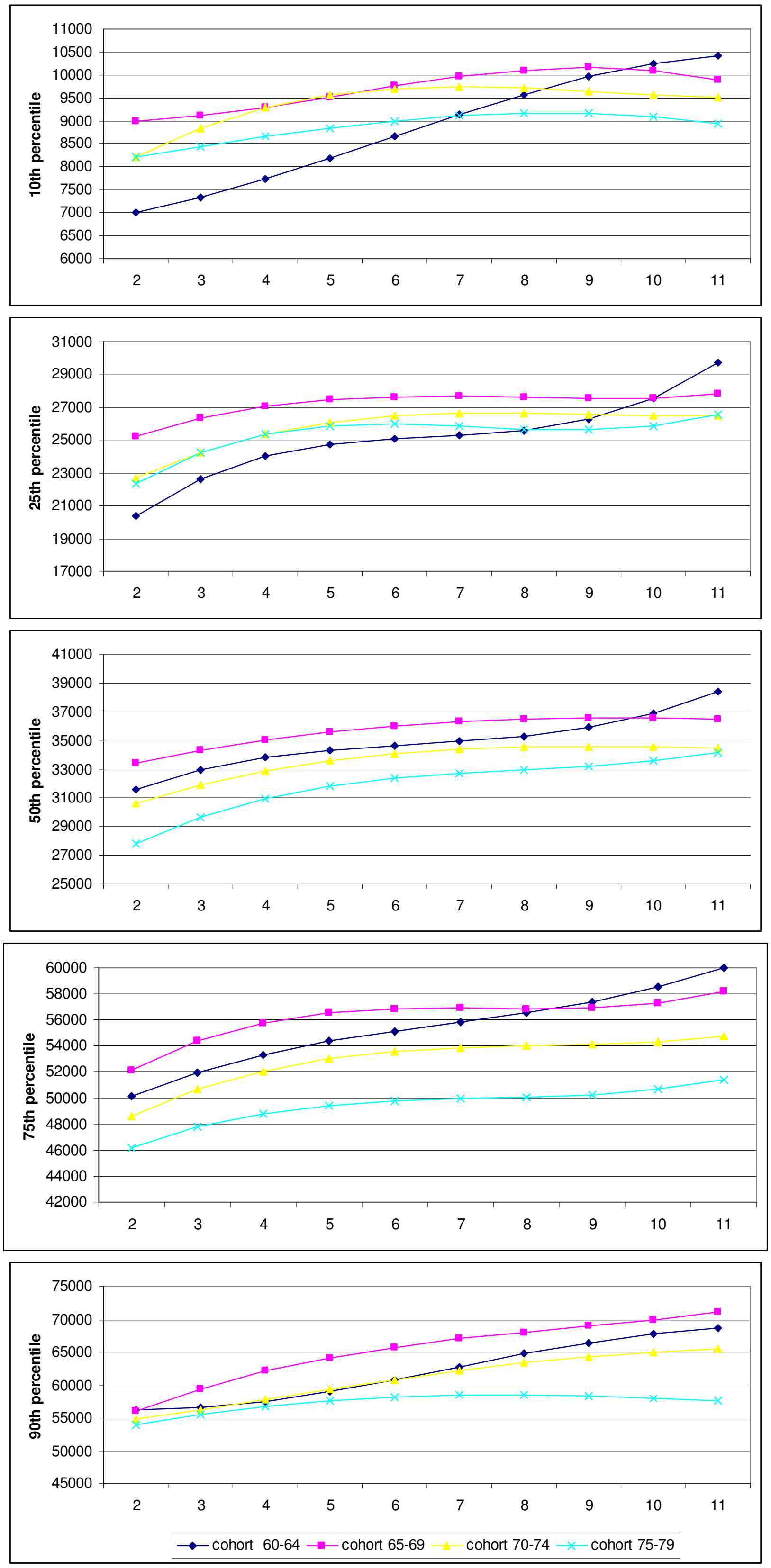


Figure 8: Estimated dynamics (graduates) of the 10th, 25th, 50th, 75th, 90th percentiles by cohorts