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Education, Employment and Wage Risk

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Mario Padula* **and Luigi Pistaferri****

Abstract

We measure the return to education by accounting for differences in wage and unemployment risk confronted by individuals with different levels of education. When markets are incomplete, risk-averse individuals value jobs to which less income risk is associated. In this case a measure of the return to education based only on the expected post-schooling wages can be misleading. We estimate the implicit return to schooling under four different scenarios: no uncertainty, unemployment risk, wage risk, and both wage and unemployment risk. The empirical analysis uses US and Italian microeconomic data. The main finding is that the return of schooling is downward biased if no account is made for risk.

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1 Introduction

Estimating the economic return to schooling is a popular and controversial exercise in labor economics (see Card, (2000), for an exhaustive survey of the empirical literature). Many studies estimate the parameter of interest by running a simple OLS regression of log earnings on years of schooling, a polynomial in labor market experience, and other individual attributes. This is the celebrated Mincer equation. Instrumental variable estimation acknowledges the endogeneity of the schooling variable, although considerable controversy arises regarding the interpretation of the IV estimates (see the discussion in Heckman et al. (1999)).

In this paper we abstract from such controversy and focus on a quite different issue: the introduction of uncertainty in lifetime income confronted by individuals with different levels of schooling. We compute the return to schooling using a procedure that accounts for unemployment and wage risk conditional on the schooling choice. We thus ignore the problem of why individuals with similar observable characteristics choose different levels of human capital investments, and focus instead on their post-schooling experience in the labor market.

The basic point of the paper is that neglecting unemployment and wage risk in a world of incomplete markets may lead to underestimating the return to education if, say, more education gives access to less risky jobs and wage profiles. Consider for instance unemployment risk. In each period individuals face a positive probability of being unemployed and getting zero earnings. Lifetime earnings are therefore lower in expected value than in the absence of unemployment risk. If unemployment risk were the same across schooling levels, there would be no difference with respect to the case of no uncertainty. However, if the more educated are less likely to face unemployment, then the return to schooling is higher and standard estimates of the return from schooling biased downward. If wage risk comes into the picture over and above unemployment risk, then the bias cannot be signed in general: it will depend on whether wage risk is lower among the more educated (which would reinforce the downward bias above), or higher (a fact that may be explained by a simple mean-variance scheme in which those facing high uncertainty are compensated by high earnings on average).

Our paper is not the first to explore this issue. Lehvari and Weiss (1974) present a two-period model of human capital investment with uncertainty, and show that an increase in uncertainty increases the level of investment for plausible assumptions concerning risk aversion and technology. Their simple model has been extended in a variety of directions (see the discussion in Snow and Warren, (1990)). An empirical test of the main implication of their model is Kodde (1986), who uses subjective expectations of future earnings reported by a sample of Dutch high-school graduates. The paper that is closest in spirit to ours is Olson, White, and Shefrin (1979), who allow for wage risk and estimate risk-adjusted and riskless rates of return to high school and college education using NLS data. They find that the difference between the risk-adjusted and the riskless rate is positive, higher for high school graduates, it increases with the amount borrowed to finance tuition costs, and it decreases with risk aversion. There are several differences between their paper and ours. First, we extend the analysis to a longer sample period and consider both the US and Italy, so as to highlight the effect of risk on the rate of return to education in different institutional settings. Second, we allow for heterogeneity in the returns to education, assuming that people entering the labor market in different years face different returns to human capital investment. Third, we estimate age-earnings profiles for different cohorts using a non-parametric approach. Their approach ignores cohort effects. Finally, we consider both wage and employment risk, and show that the unemployment risk adjustment is as important as the wage risk adjustment, if not bigger. Moreover, we allow both wage and employment risk to vary over the life cycle, while wage risk is a constant parameter in their paper.

The plan of the paper is as follows. We start in Section 2 by describing the problem and detailing the numerical solution method for estimating the return to schooling. Section 3 deals with the data. We focus on two countries, Italy and the US, which greatly differ in terms of labor market institutions. Our empirical analysis uses three microeconomic data sets: repeated cross-sections drawn from the 1984-1998 Bank of Italy Survey of Household Income and Wealth (hereafter, SHIW), the 1967-1991 Panel Study of Income Dynamics (hereafter, PSID), and the 1994-1998 Survey of Economic Expectations (hereafter, SEE). We allocate individuals in our sample to cohorts defined on the basis of year of birth and years of schooling. For each group we take actual earnings profiles and extrapolate back and forth over the missing ages. This gives us an estimate of the entire lifetime earnings profile that can be used to infer expected earnings over the life cycle. Wage and unemployment risk are obtained using the variability of individual earnings around the estimated earnings profile and perceived unemployment risk. For Italy, the latter is estimated using subjective unemployment probabilities available in the SHIW; for the US, we rely on those available in the SEE. We discuss the extrapolation technique in Section 4. The rate of return to schooling is obtained *via* numerical solutions under four different scenarios: no uncertainty, unemployment risk, wage risk, and both wage and unemployment risk. The results are reported in Section 5, while Section 6 concludes.

2 The return to education

An individual endowed with isoelastic preferences chooses years of schooling s to maximize the expected utility of lifetime consumption:

$$E_s \sum_{j=s}^{T} (1+\rho)^{j-s} \frac{c_{ij}(s)^{\gamma}}{\gamma}$$

where $1-\gamma$ is the coefficient of relative risk aversion, ρ the discount rate, E_s the expectation operator conditional on information available at time s (the school-leaving age), and T the expected age of retirement, which is known with certainty at the beginning of the life cycle.

Following the previous literature, we will focus on an incomplete markets case in which consumption equals income in each period, i.e. $c_{ij}(s) = y_{ij}(s)$ for all j and s. This is an extreme case in that both borrowing and savings are not available; thus, self-insurance through savings is not allowed. The only form of insurance is, in fact, choosing a more stable earnings profile, i.e., selecting the schooling level that is associated with it. The extreme incomplete market case provides an upper bound of the amount of insurance provided by education.

Mincer-type earnings equations assume that there are no direct costs of human capital investments, an assumption that we also make. We assume for simplicity that retirement age is independent of schooling (and set $T = 65$ for all schooling choices), and that individuals live with their parents while in school, receiving a minimum consumption level at no cost. This should minimize the effect of institutional or demographics differences across countries that we do not model explicitly.

As far as these two assumptions are concerned, the following should be noticed. In Italy, workers are entitled to old age pensions (retirement age is 60 for males, 55 for females, recently raised to 65 and 60, respectively), or social security contributions pensions (set to 35 years for both males and females, with some exceptions in the public sector and for some worker categories), independently of education levels.[1] Furthermore, children tend to leave parental home later in life, and usually just before marriage (Becker, Bentolilla, and Ichino, (2001)).

In the US, heterogeneity of retirement ages across education groups is less documented. On the other hand, student mobility at the college level is much higher than in Italy, which implies that the assumption that children live with their parents before the college completion may be less accurate. Our focus on the return to schooling gross of investment costs, however, should lessen this problem.

Individuals in this model confront two types of risk. First, they may be unemployed with positive probability. Second, conditioning on being employed, their earnings may be uncertain. The return to schooling level $s' > s$ is the implicit rate ρ^* that solves:

$$\sum_{j=s}^{T} (1+\rho^*)^{j-s} \frac{\pi_{ij}(s) E_s \left[y_{ij}(s)^{\gamma} | e \right]}{\gamma} = \sum_{j=s'}^{T} (1+\rho^*)^{j-s'} \frac{\pi_{ij}(s') E_s \left[y_{ij}(s')^{\gamma} | e \right]}{\gamma} \tag{1}$$

where $\pi_{ij}(s)$ is the probability of employment that individual i with schooling s faces at age j, and $E_s(.|e)$ is an expectation that conditions on the information set available at time s and on the status of being employed, e.[2] To save on notation, from now on we remove the conditioning on the employment status e and leave it implicit.[3]

Individuals with schooling level s may choose to enter the labor market and earn $y_{ij}(s)$ or else invest in additional schooling $(s' - s)$, which ensures earnings $y_{ij}(s')$. The discount rate ρ^* makes individuals indifferent between the two schooling choices s and s'. We estimate ρ^* as the numerical solution to (1), in the spirit of Becker (1967), who defines the rate of return ρ^* to switching from education level 1 to education level 2 (with school-leaving ages of s and s', respectively) as the value that equalizes the present discounted value of the age-earnings profiles calculated under the two schooling regimes.

To make (1) operational one should know expected earnings for an individual with schooling level s, expected earnings for the same individual had he chosen to invest in

[1] Social security contributions pensions obviously depend on the age of entry in the labor market, which in turn depends on school leaving age. However, pension legislation allows college graduates to make college years counting as working years *via* payment of additional contributions.

[2] We assume that in the case of unemployment people receive a subsistence level of utility independent of schooling and age. This term thus drops out from expression (1).

[3] The Mincer regression is a special case of (1), obtained assuming no uncertainty, and $\pi_{ij}(s) = \pi_{ij}(s') = 1$ for all i,j.

additional schooling $(s' - s)$, and the preference parameter γ. Note also that what appears in (1) is the expectation of a non-linear function of y_{ij}.[4]

To avoid dealing with the expectation of a non-linear function of earnings, we use the following approximation based on a second-order Taylor expansion:

$$\frac{E_s\left[y_{ij}^{\gamma}\right]}{\gamma} \cong \frac{\left[E_s\left(y_{ij}\right)\right]^{\gamma}}{\gamma} + \frac{\gamma - 1}{2} var_s\left[y_{ij}\right]\left[E_s\left(y_{ij}\right)\right]^{\gamma-2}$$

for all i, j, and schooling level. Note that under risk neutrality $(\gamma = 1)$ higher moments of the conditional distribution of earnings do not affect utility. Individuals will choose schooling levels only on the basis of expected lifetime earnings.

The next step is to compute expectations and variances of earnings over the life-cycle. We estimate expected earnings with the average earnings of the individual's cohort. For example, an individual born in 1920 can choose to leave school at around 14 (less than high school), 19 (high school diploma), or 24 (college degree). We need to calculate average earnings over the working career for all individuals born in 1920, entering the labor market respectively in 1934, 1939, and 1944, and retiring in 1985. Estimation of the expected earnings variability is done in a similar way focusing on the variability of individual profiles around the cohort profile. More details are provided in the section that follows.

We estimate process in logs assuming log-normality (i.e., $\ln y_{ij} \sim N$) and substitute back using the formulae for the first and second moments of the exponential distribution, i.e.:

$$\begin{aligned}
E_s\left[y_{ij}(s)\right] &= E_s\left[e^{\ln y_{ij}(s)}\right] = e^{E_s[\ln y_{ij}(s)]+0.5var_s[(\ln y_{ij}(s))]} \\
var_s\left[y_{ij}(s)\right] &= var_s\left[e^{\ln y_{ij}(s)}\right] = e^{2E_s[\ln y_{ij}(s)]+var_s[(\ln y_{ij}(s))]}\left(e^{var_s[(\ln y_{ij}(s))]} - 1\right)
\end{aligned}$$

If log-normality is violated, these expressions should thus be seen as second order Taylor approximations to the true mean and variance.

3 Data

To perform the empirical exercise outlined in the previous section one needs microeconomic data. For this purpose we use the Bank of Italy SHIW, available for the years 1984, 1986, 1987, 1989, 1991, 1993, 1995 and 1998, and the PSID, available annually from 1967 to 1991. Our exercise also requires estimates of unemployment risk. We use subjective unemployment expectations available in the 1995-1998 SHIW (for Italy), and the 1994-1998 SEE (for the US). The three data-set are briefly described in turn.

[4]In previous empirical work, the evaluation problem is solved by making two crucial assumptions. First, there is no selection based on unobservables. This will be violated if those who go to college would earn more than a representative high school graduate had they chosen not to go to college, due to the effect of unobserved ability traits. Second, there are no cohort effects. This implies that a 20-years old individual will earn at 30 what a 30-years old individual is earning today, at least on average. We remove the second assumption and account for the first, albeit imperfectly, by focussing on narrowly defined population subgroups.

3.1 The SHIW

The 1984-1998 SHIW contains measures of family income and consumption, demographic characteristics of households, and information on labor market status, labor supply and earnings for all labor income recipients in the household. In 1995 and 1998 respondents are also asked to provide perceived unemployment probabilities for the following 12 months.

The SHIW is conducted by the Bank of Italy that surveys a representative sample of the Italian resident population. Sampling is in two stages, first municipalities and then households. Municipalities are divided into 51 strata defined by 17 regions and 3 classes of population size (more than 40,000, 20,000 to 40,000, less than 20,000). Households are randomly selected from registry office records. From 1987 through 1995 the survey was conducted every other year and covered about 8,000 households, defined as groups of individuals related by blood, marriage or adoption and sharing the same dwelling. Ample details on sampling, response rates, processing of results and comparison of survey data with macroeconomic data are provided by Brandolini and Cannari (1994).

3.2 The PSID

The PSID is a panel data set of US households and of their offsprings. It began in 1968 with a sample of approximately 5000 families drawn from the US non-institutional population. The PSID includes a variety of socio-economic characteristics, including age, education, labor supply, and income of family members. Families are interviewed annually and family members in the 1968 are followed through time if they form or join new families. This made the sample size to increase over time: around 18000 individuals were present in 1968 and around 30000 in 1992.

Three-fifths of the observations are drawn from a representative US sampling frame (the SRC sample). About two-fifths of the observations from a low-income sample (the SEO sample). The analysis below excludes SEO households. For a more detailed discussion of the PSID we refer to Hill (1992).

3.3 The SEE

The SEE is run by the Survey Center at the University of Wisconsin as a periodic module of the WISCON Survey. It is a nationwide representative survey consisting of daily telephone interviews that includes a set of constant core questions about people's experiences, attitudes, and their economic perspectives. A total of 5423 interview cover a time span of four years and are collected in 8 consecutive waves, 2 a year, one in the May-July and the other in the November-January interview period. Dominitz and Manski (1996) offer a detailed description of the data.

4 Constructing life cycle profiles

In both the Italian and US samples we drop households where the head is self-employed and those with missing observation for at least one of the variables relevant to the analysis, i.e., age, education, and earnings. We group the resulting observations into ten year-of-birth cohorts. The first cohort (the oldest) includes individuals born between 1920 and 1924; the second cohort includes individuals born between 1925 and 1929, and so on. The youngest cohort includes individuals born between 1965 and 1969.

As a measure of earnings, we use labor income from employment before taxes for year-round employed. Real earnings are obtained by dividing nominal earnings by the CPI. For Italy the base year is 1991, and for the US 1982-1984. We split the sample on the basis of education, distinguishing between three groups: less than high school (which in Italy corresponds to 8 years of full-time schooling and in the US to 9-11 grades), high school degree (13 years and 12-15 grades, respectively), and college degree or more (between 18 and 21 years of full-time schooling in Italy, and at least 16 grades in the US).

Given the limited time span of our data set, we do not observe the entire life cycle profile of individual earnings. To estimate life cycle earnings profiles several alternatives are available, parametric and non-parametric. Parametric techniques of the type illustrated in Deaton and Paxson (1993) impose strong restrictions on the effect of cohort, age, and time effects. We use a non-parametric approach. In particular, instead of assuming that aggregate shocks average out, we assume that cohorts of individuals born in adjacent years and choosing similar levels of schooling face similar aggregate shocks.

The non-parametric approach adopted here is similar to that used by Attanasio and Banks (1998) in a very different context. It consists of extrapolating backward and forward the value of the variable of interest (in our specific case, unobserved earnings at different points of the life cycle).

To see how the extrapolation technique works, consider figure 1, where we plot the actual age-earnings profile for each cohort/education group in the Italian data (figure 2 refers to the US). If there were no significant cohort or year effects, a cross-sectional graph could be interpreted as the life cycle of earnings for a representative individual. However, both cohort and time effects are likely to be present.

A complete life cycle earnings profile is unavailable because each cohort is observed only for a limited number of years: from 1984 to 1998 in Italy, and from 1967 to 1991 in the US. Thus, young cohorts are not observed when they age, while old cohorts are not observed when young. We extrapolate the unobserved values of the variable of interest using information available for adjacent cohorts. For simplicity of exposition, we illustrate the extrapolation technique with reference to the Italian data.

Suppose that the variable of interest is $x_{c,a}$, where c is a subscript for cohort and a for age. Let's assume that $c = 1, 2, ..., C$, with C being the youngest cohort considered. Our problem is that for a young cohort we observe x from age 14 to age 25 (i.e., from 1991 to 1998), but not afterwards; similarly, for the adjacent cohort we observe x from age 14 to age 30 (i.e., from 1986 to 1998), and so forth. For the oldest cohort, we observe x from age 62 in 1984 to age 65 in 1987, but not before. Thus, we need to predict future values of x for the youngest cohorts, past values of x for the oldest cohorts, and both future and past the values of x for the intermediate cohorts. Note that almost at all ages values of x overlap for different cohorts. Formally, suppose that for a generic cohort c we have a series: $[x_{c,1}$, $x_{c,2}$,..., $x_{c,a}]$ of values for the variable x. The scope is to obtain an estimate of $x_{c,a+j}$ (with $1 < j < T - a$, with T being the maximum age, set to 65) from data available for older cohorts. Suppose there is just one such cohort, for which we have the series: $[x_{c+1,2}$, $x_{c+1,3}$,..., $x_{c+1,a+1}]$. Define the rate of growth: $g_{c,a,a+1} = \frac{x_{c,a+1}}{x_{c,a}} - 1$ (which is unobserved) and $g_{c+1,a,a+1} = \frac{x_{c+1,a+1}}{x_{c+1,a}} - 1$ (which is observed). Since $x_{c,a+1} = x_{c,a}(1 + g_{c,a,a+1})$, the knowledge of $g_{c,a,a+1}$ would provide us with the requested value for $x_{c,a+1}$.

The problem is that $g_{c,a,a+1}$ is unobserved. However, we can use as an estimate of $g_{c,a,a+1}$ the value of $g_{c+1,a,a+1}$ available for the older cohort. This amounts to assume that $-$between ages a and $a+1-$ adjacent cohorts have a similar age profile for the variable of interest x. Clearly, when more cohorts are available, the estimate of g can be considerably refined (for instance, through simple or weighted averages of the available growth rates). This has of course an element of arbitrariness, as weights must only satisfy the condition that they sum to one and that they should be larger as less distant is the available cohort's growth rate to the cohort of reference. In the end, we decided to weight each available growth rate by the squared value of the reciprocal of the distance between cohorts. So, the weights are chosen to be inversely proportional to the distance between the cohort of reference and the adjacent cohorts for which data are available: more adjacent cohorts thus receive more weight than more distant cohorts.

Figures 3 and 4 show, respectively, the Italy and US extrapolated and actual age-earnings profiles, separately for each education group. In this figure, the dotted lines represent the (forward and backward) extrapolated values, while the straight lines represent the original survey values. This technique reconstructs the entire life cycle earnings profile for a representative individual belonging to a given cohort. All profiles are concave as predicted by the human capital theory. Moreover, there is a negative correlation $-$across education$-$ between the slope and the intercept of the earnings profile, another important implication of the human capital theory (see Ben-Porath, (1967); Hause (1980)). This evidence is quite strong in the Italian case, much less clear in the US case.

We smooth the extrapolated profiles with a quartic in age, save the parameters, and use them to construct the expected earnings profile for an individual who is entering the labor market, conditional on his schooling choice.

We use a similar extrapolation technique to predict the variance of earnings at all ages for different cohort/schooling combinations. We first regress earnings on a quartic in age, and dummies for sex and time, separately by education. We take the squares of the residuals of these regressions, and average them for each age/cohort/schooling combination. We then apply the extrapolation technique described above. The age-variance profiles for Italy and the US are shown in figure 5 and 6. The variance profiles decline slightly at the beginning of the life cycle, and increase around age 30-35. In the US case, the increase is much stronger for the more educated and there appear to be some significant cohort effects. In the Italian case the evidence is similar, but the decrease at the beginning of the life cycle is much more pronounced and the increase at the end is less. The two figures show that the variance levels are generally higher in the US than in Italy. The most natural explanation for this is that it reflects tighter labor market regulations and more generous welfare programs in Europe.

Finally, we estimate unemployment risk. To this purpose, we use subjective unemployment probabilities elicited in the 1995-98 SHIW and in the 1994-98 SEE. We take averages of subjective probabilities by age and schooling level (see figure 7 for Italy, and figure 8 for the US). Figure 7 shows that unemployment risk declines quite rapidly in the first few years after entering the labor market, it stabilizes around age 40, before increasing slightly towards the end of the life cycle, perhaps reflecting early retirement. Looking across education, two things are worth noting: (1) the more educated face less unemployment risk, and

(2) the decline in unemployment probabilities at the start of the life cycle is much slower for the less educated. Figure 8 shows that unemployment risk declines over the life cycle for all education groups (apart from a slight increase at the beginning of the life cycle for those with high-school and beyond). The ordering of education groups in terms of unemployment is similar to that noticed above for Italy. Comparison across countries shows that Italian face slightly higher unemployment risk than the US counterparts regardless of education (an average of 22 percent in Italy *vis-à-vis* 14 percent in the US). Guiso, Jappelli, and Pistaferri (2000) notice that the two distributions differ dramatically only at low levels of the probability of unemployment, with the fraction of individuals reporting no unemployment risk altogether being much higher in Italy than in the US.

Unemployment averages obviously neglect year and cohort effects. This is a strong assumption, but unfortunately the time span of unemployment probability data is too limited (two years in the SHIW, five in the SEE) to extend our extrapolation technique to unemployment risk.

5 Results

We use the estimates of the first two moments of the distribution of expected earnings (conditioning on employment) and the perceived unemployment probabilities to compute the rate of return to schooling in equation (1). We focus on four cases of interest: no uncertainty, unemployment risk, wage risk, and both unemployment and wage risk. We experiment with different values for the coefficient of relative risk aversion (RRA) ranging between 1 and 3.

The first two columns of table 1 display the return to high school (ρ_{12}) and college (ρ_{23}) when the coefficient of relative risk aversion is set to 1. In these and other columns, Panel A refers to Italy, Panel B to the US.

Two main findings emerge: (1) the return to education is higher in the US than in Italy, at both the high school and college level, and (2) in both countries the return to college is higher than that for high school. These results are consistent with previous evidence. Brunello, Comi and Lucifora (2000) find that the return to an additional year of education ranges between 5 and 7 percent in Italy. For the US, the return to an additional year of education ranges between 6 and 13 percent (see Card (2000)).[5]

In Italy the return to high school declines almost monotonically with year of birth, while the return to college exhibits a distinctive U-shape: workers born in the 1940s and in the 1950s enjoy lower return to college than those born before or after these two decades.[6] The U-shape for college education returns is the result of two contrasting forces. On the one hand, the supply of college graduates has increased relatively to that of high school graduates; on the other, the demand for college educated individuals has increased more rapidly than supply, due perhaps to skill biased technological changes. Moreover, the strong increase in the return to college education enjoyed by the youngest cohort is likely to reflect important institutional changes, such as the removal of the wage indexation mechanism

[5]Averaging the return to education over different cohorts and levels of schooling and weighting by the cell size, we obtain a return of around 6 percent for Italy and 12 percent for the US.

[6]Consistently with these findings, Brunello, Comi and Lucifora (2000) find that the return to education is flat in the 1980s and it rises in the 1990s.

(1985), which increased wage differentials after a long period of wage compression (see Manacorda (2000)), and the decline in unionization rates and unions' power.

In the US the return to high school is virtually flat across cohorts, while the return to college is stable for the first six cohort and increases quite rapidly for the cohorts entering the labor market from the late 1970s onward (i.e., with the baby-boomers). This evidence is not novel to our paper, and it has been documented quite extensively elsewhere. The conventional view is that the skill biased technological change of the last two decades has dramatically increased the price of both observable (i.e., education) and unobservable skills (i.e., ability).

As remarked in Section 1, the return to education can be biased by the failure to account for higher moments of the distribution of earnings and for the risk of unemployment. We thus consider the introduction of uncertainty about employment status and future earnings.

The third column of table 1 reports estimates of the return to high school accounting only for employment uncertainty (ρ_{12}^{ur}). For all cohorts, the return is now higher than that in the absence of unemployment risk. In Italy, such increase is both higher and exhibits more heterogeneity than in the US (9-18 percent *vis-à-vis* 10-11 percent). This is due to the fact that high school graduates face less unemployment risk in the US than in Italy relatively to high school dropouts.

Column 4 repeats the same exercise for ρ_{23}^{ur}, the return to college education. Also in this case, the return increases (by anything between 7-19 percent in Italy, and by 6-7 percent in the US). Two remarks are in order. First, extra-returns are again higher and more disperse in Italy than in the US, mainly due to a *level* effect (unemployment risk is generally higher in Italy than in the US). Second, extra-returns to college are in both countries lower than extra-returns to high school education. The reason is that differences in unemployment risk between compulsory and high school educated individuals are stronger than those between high school and college educated individuals.

The fifth columns of table 1 deals with wage risk in isolation. One interesting finding is that in both countries the extra-return to high school due to wage risk is lower than the one due to unemployment risk. In Italy, the increase in the return to high school (ρ_{12}^{wr}) is higher than in the US (4-12 percent *vis-à-vis* 5-6 percent). Recall that our measure of wage risk reflects the uncertainty faced by those working full-time. This uncertainty varies across education group, but to a lower extent than unemployment risk. Furthermore, the variation across education groups is larger in Italy than in the US.

The sixth columns of table 1 reports estimates of the return to college that account for wage risk, ρ_{23}^{wr}. In both countries, the return to college increases, but less than the return to high school. In Italy, the increase is between 4 and 10 percent, in the US around 3 percent.

The last two columns of table 1 report the return to high school (ρ_{12}^{uwr}) and college education (ρ_{23}^{uwr}), jointly accounting for unemployment and wage risk. Overall, when both sources of risk are considered, the return to high school increases on average by 21 percent in Italy and 15 percent in the US. The increase in the return to college is lower than that to high school, and generally higher in Italy than in the US (13 percent *vis-à-vis* 9 percent). Perhaps more interestingly, the extra-return to high school and college education is quite stable over time in the US, while it is increasing until the end of the 1970s in Italy and it declines afterwards, which, again, may be due to the changing institutional framework.

To check the robustness of our experiment, in table 2 we set the coefficient of relative risk aversion to 2. The results are similar to those reported in table 1. In both countries the effect of wage and unemployment risk on the return to schooling is larger than in table 1. This is because more risk averse individuals are willing to pay more for settling in less risky jobs. After accounting for wage and unemployment risk, the return to high school increases by around 84 percent in Italy and 45 percent in the US; that for college by 44 percent and 18 percent, respectively.

The main difference between table 1 and table 2 is in the balance between the extra-return due to unemployment risk and that due to wage risk. Comparing the third and the fifth column of table 2, one can notice that ρ_{12}^{ur} and ρ_{12}^{wr} are now very similar, as the increase in risk aversion magnifies the effect of wage risk on the return. The same holds true to the comparison between ρ_{23}^{ur} and ρ_{23}^{wr}.

In the US, the gap between the extra-return for unemployment risk and that for wage risk declines even more than in Italy, due to the fact that unemployment and wage risk vary across education groups in a similar fashion.

The general pattern of results is confirmed in table 3, where we set the coefficient of relative risk aversion to 3. Once we account for unemployment and wage risk, the return to high school increases by 82 percent in Italy and 47 percent in the US; that to college by 53 percent and 23 percent, respectively.

6 Conclusion

This paper proposes a measure of the return to education that accounts for unemployment and wage risk. Individuals with different level of schooling are confronted with different levels (and types) of uncertainty. This should be taken into account when the return to each schooling choice is evaluated.

Intuitively, two schooling choices are pay-off equivalent if they give rise to the same pay-off. This pay-off depends potentially on the entire distribution of future earnings. We restrict this dependency to the first two moments. The second moment measures the amount of wage risk faced by human capital investors. Risk also arise from the possibility of facing unemployment spells over one's career. These two factors affect the pay-off of schooling choices if different alternatives give rise to different levels of risk. We thus cast schooling choices in the framework of individual choices under uncertainty, following an early theoretical and empirical literature (see Lehvari and Weiss, (1974)).

We measure the return to high school and college education allowing for heterogeneity across year of birth cohorts. Our methodology require the use of synthetic panel technique since individuals are not typically observed over the entire life cycle. Moreover, individuals belonging to different cohorts enter the labor market in different years and are likely to exhibit different level of productivity. These two factors interact and may affect quite dramatically the return to different types of education. Institutional factors are likely to influence the amount of unemployment and wage risk by which individuals are confronted. This prompts the use of samples drawn from Italy and the US, two countries that are very diverse in terms of labor market institutions.

For the sake of comparability, we concentrate on three schooling groups: high school dropout, high school graduate, and colllege graduate.

Some of the findings of the paper have been documented in previous empirical work, but some are novel to our paper. First, the return to both high school and college is, on average, higher in the US than in Italy. Furthermore, the return to high school declines with year of birth in Italy, while it remains about the same in the US. Conversely, in the US the return to college start increasing for individuals entering the labor market at the end of the 1970s, while in Italy it declines slightly in the 1970s and part of the 1980s and increases afterwards. The effect of skill biased technological change is common across countries, but it appears in Italy much later than in the US due to the effect of institutional constraints.

Second, accounting for risk increases the return to schooling in both countries. In particular, the extra-return is higher for high school graduate than for college graduates, and is higher for unemployment risk than for wage risk. Moreover, this extra-return increases with risk aversion.

There are some differences between Italy and the US, though. The first is related to the level of the extra-return, which is higher in Italy at any level of schooling, regardless of risk type. This suggests that in the US schooling choices are more risk-enhancing than in Italy. Moreover, as risk aversion increases, the gap between the extra-return for unemployment and that for wage risk shrinks more in the US than Italy. This reflects the fact that wage risk is in general higher in the US than in Italy.

Overall, this exercise suggests that failing to account for the uncertainty that different schooling choices involve can bias downward the return to education. The size of the bias depends on investors' risk aversion and labor market characteristics. Future empirical work should attempt to correct Mincer regression estimates for this important factor.

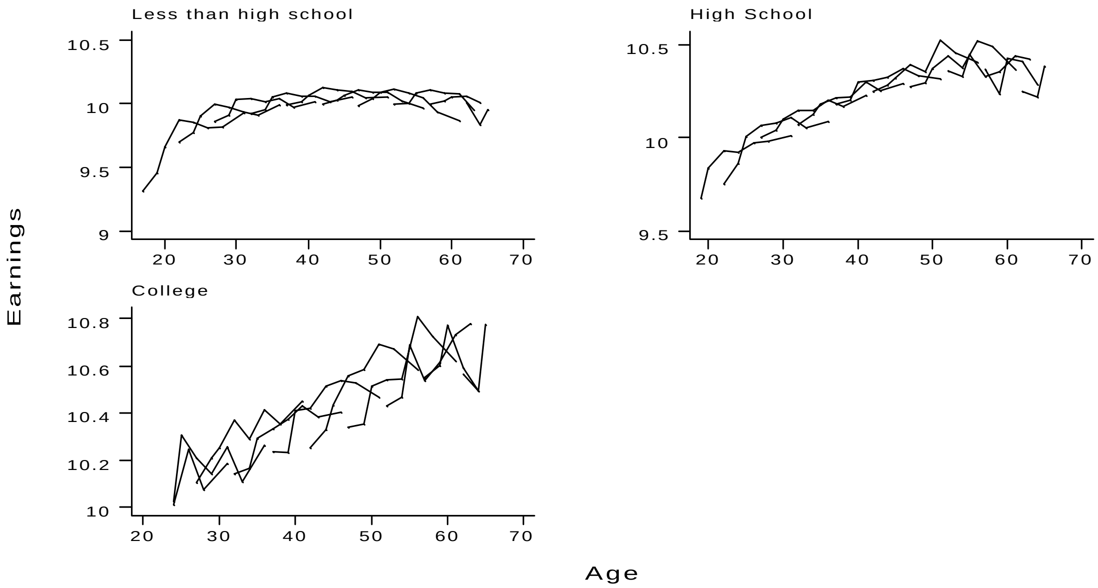

Figure 1: Actual age-earnings profile, by cohort and education group, Italy

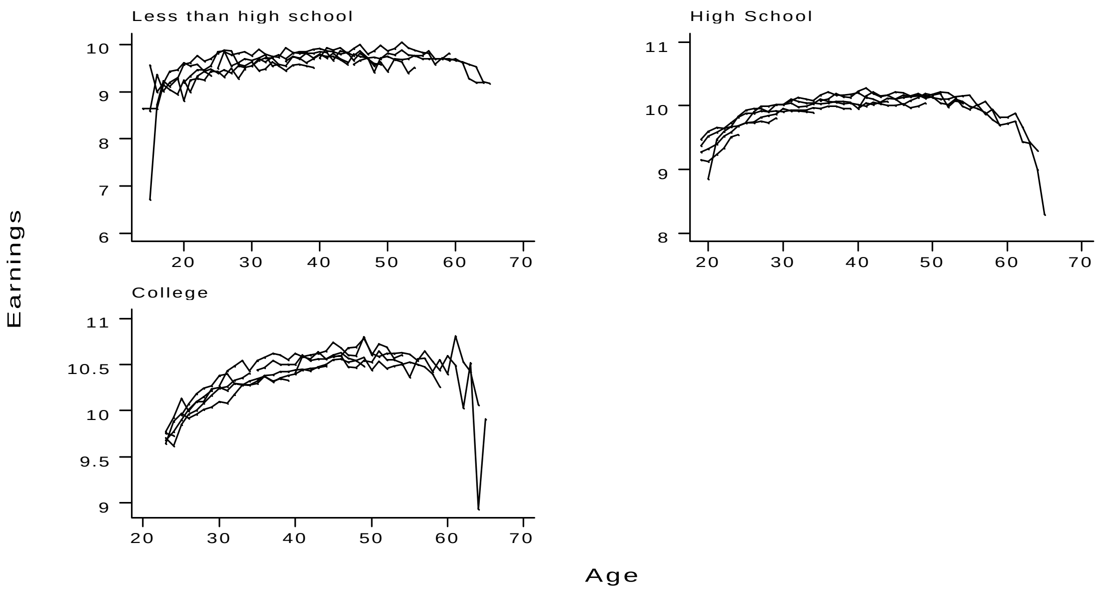

Figure 2: Actual age-earnings profile, by cohort and education group, US

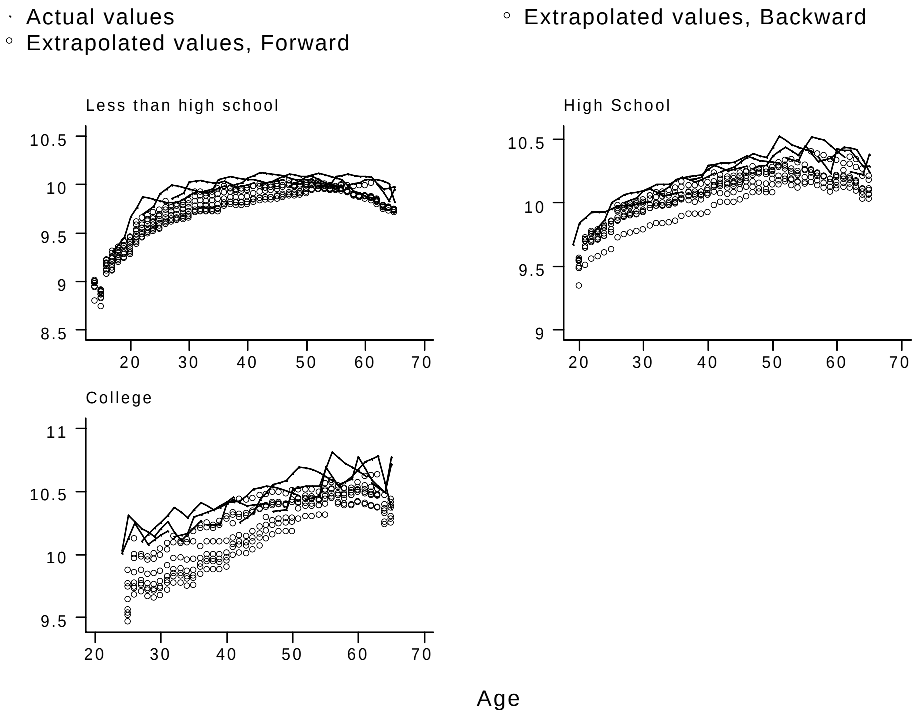

Figure 3: Extrapolated and actual age-earnings profile, mean, by cohort and education group, Italy

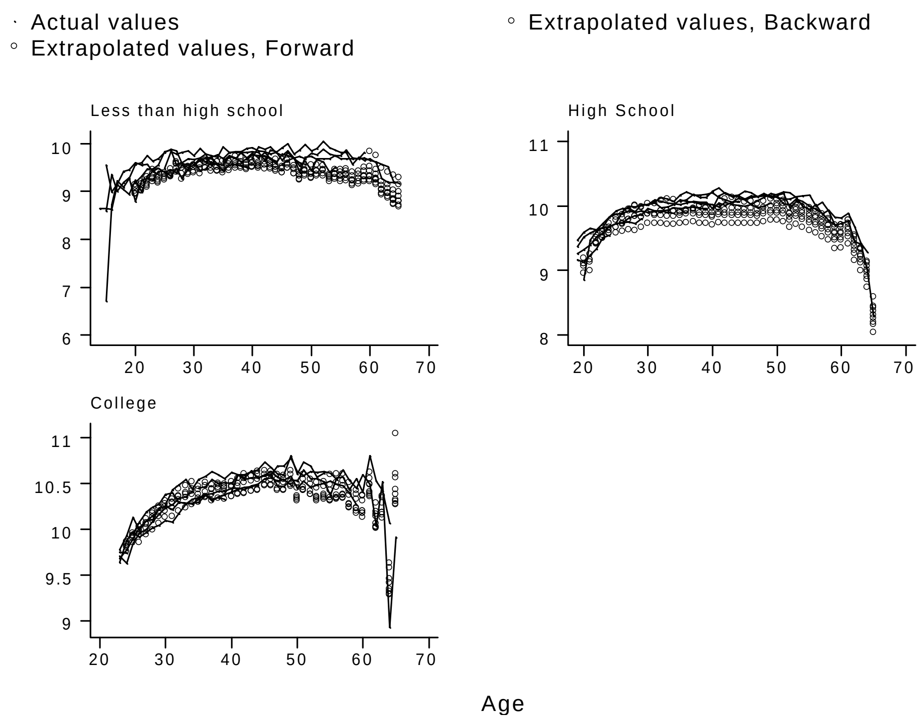

Figure 4: Extrapolated and actual age-earnings profile, mean, by cohort and education group, US

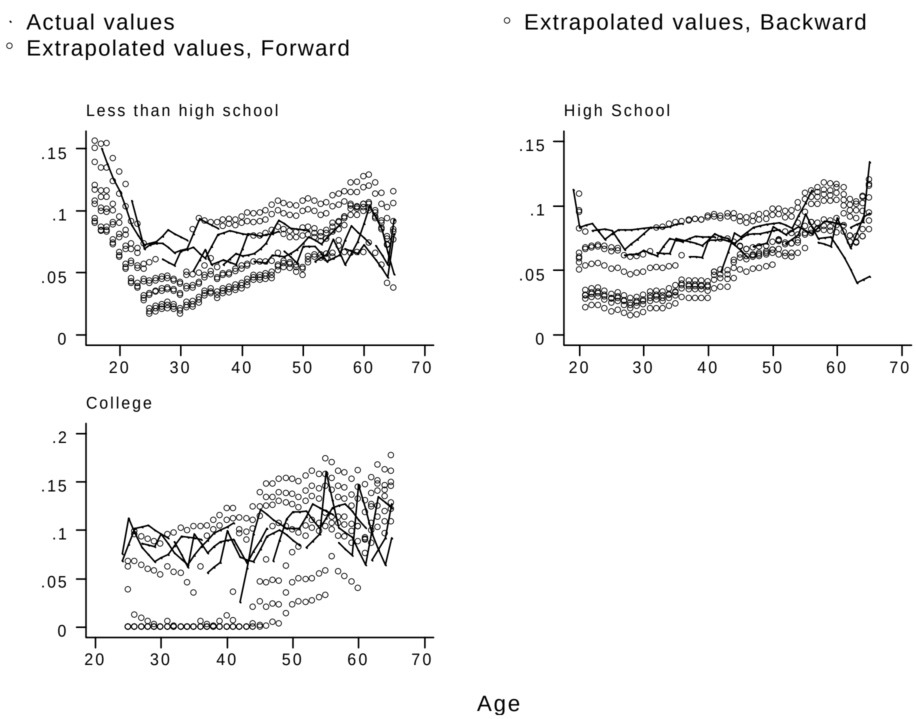

Figure 5: Extrapolated and actual age-earnings profile, variance, by cohort and education group, Italy

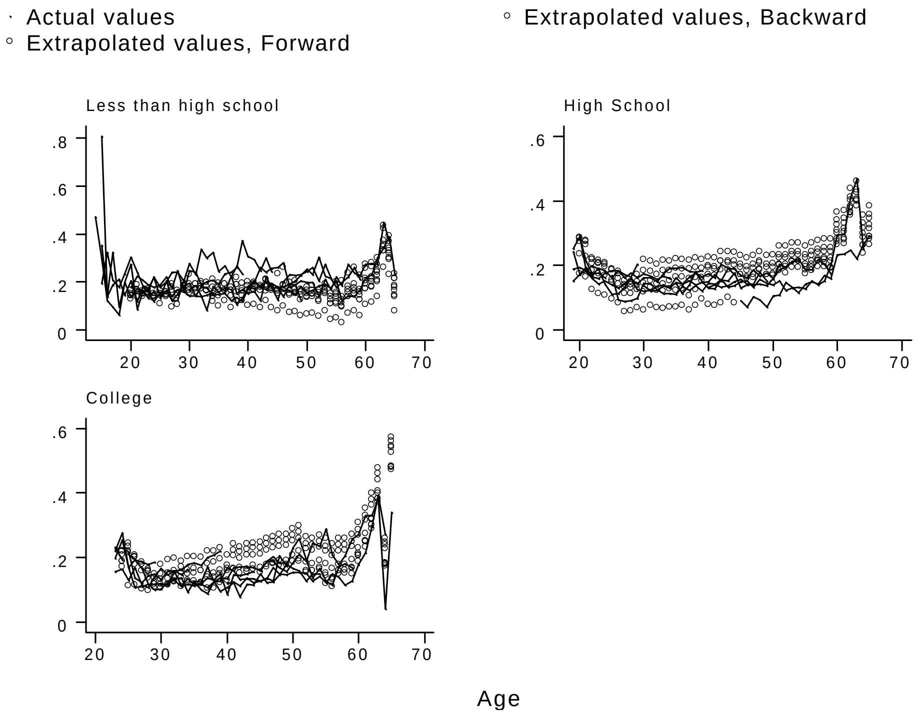

Figure 6: Extrapolated and actual age-earnings profile, variance, by cohort and education group, US

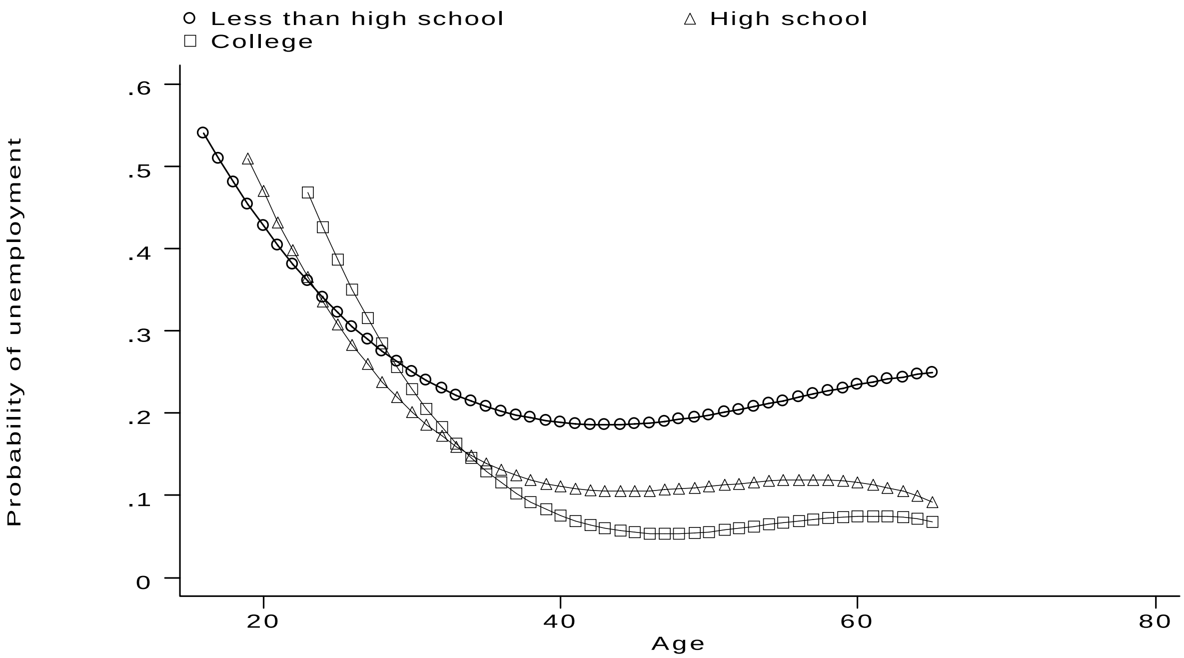

Figure 7: Probability of unemployment, by age and education group, Italy

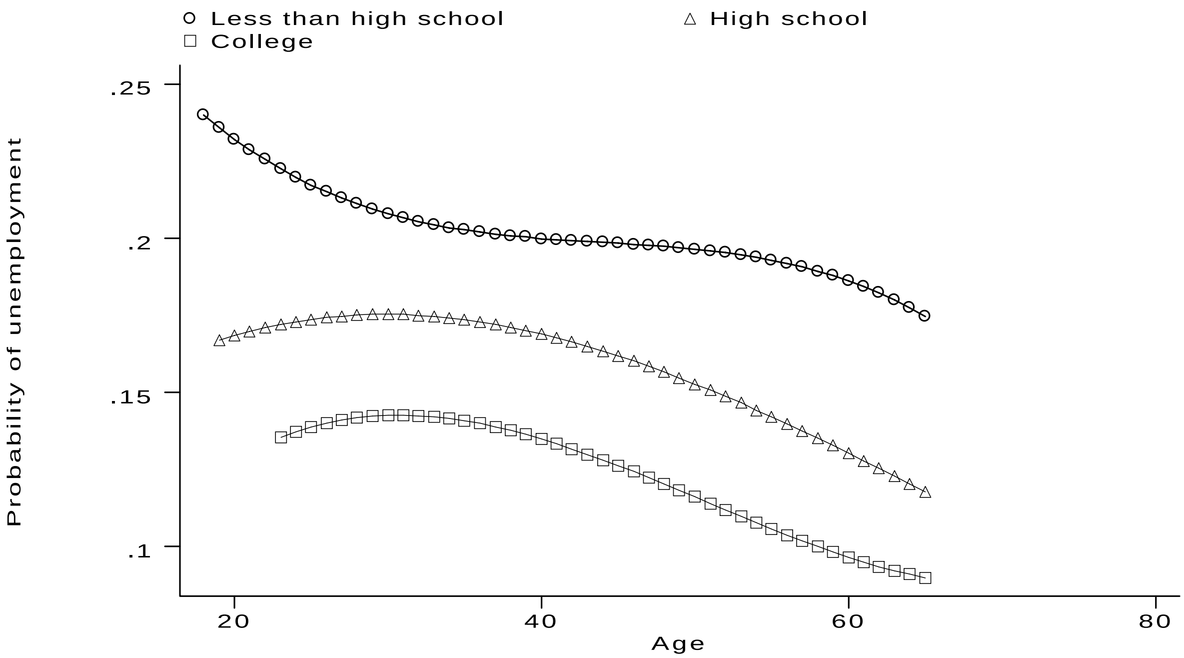

Figure 8: Probability of unemployment, by age and education group, US

Table 1: Return to education, $RRA = 1$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{ur}	ρ_{23}^{ur}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uwr}	ρ_{23}^{uwr}
Panel A: Italy								
1	0.1206	0.1507	0.1319	0.1624	0.12629	0.1565	0.1353	0.1659
2	0.1095	0.1442	0.1207	0.1558	0.11511	0.1500	0.1241	0.1593
3	0.0975	0.1315	0.1086	0.1429	0.10316	0.1371	0.1120	0.1464
4	0.0858	0.1190	0.0968	0.1303	0.09136	0.1246	0.1001	0.1337
5	0.0743	0.1067	0.0851	0.1179	0.07971	0.1123	0.0885	0.1213
6	0.0631	0.0946	0.0738	0.1058	0.06840	0.1003	0.0770	0.1092
7	0.0520	0.0604	0.0627	0.0710	0.05733	0.0657	0.0660	0.0743
8	0.0413	0.0548	0.0518	0.0655	0.04659	0.0601	0.0559	0.0687
9	0.0466	0.1116	0.0572	0.1228	0.05199	0.1171	0.0604	0.1262
10	0.0575	0.1165	0.0682	0.1278	0.06284	0.1221	0.0714	0.1312
Panel B: US								
1	0.1022	0.1567	0.1134	0.1684	0.1078	0.1626	0.1167	0.1720
2	0.0999	0.1606	0.1110	0.1723	0.1055	0.1664	0.1144	0.1759
3	0.0959	0.1631	0.1070	0.1749	0.1014	0.1690	0.1104	0.1784
4	0.0988	0.1651	0.1099	0.1768	0.1043	0.1709	0.1133	0.1804
5	0.0976	0.1664	0.1087	0.1781	0.1032	0.1722	0.1121	0.1817
6	0.0953	0.1657	0.1064	0.1775	0.1009	0.1716	0.1098	0.1811
7	0.0942	0.1696	0.1053	0.1814	0.0997	0.1755	0.1086	0.1850
8	0.0965	0.1894	0.1076	0.2014	0.1020	0.1954	0.1109	0.2051
9	0.0948	0.1921	0.1058	0.2041	0.1003	0.1981	0.1092	0.2078
10	0.0945	0.1962	0.1056	0.2083	0.1000	0.2022	0.1089	0.2119

Note: Each row refers to a different cohort. The cohort number is reported in the first column and is increasing with year of birth. The coulmns headed by ρ_{12}, ρ_{12}^{ur}, ρ_{12}^{wr}, ρ_{12}^{uwr} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The coulmns headed by ρ_{23}, ρ_{23}^{ur}, ρ_{23}^{wr}, ρ_{23}^{uwr} refer to the return to college.

Table 2: Return to education, $RRA = 2$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{ur}	ρ_{23}^{ur}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uwr}	ρ_{23}^{uwr}
Panel A: Italy								
1	0.0928	0.1251	0.1217	0.1548	0.1149	0.1478	0.1240	0.1572
2	0.0821	0.1188	0.1107	0.1483	0.1039	0.1414	0.1129	0.1507
3	0.0704	0.1063	0.0987	0.1355	0.0920	0.1286	0.1009	0.1378
4	0.0589	0.0940	0.0869	0.1229	0.0803	0.1161	0.0891	0.1252
5	0.0477	0.0821	0.0754	0.1107	0.0689	0.1039	0.0776	0.1129
6	0.0367	0.0704	0.0641	0.0987	0.0577	0.0920	0.0663	0.1009
7	0.0260	0.0367	0.0531	0.0641	0.0467	0.0577	0.0553	0.0663
8	0.0155	0.0313	0.0423	0.0586	0.0360	0.0521	0.0444	0.0608
9	0.0207	0.0868	0.0477	0.1155	0.0413	0.1088	0.0498	0.1178
10	0.0313	0.0916	0.0586	0.1205	0.0522	0.1137	0.0608	0.1227
Panel B: US								
1	0.0471	0.0989	0.0685	0.1213	0.0630	0.1156	0.0663	0.1190
2	0.0449	0.1025	0.0662	0.1250	0.0608	0.1193	0.0641	0.1227
3	0.0411	0.1050	0.0624	0.1275	0.0570	0.1218	0.0602	0.1252
4	0.0438	0.1068	0.0651	0.1294	0.0597	0.1237	0.0630	0.1271
5	0.0427	0.1080	0.0640	0.1306	0.0586	0.1249	0.0619	0.1283
6	0.0406	0.1074	0.0618	0.1300	0.0564	0.1243	0.0597	0.1277
7	0.0395	0.1111	0.0607	0.1338	0.0553	0.1280	0.0586	0.1315
8	0.0417	0.1299	0.0629	0.1530	0.0575	0.1472	0.0608	0.1507
9	0.0400	0.1325	0.0613	0.1556	0.0559	0.1497	0.0591	0.1533
10	0.0397	0.1364	0.0610	0.1596	0.0556	0.1537	0.0588	0.1572

Note: Each row refers to a different cohort. The cohort number is reported in the first column and is increasing with year of birth. The coulmns headed by ρ_{12}, ρ_{12}^{ur}, ρ_{12}^{wr}, ρ_{12}^{uwr} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The coulmns headed by ρ_{23}, ρ_{23}^{ur}, ρ_{23}^{wr}, ρ_{23}^{uwr} refer to the return to college.

Table 3: Return to education, $RRA = 3$

Cohort	ρ_{12}	ρ_{23}	ρ_{12}^{ur}	ρ_{23}^{ur}	ρ_{12}^{wr}	ρ_{23}^{wr}	ρ_{12}^{uwr}	ρ_{23}^{uwr}
Panel A: Italy								
1	0.1151	0.1480	0.1493	0.1832	0.1856	0.2206	0.1671	0.2016
2	0.1042	0.1416	0.1380	0.1765	0.1739	0.2137	0.1556	0.1948
3	0.0922	0.1288	0.1257	0.1634	0.1612	0.2001	0.1431	0.1815
4	0.0805	0.1164	0.1136	0.1505	0.1488	0.1869	0.1309	0.1684
5	0.0691	0.1042	0.1018	0.1380	0.1366	0.1739	0.1190	0.1556
6	0.0579	0.0922	0.0903	0.1256	0.1247	0.1612	0.1072	0.1431
7	0.0469	0.0579	0.0790	0.0902	0.1130	0.1247	0.0958	0.1072
8	0.0362	0.0524	0.0679	0.0846	0.1017	0.1189	0.0845	0.1015
9	0.0415	0.1090	0.0734	0.1429	0.1073	0.1790	0.0901	0.1607
10	0.0524	0.1139	0.0846	0.1480	0.1189	0.1842	0.1015	0.1658
Panel B: US								
1	0.0577	0.1100	0.0848	0.1385	0.0793	0.1327	0.0826	0.1361
2	0.0555	0.1137	0.0825	0.1422	0.0770	0.1364	0.0803	0.1399
3	0.0516	0.1161	0.0786	0.1448	0.0731	0.1389	0.0764	0.1424
4	0.0543	0.1180	0.0814	0.1467	0.0759	0.1408	0.0792	0.1443
5	0.0533	0.1192	0.0803	0.1479	0.0748	0.1421	0.0781	0.1456
6	0.0512	0.1186	0.0780	0.1473	0.0725	0.1414	0.0758	0.1449
7	0.0500	0.1223	0.0770	0.1511	0.0714	0.1452	0.0747	0.1488
8	0.0522	0.1414	0.0792	0.1706	0.0737	0.1647	0.0770	0.1682
9	0.0505	0.1439	0.0774	0.1733	0.0719	0.1673	0.0753	0.1709
10	0.0503	0.1478	0.0772	0.1773	0.0717	0.1713	0.0750	0.1749

Note: Each row refers to a different cohort.The cohort number is reported in the first column and is increasing with year of birth. The coulmns headed by ρ_{12}, ρ_{12}^{ur}, ρ_{12}^{wr}, ρ_{12}^{uwr} refer to the return to high school in the baseline case, accounting for unemployment risk, for wage risk and for the two risks together, respectively. The coulmns headed by ρ_{23}, ρ_{23}^{ur}, ρ_{23}^{wr}, ρ_{23}^{uwr} refer to the return to college.

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