Off to a bad start: youth nonemployment and labor market outcomes later in life*

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Abstract

We estimate the effect of nonemployment experienced by Italian youth after leaving secondary school on subsequent labor market outcomes. We focus on the impact on earnings and labor market participation both in the short- and in the long-term, up to 25 years since school completion. By estimating a factor analytic model which controls for time-varying unobserved heterogeneity, we find that the negative effect of nonemployment on earnings is especially persistent, being sizeable and statistically significant up to 25 years after school completion, for both men and women. Penalties in terms of participation last instead shorter; they disappear by the 10th year after school completion. Hence, early nonemployment operates by persistently locking the youth who get off to a bad start into low-wage jobs.

Keywords: Youth nonemployment; scarring effects; earnings; labor market participation; factor analytic model. **JEL Classification:** J01, J08, J31, J64

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1 Introduction

Since the 1980s, many labor economists have studied the consequences of early nonemployment (or unemployment) on subsequent labor market performances. They have especially sought to understand whether they are temporary, persistent or even permanent. The empirical literature provides several findings about the so-called "scarring effects" of nonemployment on both wages and employability in the future. In addition to the immediate loss in terms of forgone earnings and accumulation of human capital, nonemployment episodes may also have longer-term or permanent effects by increasing the likelihood of experiencing future joblessness and lower subsequent wages (Arulampalam et al., 2001; Gregg and Tominey, 2005).

Filomena (2021) provides an up-to-date survey of the empirical literature on scarring effects of nonemployment on subsequent labor market outcomes. The empirical findings are unambiguous in detecting significant, and often persistent, wage penalties and lower employment probabilities after episodes of joblessness, despite different dataset used, countries considered, time span covered and identification strategies of the causal effect. Some marginal finding heterogeneity concerns the magnitude of the scarring effects: for instance, unemployment episodes experienced by school-leavers or by laid-off workers are particularly penalizing (see e.g. Burda and Mertens, 2001; Jacobson et al., 1993; Mroz and Savage, 2006; Spivey, 2005), while the negative effect is less stigmatizing in cases of plant closures (Gibbons and Katz, 1991) or during economic downturns (Omori, 1997).

We study the impact of nonemployment events after secondary school completion on subsequent labor market performances in Italy. More in details, we try to give credible answers to the following research questions: i) What is the causal impact of early nonemployment on subsequent earnings and labor market participation for Italian school-leavers? ii) If penalties are detected, how long do they take to fade away?

The contribution of our analysis is twofold. First, we shed further light into the scarring effects of early nonemployment by estimating short, medium and long-term impacts, measured up to 25 years after school completion. Second, we focus on the Italian case, which is particularly interesting. Understanding the scarring effects of early nonemployment in Italy is of crucial relevance from both a socioeconomic point of view and a policy perspective. Indeed, new labor market entrants face significant difficulties in Italy, where the average duration of the school-to-work transition, 2.88 years for those aged 18-34, is the highest in Europe, discouraging young people from investing in tertiary education (Pastore et al., 2021b,a). To the best of our knowledge, the stigma effects of nonemployment for Italian youth have not been investigated in sufficient detail for a proper understanding of the rigidity of the youth labor market. Lupi et al. (2002) examined the effect of unemployment events on future wages only and found that they are scarring only in the North, where the aggregate unemployment rate is lower than in the rest of the country. Tanzi (2022) obtained similar findings; the negative effects of early nonemployment on the propensity to experience further nonemployment events are smaller during recession or in regions with high unemployment rates.

To answer our research questions, we use the AD-SILC database, which is the result of the match between the IT-SILC database and administrative labor market data from the National Social Insurance Agency (INPS). For each interviewee of the IT-SILC, the dataset contains and allows us to reconstruct all the working history as an employee up to the end of 2013. The AD-SILC database has already been exploited to analyze the labor market performances of Italian youth, but without a focus on the scarring effects of early nonemployment. For example, Naticchioni et al. (2016) showed that labor market performances have deteriorated across cohorts, with lower entry wages for younger cohorts. Raitano and Fana (2019) studied the labor market outcomes of new entrants, finding that they work more frequently through atypical contracts and are paid lower wages in the first six years of their career.

We model and estimate the sequence of labor market experiences as of school completion. We start modeling the fraction of time the youth spent in nonemployment in the first three years after the secondary school diploma, which is the treatment. Then, we relate this treatment intensity to the realization of earnings and fraction of time spent in employment 5 years after school completion and, every 5 years, until 25 years since the secondary school diploma.

The treatment intensity is very likely to be an endogenous variable as there will be almost with certainty characteristics, both time-constant and time-varying, which we cannot observe or measure but which could nonetheless affect the likelihood of experiencing long nonemployment events after school exit and future labor market performances. Persistent or time-changing latent variables like ability, motivation, search intensity, family/social/economic background, household duties are typical examples of such crucial latent variables. This makes it difficult to credibly identify the causal effect of early nonemployment on subsequent labor market outcomes. Our identification approach of the causal effect fits into the factor-analytic dynamic models (FADM) (Carneiro et al., 2003; Heckman and Navarro, 2007), which has been more recently exploited by Fruehwirth et al. (2016) and Cockx et al. (2019) to study the impact of grade retention on subsequent school performances or by Picchio et al. (2021) to investigate the effect of fertility on subsequent labor market outcomes. Our model is a simplified version of those in Fruehwirth et al. (2016) and Picchio et al. (2021). Compared to the former, we do not integrate *essential heterogeneity* (Heckman et al., 2006), i.e. we do not allow the treatment effect to depend on observed and unobserved characteristics.[1] Compared to the latter, our treatment is unique and not multiple, being the fraction of time spent in nonemployment in the first three years after school completion. As such, the assumptions in Fruehwirth et al. (2016) or Picchio et al. (2021) are sufficient to attain the nonparametric identification of the treatment effect in our framework. The nonparametric identification is based on three main ingredients. First, we impose a loading factor structure on the unobserved determinants. Second, since we can rebuild all the working history, we can take advantage of the longitudinal information in our data and observe multiple realizations over time of the endogenous variables. Third, as in Picchio et al. (2021), we exploit measures of the latent factor which are free of selection into treatment (Carneiro et al., 2003), like the work experience before school completion and the number of siblings when the individual was 14. Because these measures are realized before the treatment occurs, i.e. before school completion and eventual accumulation of nonemployment events, they are free of selection into treatment and convey information on the distribution of the latent factor, as they may be related to social, economic and family background.

Once we control for time-varying unobserved heterogeneity, we find that the negative effect of nonemployment on earnings is very persistent, being sizeable and statistically significant up to 25 years after school completion, for both men and women. Penalties in terms of participation last instead much shorter. They indeed disappear by the 10th year after school completion. Hence, early nonemployment operates similarly for men and women by persistently locking the youth who get off to a bad start into lower wage jobs.

This paper is organized as follows. Section 2 summarizes the empirical literature. Section 3 describes data and sample. Section 4 illustrates the econometric strategy for the identification of the causal effect of early nonemployment on subsequent labor market outcomes. We report the estimation results and comment on them in Section 5. Section 6 concludes.

[1] See also Cockx et al. (2019) for another application in which the treatment effect is allowed to depend on observed and unobserved characteristics.

2 Literature review

Theoretical predictions on the scarring effects of unemployment or nonemployment events can be derived from two main strands of the economic theory: the human capital theory and the signaling theory. According to the former, scarring effects are related to the depreciation of workers' general skills and knowledge during the nonemployment spell and to the lack of accumulation of human capital (Mincer, 1974; Becker, 1975; Pissarides, 1992). Following the signaling theory, employers may use past nonemployment events of a worker as a signal of low productivity, with the magnitude of the stigma effect on worker's subsequent labor market outcomes which may depend on the cause of previous nonemployment spells (Spence, 1973; Vishwanath, 1989; Lockwood, 1991).

The empirical literature on the scarring effects of joblessness has adopted different perspectives and displayed a special interest not only on the impact of youth nonemployment episodes, but also on the impact following plant closures and job displacements. Large and permanent wage scars caused by displacements or mass-layoffs were found in the US labor market (see e.g. Ruhm, 1991; Jacobson et al., 1993; Stevens, 1997). In Europe, permanent wage penalties were detected in the UK (Arulampalam, 2001; Gregory and Jukes, 2001), as well as in Germany or Scandinavian countries for displaced workers (see e.g. Burda and Mertens, 2001; Eliason and Storrie, 2006) or plant closure (Couch, 2001). Strong evidence of significant structural dependence induced by previous nonemployment experience was highlighted by several authors too (Arulampalam et al., 2000; Gregg, 2001; Böheim and Taylor, 2002; Stewart, 2007; Biewen and Steffes, 2010; Deelen et al., 2018).

About the impact of early unemployment, Corcoran (1982) and Ellwood (1982) found that it causes lower future earnings also 10 years after school completion. Similarly, Mroz and Savage (2006) detected that early unemployment experienced as long ago as ten years continues to negatively affect earnings, although they provide evidence of a relevant catch-up response. Doiron and Gørgens (2008) found that the occurrence of unemployment increases the probability of being unemployed in the future for young low-skilled Australians, but its duration is not relevant, i.e. they did not detect evidence of lagged duration dependence. Gartell (2009) and Nordström Skans (2011) studied the impact of early unemployment for Swedish youth, concluding that the longer the unemployment spell upon graduation the more substantial are subsequent individual earning losses and higher the unemployment probability after five years. A similar result is in Ghirelli (2015) for Belgium; one percentage point increase in the fraction of time spent in nonemployment in the first two and a half years since graduation decreases annual earnings by 10% and hours worked by 7% six years later. According to Cockx and Picchio (2013), in Belgium the job finding probability decreases from 60% to 16% for men and from 47% to 13% for women in the subsequent two years if the labor market entry is delayed by one year. In Germany early unemployment is found to increase the probability of future unemployment by 3.4 percentage points (Manzoni and Mooi-Reci, 2011), with a relevant and persistent effects (Schmillen and Umkehrer, 2017). In the UK, Gregg and Tominey (2005) estimated large, significant and long-term wage penalties caused by youth unemployment in the magnitude of 13-21% at age 42.

Some studies sought to determine if the scarring effects of nonemployment may be heterogeneous across some dimensions. Burgess et al. (2003) found that early unemployment has a negative effect on later employment prospects for the unskilled and a small beneficial effect for the more skilled. Tanzi (2022) revealed that the size of the scarring effect of early unemployment in Italy depends on regional labor market characteristics; as suggested by the signaling theory, the higher the regional unemployment rate or the worse the regional business cycle, the smaller the scarring effect. Finally, Möller and Umkehrer (2015) detected wage penalties which are different across the distribution of earnings; an increase in early-career unemployment by one standard deviation (about 11 months) causes persistent earning losses of about 56% for workers at the bottom and 7% for workers at the top of the earnings distribution.

3 Data and sample

3.1 Sample selection criteria

Our empirical analysis was based on the AD-SILC database, which is the result of the match between two data sources: i) the IT-SILC database covering the period 2004-2012 gathered by the Italian National Institute of Statistics (ISTAT); ii) the administrative data on labor market contracts from the National Social Insurance Agency (INPS). The latter allows, for each individual interviewed in the IT-SILC survey, to rebuild her/his working history as an employee up to the end of 2013. It contains gross earnings and the number of working days for each working episode and for each year. We further enriched the database with the regional time series of unemployment, employment, and real GDP growth rates retrieved from ISTAT. We used these variables as time-varying controls in the specification of the equations for the outcome variables.

From all the waves of the IT-SILC, we kept only individuals interviewed in 2005 and 2011 (98,529 individuals). We limited our sample to individuals in these two waves because they are the only ones with the *ad hoc* module on intergenerational transmission of poverty and disadvantages, which provides information on the family situation when the respondents were 14 years old. We used indeed the number of siblings at 14 as an outcome measure of the family and social background which is free of selection into treatment, i.e. predetermined with respect to the realization of nonemployment after school completion. As such, it contains predetermined information which may proxy distribution on unobserved heterogeneity affecting labor market outcomes. As we explain later, we also have a second outcome measure, i.e. the fraction of time spent in employment during the year before obtaining the secondary school diploma. Our factor structure model would be identified even without these outcome measures, but only on the basis of exclusion restrictions and normalizations, which may be viewed as too arbitrary. As pointed out by Carneiro et al. (2003), having outcome measures which may proxy the unobserved determinants of the treatment and outcomes reduce the degree of "arbitrariness and render greater interpretability to estimates obtained from our model".

We further kept only individuals who exited school before 2003 (2009) if interviewed in 2005 (2011), in order to have at least some years of labor market information between school completion and the IT-SILC interview. Moreover, we restricted the sample to individuals who exited formal education after 1976, because the ISTAT regional time series, which we used as time-varying controls, are only available from 1977. We lost 13 individuals because they did not have information on the province of birth. Since we had no information for the trends about the status of the labor market and the business cycle for people born in foreign countries, we excluded from the final sample individuals born abroad. We were left at this point with 31,134 individuals

This IT-SILC sample was then merged with the INPS database. There were 1,558 individuals who responded to the IT-SILC survey, but they did not appear in the INPS database. This may happen for example when an individual has never had a payroll employment position up to the moment of the IT-SILC interview. We deleted these 1,558 observations from the sample.

We decided then to only focus on individuals who exited school with a secondary school diploma (12,834 individuals left).[2] We deleted those with a lower degree to have a more homogeneous sample in terms of skills. We deleted individuals with a tertiary diploma because, although we know the year in which they graduated from the replies to the IT-SILC questionnaire, the month of graduation is unknown.[3] Hence, we do not know the month in which individuals with a tertiary degree exited formal education. For individuals with a secondary school diploma, we know instead the month in which they obtained the diploma, because the final examination takes place between the second half of June and the first half of July, and the results are known around mid of July. We set to 1 September the moment of the labor market entry. It is from this date that we start counting the time spent in nonemployment.

Table 1 reports in detail all the adopted sample selection criteria, including those which only marginally affected the sample size and were not discussed in the paragraphs above. The final sample is made up of 10,295 individuals, 5,396 men and 4,899 women.

Table 1: Sample size across selection criteria

	Individuals left in the sample	Individuals removed
Individuals in IT-SILC, waves 2005 and 2011	98,529	–
After removing individuals with errors on gender	98,513	16
After removing individuals observed twice from the wave 2005	98,374	139
After keeping only individuals who exited school after 1976 and before 2003 (2009) if interviewed in 2005 (2011)	34,180	64,194
After removing individuals with missing province of birth	34,167	13
After removing individuals born abroad	31,134	3,033
After removing individuals not included in the INPS database	29,576	1,558
After removing individuals due to incorrect information related to working periods	29,481	95
After removing graduates and individuals without high school diploma	12,834	16,647
After removing individuals younger than 16 or older than 21 at the time of their highest diploma	11,787	1,047
After removing individuals with yearly earnings greater than 800,000€ or daily earnings greater than €5,000	11,781	6
After removing individuals younger than 26 at the time of the interview	10,559	1,222
After removing individuals not observed at least 5 years after high school diploma	10,447	112
After removing individuals with missing data about the number of siblings at 14	10,375	72
After removing individuals with daily earnings greater than €250 (outliers)	10,295	80
Final sample	10,295	88,234

In what follows, the descriptive statistics and the econometric analysis for the estimation of the effect of nonemployment on subsequent labor market outcomes are presented by separating men from women. The labor market functioning may indeed be gender sensitive, especially in Italy, where the labor force participation rate is traditionally quite low

[2]According to the microdata of the Italian National Institute of Statistics (ISTAT), 41% of the Italian population aged between 35 and 64 years in 2020 (about the cohorts in our final sample) had a secondary school diploma as the highest educational outcome. This figure is available online at http://dati.istat.it.

[3]In Italy the final examination (the thesis discussion) for obtaining the tertiary degree is spread over the year.

among women[4] and the gender roles and duties in the family still follow the patriarchal model consisting of the male breadwinner and the mother caretaker (Saraceno, 1994; Giuliani, 2021) in the period under analysis. If so, men and women experiencing randomly a nonemployment event could be differently affected. On the one hand, women may be more likely to react by permanently withdrawing from the labor market. On the other hand, since nonemployment is more common among women, an early nonemployment event experienced by a woman may generate a weaker signal and less adverse effects on future labor market performances. Furthermore, men and women are very likely to be differently affected by parenthood which, in our econometric approach, will end up into a time-varying unobserved factor. By keeping the female and the male sample separated, we identify gender different distributions of the time-varying unobservables and accommodate for gender differences in unobservables determining both early nonemployment and later labor market performances.

3.2 Descriptive statistics

Our sample is composed only by individuals who obtained the secondary school diploma more than 3 years before the IT-SILC interview. Since the administrative data contain information of job episodes up to the end of 2013, we can observe for each individual in our sample, even for those interviewed in 2011 as they completed the secondary school in 2008, their labor market outcomes up to 5 years after school completion. The number of individuals whose labor market histories are observed for longer time spans is decreasing with the size of the time window since the secondary school diploma. In our empirical analysis, we look at the effect of early nonemployment on labor market outcomes until at most 25 years after school completion. The number of women(men) for whom we can observe the 25th year since the secondary school diploma amounts to 2,423 (2,792). Table 2 shows the number of observations from 5 to 25 years after school completion grouped by periods of 5 years. It also provides descriptive statistics about the treatment variable, i.e. the fraction of days in nonemployment during the first 3 years after school completion, and other time-invariant characteristics predetermined with respect to the treatment. In Online appendix A we report further descriptive statistics of our sample.

Table 3 shows summary statistics of our outcome variables, yearly labor earnings and

[4] In 2005, the employment rate from 20 to 64 years was 49% for women and 75% of men (Eurostat, Labour Force Survey).

Table 2: Subsamples by different years after school completion

Year after school completion	Observations	Nonemployment during 3 years after school exit	Father's education	Mother's education	Father at work	Mother at work	Number of siblings at 14	Employment 1 year before diploma
Men								
5	5,396	0.66	1.30	1.27	0.87	0.31	1.27	0.08
10	5,310	0.65	1.30	1.27	0.87	0.31	1.28	0.08
15	4,864	0.66	1.29	1.26	0.87	0.30	1.30	0.08
20	3,947	0.66	1.27	1.23	0.86	0.28	1.35	0.08
25	2,792	0.64	1.23	1.18	0.86	0.26	1.42	0.08
Women								
5	4,899	0.66	1.27	1.23	0.88	0.32	1.29	0.04
10	4,722	0.66	1.27	1.23	0.88	0.32	1.28	0.04
15	4,235	0.66	1.28	1.23	0.88	0.31	1.29	0.04
20	3,383	0.65	1.28	1.21	0.88	0.30	1.34	0.04
25	2,423	0.64	1.25	1.18	0.88	0.29	1.38	0.04

yearly fraction of days spent in employment from 5 to 25 years after school completion. The male yearly earnings increased by 130% along the time span considered. The profile over time of female earnings is less steep, amounting to a relative variation of +92%. This translated into an increasing gender gap in earnings over time; it was 21% 5 years after school completion and reached 45% 25 years after the diploma. Men and women are also characterized by a difference in terms of labor market participation, although less evident than that in terms of earnings. The fraction of time spent in employment were 62% and 57% for men and women, respectively, 5 years after school completion, to reach 89% and 83% 25 years after the diploma. The gender employment gap peaks 10-15 years after school completion, when it amounts to 12 percentage points. Perhaps, in this period some women leave the labor market to look after their children.

Table 3: Outcome variables at different years after school completion

	Men					Women				
		Yearly labor earnings (€)[(a)]		Days in employment [(b)]			Yearly labor earnings (€)[(a)]		Days in employment [(b)]	
Year after school completion	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Mean	Std. Dev.
5	5,396	12,352.83	10,627.46	0.62	0.45	4,899	10,190.33	9,658.65	0.57	0.46
10	5,310	18,374.76	12,607.04	0.79	0.38	4,722	13,077.41	11,113.04	0.67	0.44
15	4,864	22,759.81	14,176.09	0.85	0.34	4,235	14,770.19	11,989.04	0.73	0.41
20	3,947	25,909.90	16,449.95	0.87	0.31	3,383	17,242.18	13,109.76	0.79	0.37
25	2,792	28,344.23	18,118.38	0.89	0.28	2,423	19,601.58	13,708.33	0.83	0.33

[(a)] Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
[(b)] These outcome variables measure the fraction of days spent in employment.

Tables A.3 and A.4 report OLS estimates of the relation between nonemployment during the first 3 years after high school diploma and the two main outcome variables, after controlling for a set of regressors. This preliminary exercise reveals a significant and long lasting association between the time spent in nonemployment after school completion and labor earnings and participation in the labor market, for both men and women. A 10 percentage point increase in the time spent in nonemployment in the first three years after school completion is associated to a decrease of €1,230 (€1,280) in yearly earnings and of 5.5 (5.2) p.p. in the yearly fraction of time spent in employment for women (men) 5 years after school completion. Later, these negative correlations fade away but they are still sizable and significant; 25 years after school completion a 10 percentage point increase in early nonemployment is related to a decrease of €488 (€384) in yearly earnings and of 1.0 (0.3) p.p. in the yearly fraction of time spent in employment for women (men).

In what follows, we outline an econometric model to credibly estimate the causal effect of the time spent in nonemployment after school completion on future earnings and participation at different moments in the subsequent career. The proposed identification strategy is aimed at disentangling the true causal effect of the time spent in nonemployment from the spurious one induced by systematic differences across individuals not observed by the analyst which could jointly determine both nonemployment events and subsequent labor market outcomes. Some examples of time-constant and time-varying unobserved characteristics jointly affecting the treatment and the outcomes are ability, intelligence, labor market attachment, different job search strategies, parenthood, social and cultural background, endowment in human capital, etc.

4 Econometric model

4.1 Estimation framework and the effect of interest

We denote by Y_{it}^{j} the j-th labor market outcome, with $i = 1, ..., n$ being the index for individuals, $j = 1, 2$ being the index for our two labor market outcomes, yearly earnings and yearly fraction of time in employment, and $t = 5, ..., T_i$ being the index for the time elapsed since school completion. The observable time elapsed since school completion (T_i) differs across individuals. As mentioned at the beginning of Subsection 3.2, whereas we observe for all the sample the labor market outcomes measured 5 years after school completion ($t = 5$), we do not observe for everybody the same time span after the secondary school diploma. Since administrative data on salaried employment are available up to 2013, the labor market history of individuals of older cohorts, who therefore got the diploma in earlier calendar years, is more likely to be observed for a longer time span and, eventually, up to 25 years after school completion. Moreover, to keep the model tractable and have a limited number of equations, we restrict the set of time index t to $\{5, 10, 15, 20, 25\}$, so that the labor market outcomes are measured in 5-year intervals since school completion, up to 25 years at maximum (or the closest multiple of 5 for individuals with shorter observed labor market histories after the diploma).

The treatment intensity TR is the fraction of days spent in nonemployment in the three first years after the diploma. More in detail, the starting date of the three years time window over which we compute the fraction of time spent in nonemployment is 1 September of the year of the diploma, which is officially obtained in Italy around the mid of July, after a set of final exams taking place between the second half of June and the beginning of July.

We specify the labor market outcome j of individual i at time t since school completion as

$$Y_{it}^j = \beta_t^j TR_i + \mu_t^j(X_{it}^j) + \epsilon_{it}^j, \tag{1}$$

where β_t^j is the effect of the treatment variable TR on outcome j at time t, $\mu_t^j(\cdot)$ is a function of observed covariates X_{it}^j and ϵ_{it}^j collects the individual- and time-varying unobservables. The treatment intensity is continuously distributed from a minimum of 0, for those who spent 0 days out of salaried employment during the first three years after school completion, to 1, for those who have never been in salaried employment in the same three years. The average treatment effect of going from full employment to full nonemployment on labor market outcome j at time t since school completion is simply given by β_t^j.

The intensity of the treatment TR_i, i.e. the fraction of the first three years after school completion spent in nonemployment, is specified as follows

$$TR_i = \nu(Z_i) + u_i \tag{2}$$

where $\nu(\cdot)$ is a function of a vector of covariates Z_i, which are realized either before the end of secondary school (for example mother's highest education) or in the three years after school exit (like number of kids, labor market status or GDP growth at regional level) and u_i is individual unobserved heterogeneity.

4.2 Identification strategy

The identification of the effect of the intensity of nonemployment after school completion on future labor market outcomes requires to properly account for unobserved heterogeneity across individuals, which might affect the occurrence of early nonemployment events after school exit and subsequent labor market outcomes. For example, school leavers with high labor force attachment, ability, motivation, liquidity constraints and job search intensity may be less likely to experience early nonemployment events. A large value of these unobservables may also generate better career opportunities and, therefore, better labor market outcomes later in life. Furthermore, these unobserved characteristics may change over time. For instance, the liquidity constraints of those individuals who experience more intensively longer nonemployment events may become tighter and more relevant over time, increasing the job search intensity, lowering the reservation wages and having therefore an impact on labor market outcomes that may be varying over time. As a further example of the relevance of time-varying heterogeneity, one may refer to the labor force attachment or the career orientation of an individual. The experience of a nonemployment event at the start of the career may be related to the labor force attachment. At the same time, early nonemployment may address an individual towards a lower career track, lower levels of job satisfaction and, henceforth, a decreasing profile of the labor force attachment. Finally, some determinants of early nonemployment, like preferences for family formation or parenthood may also change over time. At some point after school exit, individuals may form a family and have kids, modifying the preference towards the work-family balance, which is a time-varying unobservable very likely to matter for future labor market outcomes.

To account for time-varying unobserved heterogeneity, we set up a factor analytic model (Carneiro et al., 2003; Heckman and Navarro, 2007; Fruehwirth et al., 2016; Cockx et al., 2019; Picchio et al., 2021).[5] The unobserved terms of the equations of the outcomes and the treatment intensity are composed of a latent factor $\boldsymbol{\theta}$, which collects the time-varying unobserved differences among individuals and error terms that are conditionally

[5] Carneiro et al. (2003) study the impact of different schooling levels on future returns; Fruehwirth et al. (2016) and Cockx et al. (2019) estimate how grade retention affects subsequent school performances; Picchio et al. (2021) study the effect of childbirth and its timing on female labor market outcomes in Italy.

independent given the latent factor:

$$\begin{aligned} \epsilon^j_{it} &= \alpha^j_t \theta_{it} + \varepsilon^j_{it} && (3) \\ u_i &= \lambda \theta_{i5} + v_i, && (4) \end{aligned}$$

where θ_{it} is the latent factor at time t in $\boldsymbol{\theta}_i = (\theta_{i5}, \theta_{i10}, ..., \theta_{i25})$, with a multivariate distribution characterized by $\mathrm{Cov}(\theta_{it}, \theta_{it'}) \neq 0$, $\forall t \neq t'$. Unobserved heterogeneity varies over time because of the factor distribution and a linear combination of the latent factor with time-varying coefficients α^j_t, the so-called *factor loadings*.[6]

As in Picchio et al. (2021), we adopt a one loading factor specification, i.e. we allow only for a single-dimensional time-varying unobserved determinant of the treatment intensity and of the outcomes. Our specification of the factor structure is therefore encompassed in the more general specification in Fruehwirth et al. (2016), who instead differentiated among several sources of unobserved heterogeneity (multidimensional factor structure).

Carneiro et al. (2003) showed that having a set of selection-free measurements related to the unobservables that jointly determine the treatment intensity and the outcomes reduces the degree of arbitrariness of factor analysis. For this reason, we also add to the model two further equations, whose dependent variables are predetermined with respect to the moment of school completion and therefore to the realization of the treatment intensity. We specify these selection-free measurements as

$$M^l_i = \omega^l(S^l_i) + \xi^l \theta_{i5} + e^l_i, \quad l = 1, 2, \tag{5}$$

where ω^l is a function of observed covariates S^l_i, ξ^l is the factor loading and e^l_i is a zero-mean error term independent of both S^l_i and θ_{i5}.

The first measure M^1_i is a variable which corresponds to the fraction of days spent at work during the year before the school completion. It is likely to be determined by a set of unobserved traits which include labor force attachment, motivation, ability, job search strategies, liquidity constraints and family, social or cultural background.

The second measure M^2_i is the number of siblings when the individual was 14 years old. There is a strand of the literature investigating the relation between the family size,

[6] Up-to-scale normalizations of the latent components are required to identify the distribution of $\boldsymbol{\theta}$. We apply the normalization suggested in Carneiro et al. (2003) and also used in Picchio et al. (2021), i.e. $\alpha^1_t = 1$ for all t.

investments in human capital and labor market outcomes later in life. On the one hand, the number of siblings in a household may be negatively correlated to the opportunity to study longer or the quality of the attended schools, because of the dilution of parents' material resources (see Steelman et al., 2002, for a review). On the other hand, a larger number of siblings may increase the need for other liquidity entries, hence determining an earlier and more active participation in the labor market. Blake (1981) suggests that the number of siblings have an important detrimental impact on a child's educational attainment and college plans, while families with fewer siblings provide more resources for the child and support the development of better educational outcomes.[7] Olneck and Bills (1979) focused on the effects of birth order and family size on individuals' adult level of wages and occupation, revealing negative effects of family size on occupation only. Kessler (1991) found that the family size is a significant determinant of employment status for women. As such, the second measure M_i^2 may encompass information on childhood household environment shaping the likelihood of success in the labor market in the adulthood.

Our factor structure is a special case of the one proposed by Carneiro et al. (2003). Furthermore, our model is a special both of Fruehwirth et al. (2016) and Picchio et al. (2021). Their identification results related to the factor analysis can be invoked directly and specialized to fit our special case. Assuming that the regularity conditions (A-1 and A-2) in Carneiro et al. (2003) hold, the nonparametric identification of the deterministic parts of the model and of the joint distribution of the unobserved terms and their components, $(\epsilon_i^j, u_i, \upsilon_i)$, with $\epsilon_i^j = (\epsilon_{i1}^j, ..., \epsilon_{iT}^j)$, $\upsilon_i = (\upsilon_i^1, \upsilon_i^2)$, $\upsilon_i^l = \xi^l \theta_{i5} + e_i^l$, $j = 1, 2$ and $l = 1, 2$, is obtained as in Heckman and Smith (1998). As suggested by Carneiro et al. (2003), we satisfy their support condition (A-3) by including some continuous variables among the set of observed determinants of one outcome but excluded from the others. These variables are the regional employment rate, the regional unemployment rate, and the regional GDP growth rate: i) at the time when each individual was born in $\omega^l(S_i^l)$, for $l = 1, 2$; ii) at the time t in which the labor market outcome is evaluated in $\mu_t^j(X_{it}^j)$, for all j and t; iii) averaged across the three years after school completion in $\nu(Z_i)$. Both Bhargava (1991) and Mroz and Savage (2006) clarified why the variation of exogenous variables, like these regional rates, may be of help to identify the causal effects of en-

[7] See also Blake (1989), Åslund and Grönqvist (2010), Wijanarko and Wisana (2019) and Li and Hiwatari (2020) for studies on the relation between the number of siblings and the risk that individuals stop their education earlier than they should.

dogenous variables in a dynamic discrete time panel data model. Indeed, these covariates implicitly provide additional identification conditions, resulting in significantly more degrees of freedom to control for endogenous determinants. Every lag of the exogenous time-varying regressor may indeed determine a separate effect on the current realization of the outcome. Table 4 clarifies in detail the exclusions across all the equations.

Table 4: Observed covariates and their exclusion across equations

	Measurement equations		Treatment equation	Outcomes
Regressors included	Employment 1 year before school completion	Number of siblings at 14	Days (%) of nonemployment during the first 3 years after school completion	Labor market outcomes t years after school completion
Age at school completion	–	–	Yes	Yes
Fraction of time spent at work 1 year before school completion	–	–	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
Number of siblings at 14	Yes	–	Yes	Yes
Mother's highest education	Yes	Yes	Yes	Yes
Father's highest education	Yes	Yes	Yes	Yes
Mother's employment at 14	Yes	Yes	Yes	Yes
Father's employment at 14	Yes	Yes	Yes	Yes
Respondent lives with both parents at 14	Yes	Yes	Yes	Yes
Quarter of birth	Yes	Yes	Yes	Yes
Year of birth	Yes	Yes	Yes	Yes
Geographical area at birth (5 areas)	Yes	Yes	Yes	–
Geographical area at t (5 areas)	–	–	–	Yes
Regional unemployment rate at birth	Yes	Yes	–	–
Regional employment rate at birth	Yes	Yes	–	–
Regional GDP growth rate at birth	Yes	Yes	–	–
Average regional unemployment rate 3 years after diploma	–	–	Yes	–
Average regional employment rate 3 years after diploma	–	–	Yes	–
Average regional GDP growth rate 3 years after diploma	–	–	Yes	–
Regional unemployment rate at t	–	–	–	Yes
Regional employment rate at t	–	–	–	Yes
Regional GDP growth rate at t	–	–	–	Yes
IT-SILC wave (2005 or 2011)	Yes	Yes	Yes	Yes
Calendar year of observation	Yes	Yes	Yes	Yes
Number of kids	–	–	–	Yes
Average number of kids 3 years after diploma	–	–	Yes	–
Days (%) of nonemployment during the first 3 years after school completion	–	–	–	Yes

4.3 Likelihood function

We estimated the model by maximum likelihood. Hence, we needed to specify the implicit functions in Equations (1), (2) and (5) as dependent on a finite set of parameters. We adopted the usual linear index specification for the deterministic parts.[8]

Let include all the parameters for our measurements, treatment and outcome equations in $\boldsymbol{\phi} = (\boldsymbol{\tau}^1, \boldsymbol{\tau}^2, \boldsymbol{\varphi}, \boldsymbol{\psi})$. The likelihood for individual i is the joint density of $(M_i^1, M_i^2, R_i, \mathbf{Y}_i)$, with $\mathbf{Y}_i = (Y_5^1, \ldots, Y_{25}^1, Y_5^2, \ldots, Y_{25}^2)$. Using the chain rule, the indi-

[8] To reduce the number of parameters to be estimated, we followed Fruehwirth et al. (2016) and Picchio et al. (2021) and imposed that, in the labor market outcome equations, the coefficients of the covariates do not vary with t.

vidual contribution to the likelihood function conditional on observable and unobservable characteristics can be written

$$\mathcal{L}_i(\boldsymbol{\phi} \mid S_i^1, S_i^2, Z_i, \mathbf{X}_i, \boldsymbol{\theta}_i) = g^1(M_i^1 \mid S_i^1, \theta_{i5}; \boldsymbol{\tau}^1) g^2(M_i^2 \mid S_i^2, \theta_{i5}; \boldsymbol{\tau}^2) h(TR_i \mid Z_i, \theta_{i5}; \boldsymbol{\varphi}) \prod_{j=1,2} \prod_{t=5,10,...,25} f(Y_{it}^j \mid TR_i, X_{it}, \theta_{it}; \boldsymbol{\psi})^{d_{it}}, \tag{6}$$

where all the sets of covariates contain the constant, g^1, g^2, h and f are standard normal density functions, and d_{it} is a dummy equal to 1 if individual i is still in our sample t years after school completion.

In order to account for the presence of individual time-varying unobserved heterogeneity, we assumed that the vector of latent factors $\boldsymbol{\theta}_i = (\theta_{i5}, ..., \theta_{i25})$ has a multivariate discrete distribution with H support points. Thus, $\boldsymbol{\theta}_i$ takes values $\boldsymbol{\theta}^h$, $h = 1, ..., H$, following a multinomial logit parametrization

$$p^h = Pr(\boldsymbol{\theta}_i = \boldsymbol{\theta}^h) = \frac{\exp(\rho^h)}{\sum_{r=1}^H \exp(\rho^r)} \tag{7}$$

with innocuous normalization $\boldsymbol{\theta}^1 = \mathbf{0}$ and $\rho^H = 0$. Moreover, we constrained the time-varying latent factor to be constant from 20 to 25 years after school completion ($\theta_{20}^h = \theta_{25}^h$ for all h). We imposed this restriction to avoid identification issues related to the fact the sample is halved when approaching $t = 25$. It should not be a too strict assumption because the latent factor determining labor market outcomes may stabilize over time.

The i-th contribution to the likelihood becomes

$$\mathcal{L}_i(\boldsymbol{\phi}, \boldsymbol{\rho}, \boldsymbol{\Theta} \mid S_i^1, S_i^2, Z_i, \mathbf{X}_i) = \sum_{h=1}^H p^h \mathcal{L}_{ih}(\boldsymbol{\phi} \mid S_i^1, S_i^2, Z_i, \mathbf{X}_i, \boldsymbol{\theta}_i = \boldsymbol{\theta}^h) \tag{8}$$

where $\mathcal{L}_{ih}$ is the likelihood in Equation (6), conditional on $\boldsymbol{\theta}_i$ taking value $\boldsymbol{\theta}^h$, the matrix $\boldsymbol{\Theta}$ contains the vectors of support points $(\boldsymbol{\theta}^1, ..., \boldsymbol{\theta}^H)$ and the vector $\boldsymbol{\rho}$ collects the weights determining the H masses of probabilities.

The sample log-likelihood is the sum across the natural logarithm of the individuals contributions in Equation (8), i.e.

$$\ln(\mathcal{L}) = \sum_{i=1}^N \ln\left[\mathcal{L}_i(\boldsymbol{\phi}, \boldsymbol{\rho}, \boldsymbol{\Theta} \mid S_i^1, S_i^2, Z_i, \mathbf{X}_i)\right]. \tag{9}$$

We maximized Equation (9) with respect to its parameters using analytical derivatives.

5 Estimation results

We estimated three different models, with three different assumptions about the presence of unobserved heterogeneity: i) without unobserved heterogeneity; ii) with a time-constant latent factor with discrete distribution; iii) with a time-varying latent factor with discrete distribution.

The simulations in Gaure et al. (2007) suggest to choose the number of support points which minimizes the Akaike Information Criterion (AIC). Following this advice, we stopped at $H = 5$ when we assumed the latent factor to be time-constant. With the time-varying latent factor, we increased the number of support points until 10, experiencing a continuous improvement in the AIC. We then stopped at 10 for the sake of model specification parsimony and because we realized that the estimated coefficients of the treatment had became very stable and unaffected by the last increases in the number of support points.

The time-varying specification of the latent factor yielded the best results in terms of information criteria, both for men and women. Table 5 shows post-estimates statistics. In the next subsections, we report and comment on the effects of early nonemployment across the three different assumptions on the latent factor. Sections B and C of the Online appendix report the full set of estimation results for all the models.

5.1 Main findings

The core question of the analysis is whether experiencing nonemployment after school completion inflicts a scar on future labor market outcomes as measured by labor earnings and yearly fraction of days spent in employment.[9] Table 6 and Figure 1 display the impact of the fraction of time spent in nonemployment in the first 3 years after school completion on yearly labor earnings evaluated at $t \in \{5, 10, 15, 20, 25\}$ after the diploma, along the three different latent factor structures.

Shifting from panel (a) to panel (c) of Table 6 or from graph (a) to graph (c) of Figure 1, it clearly emerges that if time-varying unobservables were not accounted for, the

[9] In Table D.11 in Online appendix D we report the estimated effects if we use daily earnings as outcome variable instead of yearly earnings.

Table 5: Summary statistics on the estimated models across different assumptions on the latent factor

	Without unobserved heterogeneity	Time-constant unobserved heterogeneity	Time-varying unobserved heterogeneity
a) Men			
Number of parameters	160	180	212
Log-likelihood	53,673.34	48,731.48	39,755.52
AIC	107,666.68	97,822.96	79,935.03
BIC	108,721.63	99,009.78	81,332.83
Distribution of the latent factor	–	Discrete	Discrete
Number of support points of the latent factor	–	5	10
b) Women			
Number of parameters	160	180	212
Log-likelihood	44,541.40	39,831.57	32,911.81
AIC	89,402.80	80,023.15	66,247.62
BIC	90,442.29	81,192.57	67,624.94
Distribution of the latent factor	–	Discrete	Discrete
Number of support points of the latent factor	–	5	10

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion.

negative impact of early nonemployment on subsequent earnings would be largely overestimated. Even if the early nonemployment penalty is much smaller when we control for time-varying unobserved heterogeneity, it is statistically significant up to 25 years since school completion; the scarring effect of early nonemployment is long lasting for both men and women. The estimates reported in Table 6 and Figure 1 are the impact of the fraction of time spent in nonemployment in the first three years since school completion going from 0 to 1. Hence, if the time spent in nonemployment just after school completion increases by 10 percentage points (pp), male (female) yearly earnings decrease by €382 (€492) 5 years after school completion. This penalty for men (women) is reduced to €225 (€140) 25 years after the diploma. Figure 1 visually shows that men and women experience a similar nonemployment penalty in the short run ($t = 5$ and $t = 10$). However, men suffer larger penalties in subsequent years.

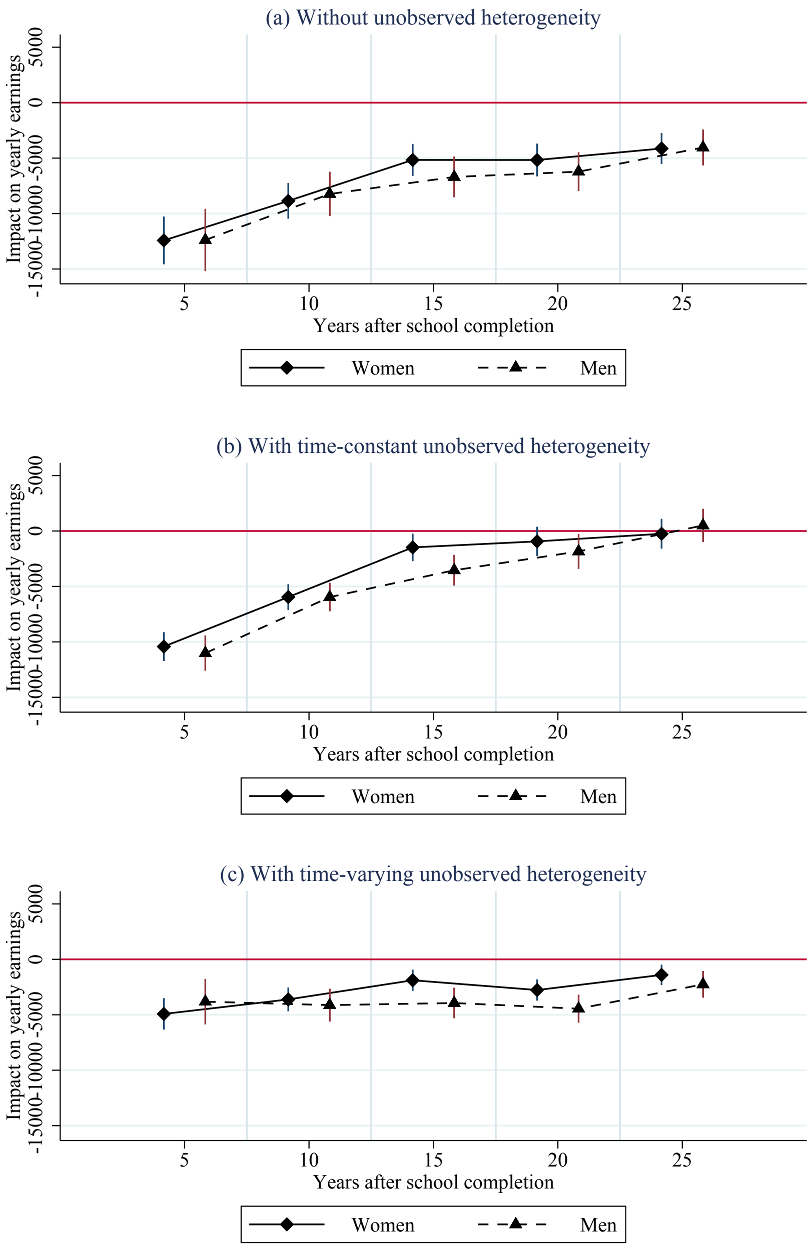
Table 7 and Figure 2 display the estimated impact of early nonemployment on the yearly fraction of days spent in salaried employment in the future. Also in this case, not controlling for time-varying unobserved heterogeneity generates a large overestimation of the scarring effect of early nonemployment, both in size and in duration. Once controlling for time-varying unobserved heterogeneity, we find that early nonemployment negatively affects the labor market participation only in the short-term; a 10 pp increase in the time spent in nonemployment after school completion reduced the fraction of days spent in

Table 6: Impact of early nonemployment on yearly labor earnings (€)

Treatment intensity: fraction of time in nonemployment during the first 3 years after school completion	Years since school completion $t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
(a) Without unobserved heterogeneity					
Men	-12,382.93***	-8,230.58***	-6,699.58***	-6,220.41***	-4,041.89***
	(1,431.78)	(1,019.47)	(940.95)	(892.95)	(828.87)
Women	-12,424.21***	-8,856.36***	-5,161.12***	-5,170.76***	-4,134.63***
	(1,099.92)	(8,220.13)	(736.22)	(755.33)	(711.54)
(b) With time-constant unobserved heterogeneity					
Men	-11,006.14***	-5,957.12***	-3,537.09***	-1,842.11**	502.03
	(814.19)	(654.60)	(707.99)	(802.19)	(762.80)
Women	-10,422.62***	-5,954.38***	-1,474.79**	-935.41	245.864
	(663.50)	(593.01)	(633.67)	(669.56)	(690.10)
(c) With time-varying unobserved heterogeneity					
Men	-3,815.09***	-4,125.82***	-3,935.38***	-4,448.10***	-2,254.04***
	(1,048.98)	(757.46)	(701.46)	(646.82)	(616.17)
Women	-4,919.67***	-3,610.87***	-1,880.88***	-2,765.47***	-1,399.38***
	(722.63)	(547.32)	(487.52)	(489.42)	(471.35)
Observations (men)	5,396	5,310	4,864	3,947	2,792
Observations (women)	4,899	4,722	4,235	3,383	2,423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are in parentheses.

Figure 1: Impact of early nonemployment on yearly labor earnings (€)



Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index. The vertical segments are 95% confidence intervals.

employment 5 years after the diploma by 0.65 (0.99) pp for men (women). This penalty becomes very close to zero and not significantly different from zero by the 10th year after school completion for both men and women. Finally, in the last year of observation ($t = 25$), individuals who experienced longer nonemployment events after school completion spend more time in the labor market, although the effect is small; an increase by 10 pp in the time spent in nonemployment after the diploma generates an increase by 0.43 (0.31) pp in the fraction of days spent at work 25 years later.

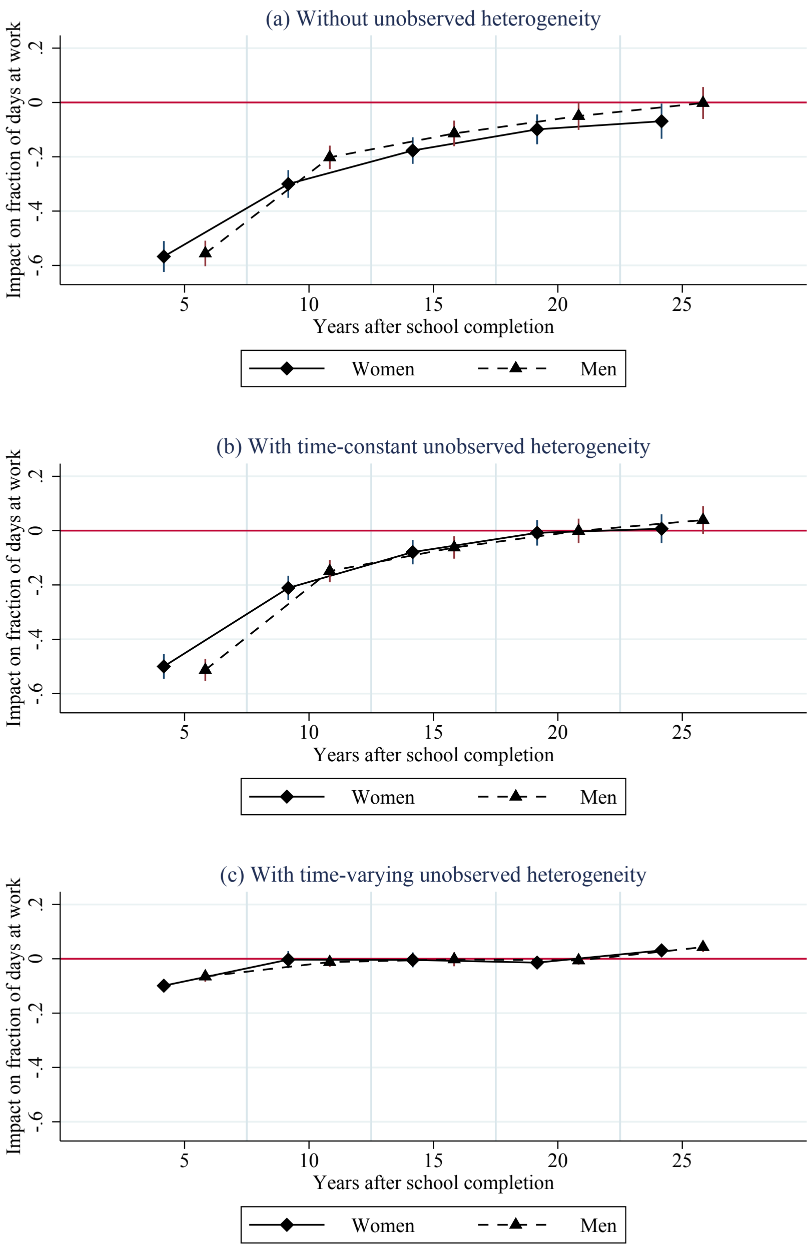
Table 7: Impact of early nonemployment on yearly fraction of days spent at work

Treatment intensity: fraction of time in nonemployment during the first 3 years after school completion	Years since school completion $t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
(a) Without unobserved heterogeneity					
Men	-0.556***	-0.202***	-0.114***	-0.050*	-0.002
	(0.024)	(0.022)	(0.024)	(0.026)	(0.030)
Women	-0.567***	-0.300***	-0.177***	-0.099***	0.069**
	(0.029)	(0.026)	(0.025)	(0.028)	(0.033)
(b) With time-constant unobserved heterogeneity					
Men	-0.513***	-0.149***	-0.062***	-0.001	0.039
	(0.021)	(0.021)	(0.021)	(0.023)	(0.026)
Women	-0.500***	-0.211***	-0.079***	-0.008	0.007
	(0.023)	(0.023)	(0.023)	(0.024)	(0.027)
(c) With time-varying unobserved heterogeneity					
Men	-0.065***	-0.012	-0.002	-0.006	0.043***
	(0.010)	(0.009)	(0.013)	(0.008)	(0.009)
Women	-0.099***	-0.003	-0.004	-0.014	0.031***
	(0.011)	(0.016)	(0.014)	(0.008)	(0.009)
Observations (men)	5,396	5,310	4,864	3,947	2,792
Observations (women)	4,899	4,722	4,235	3,383	2,423

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are in parentheses.

When we control for time-varying unobserved heterogeneity, the negative effect of early nonemployment on labor earnings becomes smaller in magnitude, whereas the penalties in terms of labor participation are present only up to 5 years after school completion. This suggests that when we include in the model the time-varying latent factor, we capture those latent traits which affect both selection into early nonemployment and future

Figure 2: Impact of early nonemployment on yearly fraction of days spent at work



Notes: The vertical segments are 95% confidence intervals.

labor market performances. As an example, career-oriented individuals with higher abilities and motivations are more likely to have success in the labor market and therefore the negative impact of nonemployment on labor market outcomes is subject to upward bias if these characteristics were not accounted for. Moreover, differences in the estimated penalties between the model with time-constant and the model with time-varying unobserved heterogeneity indicate that the latent factor is subject to relevant variations over time. For example, the influence of the family background may diminish as a person ages (Gregg, 2001); further, liquidity constraints may change over time and individuals may reduce their reservation wages as they experience longer nonemployment spells, accepting therefore low quality jobs and translating into worse labor earning profiles throughout the reminder of their working career (Ghirelli, 2015).

In summary, the main findings on the impact of early nonemployment on future labor market outcomes are the following. First, both men and women suffer sizable earnings penalties, which are persistent up to 25 years after the secondary school diploma. Second, experiencing early nonemployment causes a lower participation in the labor market only in the short-term for both men and women. Our results on earnings are consistent with the ones in Gregg and Tominey (2005), where wage scars of about 9-11% persist up to 20 years later. Our findings on labor market participation are also in line with those in Nordström Skans (2011), who found the negative effect of early unemployment on the likelihood of unemployment 5 years after graduation. Finally, both are findings in terms of earning and labor market participation are similar to those in Mroz and Savage (2006), who estimated that the effect of unemployment on hourly earnings is long-lived, whereas only a short-lived persistence of about 4 years in terms of future unemployment was detected. As suggested by Ellwood (1982), early work experience may have a large and positive earnings effect and therefore the biggest costs of being nonemployed during the first years after school completion are wage penalties and lower earning power.

Our findings are not fully in line with the predictions of the signaling theory. Early nonemployment events may be used as a signal of low productivity and employers may penalize those individuals who experienced them (Spence, 1973; Vishwanath, 1989; Lockwood, 1991). However, individuals incurring in random early nonemployment events, once hired, will show greater productivity than expected and the initial penalties should disappear after a while. Only our findings on labor market participation are in line with the signaling theory. This is not the case in terms of earnings, because we find that the earnings penalties persist up to 25 years after school completion. A potential explanation of the persistent scars on earnings may come from the job search theory. Given that people experiencing early nonemployment send a worse signal, accumulate less human capital relatively to their employed peers, and are more likely to face liquidity constraints, they could lower their reservation wage and be more likely to accept worse jobs, characterized by a career track of lower profile, which traps them in lower wages and lower chances of subsequent promotions.

5.2 Sensitivity analysis

We run some sensitivity checks in order to assess the robustness of our findings in several directions. We started by modifying the definition of nonemployment. In the benchmark model, experiences like volunteer work, internships and stages are considered as a form of employment and do not contribute to the computation of the fraction of days spent in nonemployment after the diploma. We modified this definition by considering as nonemployment also all the forms of unpaid work, for example volunteer work and unpaid internships, stages and training. Indeed, volunteer work, stages, internships and training are non-standard and so unstable positions in the labor market that one may wonder if they could be viewed as proper employment in terms of building a career, accumulating human capital, generating a network, etc. Table D.1 in Online appendix D displays the results, which are in line with the benchmark ones.

Second, we changed the definition of the treatment intensity by using, instead of the fraction of days spent in nonemployment in the first 3 years after school completion, the fraction of days spent in nonemployment during the first 2 or 4 years. The choice of measuring the intensity of early nonemployment by looking at the first 3 years after the diploma may indeed be viewed as arbitrary. Tables D.2 and D.3 display the effects of the fraction of days spent in nonemployment during the first 2 and 4 years after the diploma, respectively. They are in line with those obtained using the benchmark definition of treatment intensity. The only difference is that the penalties are somewhat: i) smaller if early nonemployment is computed in the first 2 years after the diploma; ii) larger if early nonemployment is defined in the first 4 years after school completion.

Third, we used different combinations of exclusion restrictions to test if they play a relevant role in determining the findings. For example, one may wonder whether geographical area or local labor market conditions at birth or just after school exit may, not only affect the predetermined outcomes (the measures) and early nonemployment, but also determine future labor market outcomes. In our baseline specification, as Table 4 clarifies, we indeed include these controls measured at birth in the measurement equations, measured just after school completion in the early nonemployment equation and measured at time t for the labor market equation at time t. These exclusion restrictions would not be supported by the data if, for instance, being born and growing up in more disadvantaged regions or in areas characterized by worse economic conditions increases future penalties in terms of labor market success, conditional on the current status of the economy and labor market. More in detail, we proceeded by checking the main findings with two different combinations of the exclusion restrictions: i) we included both the dummies for geographical area at birth and the regional employment, unemployment and GDP growth rates at birth in the labor market outcome equations and in the treatment equation; ii) we further added in the specification of the labor market equations also the regional rates in the first 3 years after school completion which, in the baseline model, are only included in the treatment equation. The findings from these alternative specifications are all in line with the benchmark results and are reported in Online appendix D.

We run a fourth check with the aim of understanding whether the findings are driven by cohort effects. We split the sample in individuals born in the 1960s and those born later (see Table A.1 for summary statistics). For both groups the results are very similar to those obtained in the benchmark model and the main conclusions hold for both those born in the 1960s and those born later (see Tables D.6 and D.7 in Appendix D). However, the point estimates suggest that the latter suffered larger earning penalties. We also estimate the benchmark model using only those individuals we can follow up to 25 years after school completion. Even in this case the main results are confirmed.

A final check focuses on the effect of the youth nonemployment across geographical areas. In particular, we split the sample between individuals born and graduated in Central or Northern Italy on the one hand, and individuals born and graduated in Southern Italy or Islands. Tables D.9 and D.10 in Appendix D show the results which are in line with the benchmark model, although the earning penalties in Central and Northern regions are larger than the ones in the South up to the first 10 years.

6 Conclusions

We estimated the impact of early nonemployment on subsequent labor market outcomes in Italian youth who exited formal education with a secondary school diploma. We traced the impact up to 25 years since school completion and evaluated it in terms of yearly labor earnings and participation in the labor market. We carried out the empirical analysis separately for men and women.

Using a factor analytic model, we took into account time-varying unobserved heterogeneity jointly affecting the treatment intensity, i.e. the exposure to nonemployment in the three years after school completion, and subsequent labor market outcomes. Once time-varying unobserved characteristics are accounted for, we provided evidence that early nonemployment generates relevant labor market penalties for both men and women. The negative effects are very persistent in terms of earnings: they are still sizable and statistically significant 25 years after school completion. Labor market participation, measured as the fraction of days spent at work in a year, is negatively affected by early nonemployment for a shorter span, as it disappears for both men and women by the 10th year after the school completion. Finally, the early nonemployment effect on labor market participation turns to be positive and significant 25 years after school completion, suggesting those who were exposed to early nonemployment in the long-run suffer smaller earnings and try to compensate with a larger participation in the labor market.

Our findings imply relevant policy recommendations. First, given that the exposure to early nonemployment generates persistent earnings scars and participation penalties shorter-lasting but still present, favoring work experience after school completion is a very urgent socioeconomic goal. The policy maker could confine these negative consequences operating at different levels and following the general advice coming from the meta-analysis by Kluve et al. (2019) that youth policies based on profiling systems and individualized follow-up are very effective. This is a general and apparently obvious advice, which may be however complemented by a second peculiarity of our findings. The fact that earnings are persistently and negatively affected, while participation at the intensive margins is able to catch up after a bunch of years, suggests that those individuals who randomly experienced nonemployment after school completion were able to get reintegrated after a while, but in a downgraded track. Individuals suffering early nonemployment could have experienced the depreciation of their human capital (or they could have lost the opportunity to accumulate general human capital) and, under tighter liquidity constraints, could have been forced to lower their reservation wages and accept worse job conditions, limiting the transition to better career profiles. The policy maker could confine these negative consequences operating at different levels. First, the policy maker could favor training programs and apprenticeships for those who were exposed to early nonemployment, so as to facilitate their recoup of general human capital. For example, as shown by Picchio and Staffolani (2019), apprenticeships are effective ways for Italian workers to increase the probability of promotion to an open-ended contract. Second, the policy maker could intervene facilitating the match between employers and the youth who suffered early nonemployment, for example by *ad hoc* subsidies for hiring school-leavers with difficulties in making the school-to-work transition. Finally, to limit the lowering of the reservation wage and the acceptance of bad jobs in downgraded tracks, the welfare state could play a role: benefits and, to circumscribe moral hazard, monitoring job search behaviors, so as to guide the school leavers exposed to nonemployment towards more efficient and better quality job matches.

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Online appendix

A. Further descriptive statistics

In this section we provide further descriptive statistics. Figure A.1 shows the fraction of days in nonemployment in the first 3 years after school completion. Our sample counts 3,467 individuals with no days in employment in this time window. Figure A.2 and A.3 show the distribution of individuals across the age at school completion for the samples observed at different moments after diploma and Table A.1 reports the distribution of the age at school completion by birth cohorts.

Table A.1: Distribution of the age at school completion by birth cohorts

	Age at school completion					
	Born in 1960s		Born in 1970s		Born in 1980s	
	Men	Women	Men	Women	Men	Women
Mean	18.782	18.551	18.809	18.690	18.742	18.773
Std. Dev.	1.222	1.110	1.113	1.024	1.141	0.921
10th percentile	17	17	17	17	17	18
25th percentile	18	18	18	18	18	18
50th percentile	19	19	19	19	19	19
75th percentile	20	19	19	19	19	19
90th percentile	20	20	20	20	20	20
Observations	2,724	2,570	2,176	1,968	496	361

Table A.2 displays more detailed descriptive statistics on labor market outcomes than those reported and discussed in Section 3.

In order to understand the gross relation between early nonemployment and labor market outcomes, we estimated by Ordinary Least Squares (OLS), for each $t \in \{5, 10, 15, 20, 25\}$, the following equation:

$$Y_{it} = \beta_t TR_i + X_{it}\pi_t + \varepsilon_{it}, \tag{10}$$

where:

- Y_{it} is either labor earnings or the fraction of time spent in employment t years after school completion;
- X_{it} is a vector of covariates: the constant term, age at school completion, regional dummies, calendar year dummies, regional unemployment, employment and GDP

Table A.2: Summary statistics of the outcome variables at different years after school completion

Men							
Year after school		Yearly labor earnings (€)[a]		Daily earnings (€)		Total annual income (€)[b]	
completion	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
5	5,396	12,352.83	10,627.46	37.43	29.08	12,485.36	10,742.46
10	5,310	18,734.76	12,607.04	53.20	32.81	19,016.21	12,777.53
15	4,864	22,759.81	14,176.09	63.69	37.06	23,281.36	14,318.02
20	3,947	25,909.90	16,449.95	71.25	41.33	26,657.92	16,539.70
25	2,792	28,344.23	18,118.38	77.25	44.38	29,254.81	18,253.51

Women							
Year after school		Yearly labor earnings (€)		Daily earnings (€)		Total annual income (€)	
completion	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
5	4,899	10,190.33	9,658.65	32.17	27.55	10,288.02	9,720.26
10	4,722	13,077.41	11,113.04	40.16	30.66	13,468.62	11,251.32
15	4,235	14,770.19	11,989.04	46.80	32.92	15,483.36	12,222.27
20	3,383	17,242.18	13,109.76	55.09	34.92	17,954.16	13,347.73
25	2,423	19,601.58	13,708.33	62.53	36.31	20,156.64	13,842.76

Men							
Year after school		Days in employment[c]		Days in part-time		Days in full-time	
completion	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
5	5,396	0.62	0.45	0.01	0.11	0.60	0.46
10	5,310	0.79	0.38	0.02	0.12	0.77	0.40
15	4,864	0.85	0.34	0.02	0.13	0.83	0.35
20	3,947	0.87	0.31	0.02	0.12	0.86	0.32
25	2,792	0.89	0.28	0.02	0.12	0.88	0.30

Women							
Year after school		Days in employment		Days in part-time		Days in full-time	
completion	Observations	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
5	4,899	0.57	0.46	0.04	0.19	0.53	0.47
10	4,722	0.67	0.44	0.08	0.25	0.60	0.47
15	4,235	0.73	0.41	0.14	0.33	0.60	0.47
20	3,383	0.79	0.37	0.17	0.36	0.63	0.46
25	2,423	0.83	0.33	0.19	0.38	0.65	0.45

(a) Yearly labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
(b) Total annual income includes any subsidies in addiction to wages.
(c) It is the fraction of days spent in employment in a year.

growth rates t years after school completion, number of kids at t, quarter of birth and further personal information;

- TR_i is the treatment intensity, i.e. the fraction of days of nonemployment during the 3 years after school completion;
- ε_{it} is the error term.

The estimated β_t, along with their 95% confidence intervals, are graphically displayed in Figure A.4. Given the model specification, the estimated β_t are interpreted as the changes in the labor market outcome t years after school completion if the fraction of days spent in nonemployment in the first three years after school completion goes from 0 to 1, *ceteris paribus*. Graph (a) of Figure A.4 displays the evolution over time of the earning effect, where the continuous line is for women and the dotted line is for men. Graph (b) of Figure A.4 reports instead the impact on the fraction of time spent in employment.

We refrain from commenting on these OLS estimation results: they cannot be easily given a causal interpretation because of endogeneity of the treatment intensity: there may be a wide series of unobserved determinants, both time-constant and time-varying, which jointly determine both the experiences after school completion and the future labor market performances. The econometric model in the main text is aimed at disentangling the causal effect of nonemployment experiences from the spurious effect induced by systematic differences across individuals unobserved by the analyst.

Figure A.1: Distribution of the fraction of days spent in nonemployment in the first three years after school completion by gender

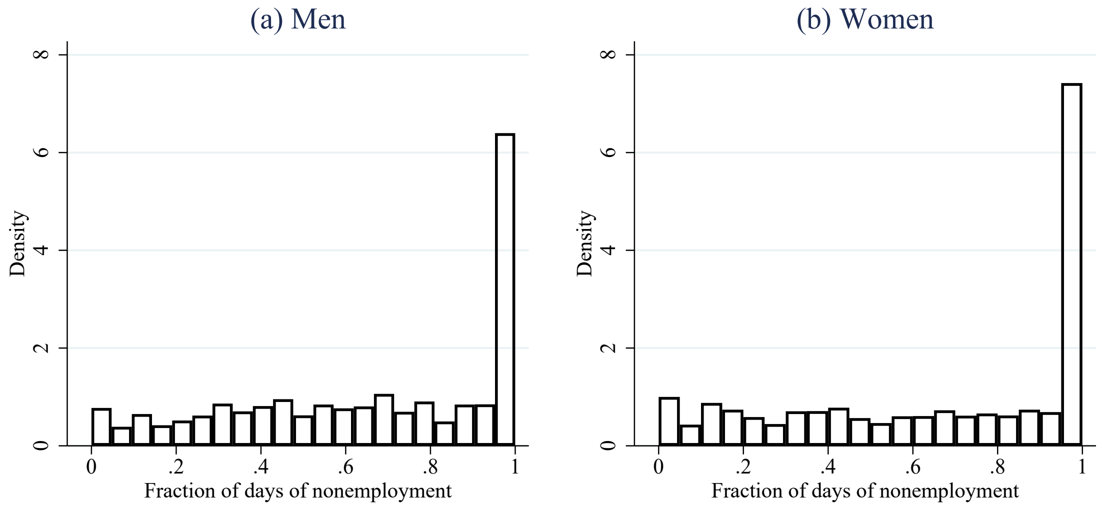
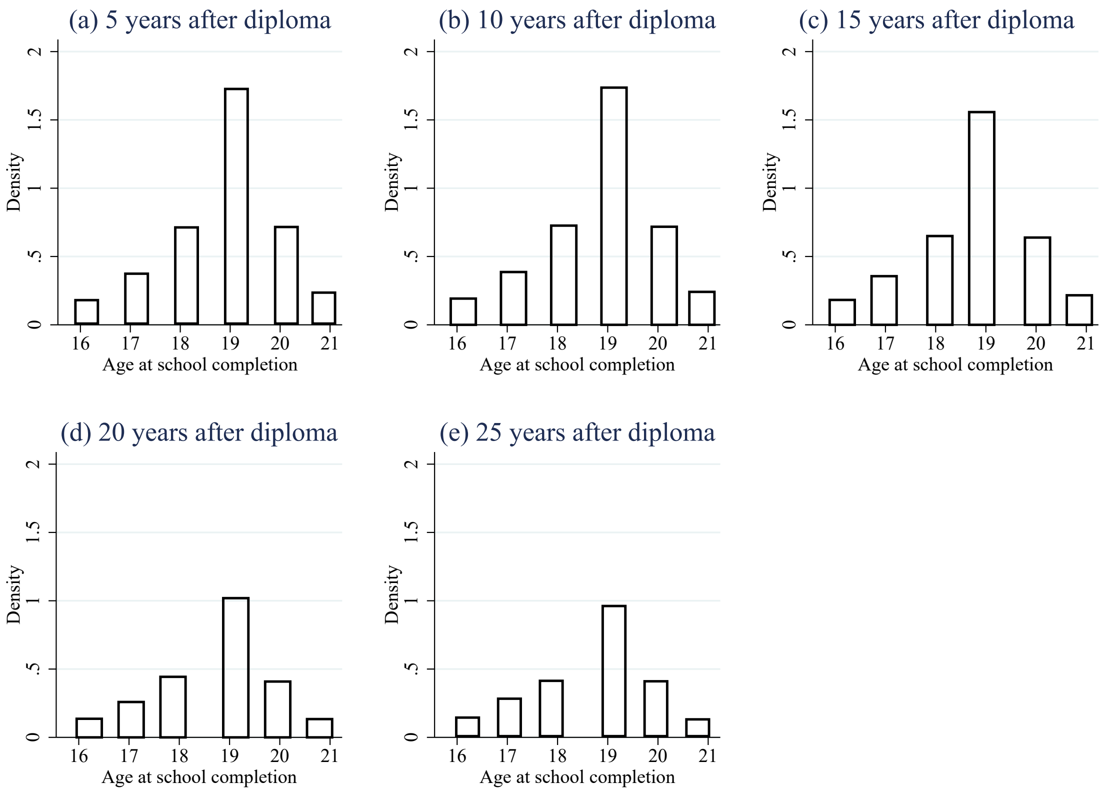


Table A.3: OLS estimates of the relation between early nonemployment and yearly labor earnings

	Years since school completion				
	$t=5$	$t=10$	$t=15$	$t=20$	$t=25$
a) Men					
Nonemployment during the	-12881.81***	-8672.32***	-6630.59***	-5737.47***	-3843.00***
first 3 years after school completion	(471.41)	(586.48)	(688.59)	(896.69)	(1170.94)
b) Women					
Nonemployment during the	-12242.88***	-8862.98***	-5253.49***	-5482.48***	-4881.49***
first 3 years after school completion	(395.24)	(500.42)	(589.27)	(696.32)	(906.45)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

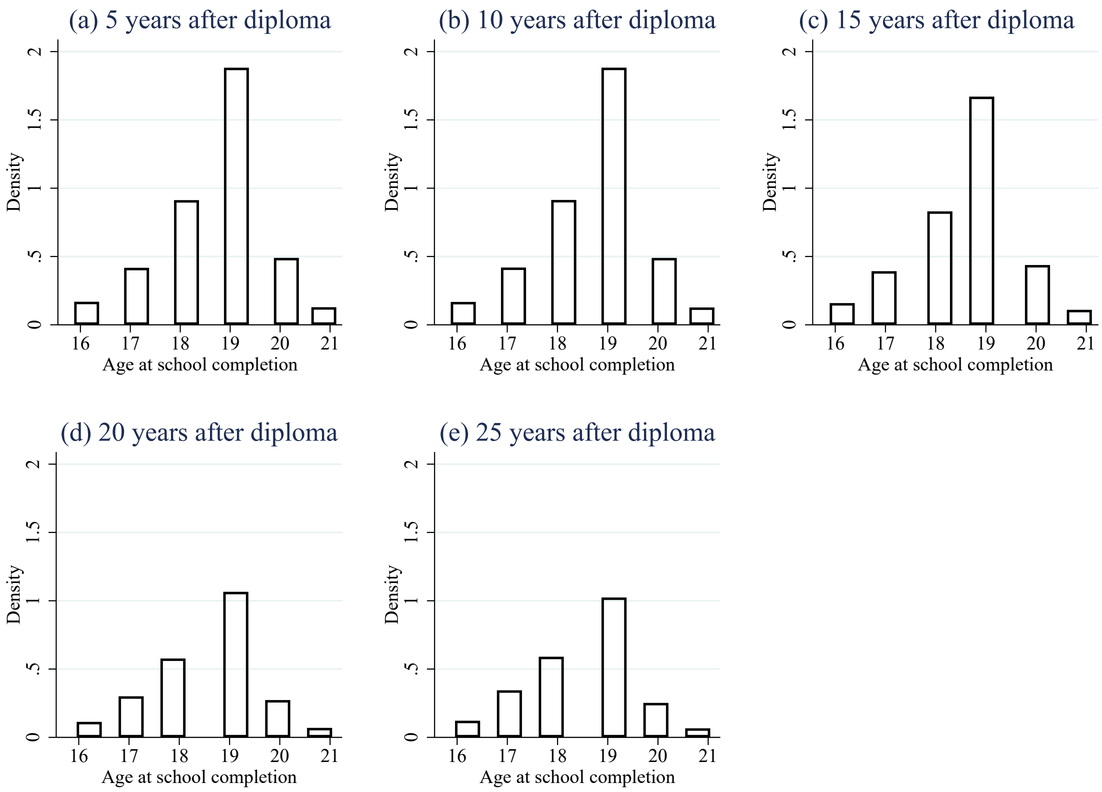
Notes: The equations for the labor market outcomes also include age at school completion, regional dummies, calendar year dummies, regional unemployment, regional employment, regional GDP growth, the number of kids, the number of siblings when the individual was 14 years old, predetermined information, quarter of birth, year of birth, and parents' characteristics when the respondent was 14. Their OLS estimated parameters are not reported for the sake of brevity. Yearly wages are in 2014 prices and deflated by the ISTAT consumer price index.
*** Significant at 1%, ** significant at 5%, * significant at 10%. Standard errors robust to heteroskedasticity are reported in parentheses.

Figure A.2: Distribution of age at school completion for men at different years after school completion



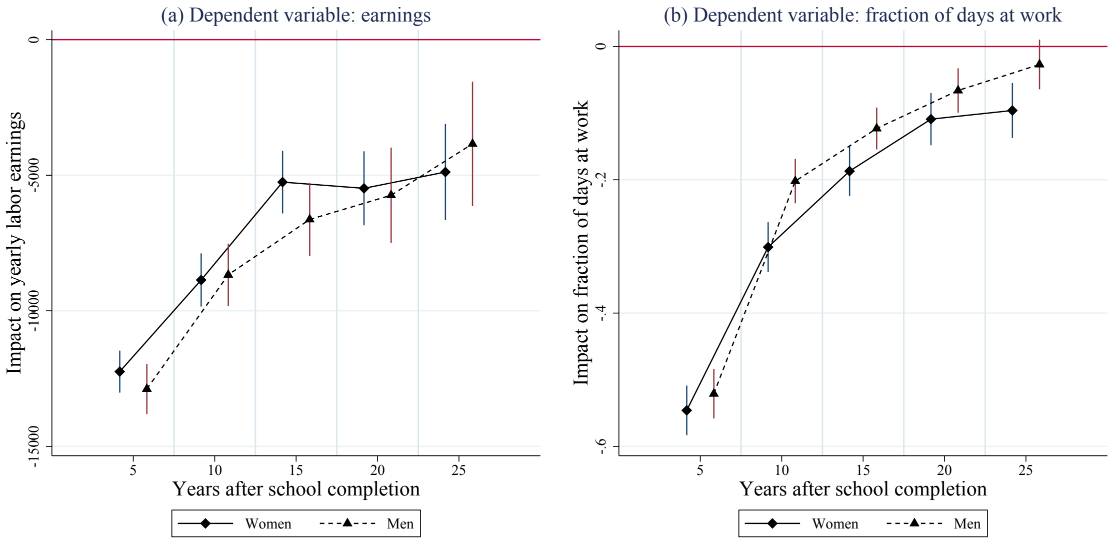
Notes: Graph (a) is based on 5,396 men for whom we can observe the labor market outcomes 5 years after diploma. Graphs (b), (c) and (d) are constructed using 5,310, 4,864, 3,947 and 2,792 men for whom we can observe the labor market outcomes 10, 15, 20 and 25 years since school exit, respectively.

Figure A.3: Distribution of age at school completion for women at different years after school completion



Notes: Graph (a) is based 4,899 women for whom we can observe the labor market outcomes 5 years after the diploma. Graphs (b), (c) and (d) are constructed using 4,722, 4,235, 3,383 and 2,423 women for whom we can observe the labor market outcomes 10, 15, 20 and 25 years since school exit, respectively.

Figure A.4: OLS estimates of the impact of early nonemployment on labor market outcomes



Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index. The vertical segments are 95% confidence intervals.

Table A.4: OLS estimates of the relation between early nonemployment and yearly fraction of days spent at work

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Men					
Nonemployment during the first 3 years after school completion	-0.521*** (0.019)	-0.202*** (0.017)	-0.123*** (0.016)	-0.066*** (0.017)	-0.027 -0.019
b) Women					
Nonemployment during the first 3 years after school completion	-0.546*** (0.019)	-0.301*** (0.019)	-0.187*** (0.019)	-0.109*** (0.020)	-0.096*** (0.021)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: See Table A.3.
*** Significant at 1%, ** significant at 5%, * significant at 10%. Standard errors robust to heteroskedasticity are reported in parentheses.

B. Full set of estimation results without unobserved heterogeneity

Table B.1: Estimated coefficients of the covariates of the labor market outcome equations without unobserved heterogeneity

	Yearly labor earnings (Men)			Yearly fraction of days spent at work (Men)			Yearly labor earnings (Women)			Yearly fraction of days spent at work (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	13.986		15.534	0.000		0.000	5.373		13.857	0.000		0.001
Mother's age at respondent's birth is missing	151.226		494.199	-0.012		0.014	605.540		443.407	-0.009		0.017
Respondent's father has at least secondary education	951.422	***	183.232	-0.022	***	0.005	779.680	***	164.870	-0.006		0.007
Respondent's mother has at least secondary education	26.658		196.572	-0.025	***	0.006	412.113	**	176.057	0.000		0.008
Mother's employment at 14	-495.826	***	165.475	-0.007		0.005	409.957	***	152.685	0.002		0.006
Father's employment at 14	1000.903	***	263.783	0.027	***	0.007	9.044		279.571	0.001		0.011
Respondent lived with both parents at 14	125.569		369.431	-0.006		0.011	422.309		368.693	0.026	*	0.014
Number of siblings at 14 if IT-SILC wave is 2005	-356.875	***	91.883	-0.004	*	0.002	-228.369	***	81.537	-0.006		0.003
Number of siblings at 14 if IT-SILC wave is 2011	-689.988	***	109.041	-0.01	***	0.003	-321.668	***	102.296	-0.016	***	0.004
Quarter of birth - Reference category: October, November, December												
January, February, March	-9.733		205.828	-0.002		0.006	-429.952	**	197.745	-0.005		0.008
April, May, June	-400.657	*	209.006	-0.005		0.006	-332.514		200.968	-0.016	*	0.008
July, August, September	-494.726	**	204.568	-0.002		0.006	141.873		198.403	0.006		0.008
Year of birth/10 (normalized to its minimum)	157.570		482.506	0.020		0.014	-609.114		454.063	0.031		0.018
Geographical area at t - Reference category: North-West												
North-East	-686.557	***	194.280	-0.013	*	0.007	-780.458	***	181.858	-0.013		0.008
Center	-2466.930	***	205.858	-0.015	**	0.007	-1451.317	***	191.579	-0.019	**	0.008
South	-2877.356	***	424.089	-0.044	***	0.012	-1340.293	***	421.772	-0.031	*	0.015
Islands	-1750.283	***	558.850	0.004		0.015	-170.089		589.975	-0.008		0.020
Regional unemployment rate at t	-147.373	***	53.494	-0.009	***	0.001	-313.564	***	626.012	-0.017	***	0.002
Regional employment rate at t	231.668	***	31.988	0.003	***	0.001	86.798	**	37.289	0.000		0.001
Regional growth rate at t	1193.699		3576.819	0.104		0.099	-401.505		3438.835	0.010		0.128
IT-SILC wave 2011	490.063	**	233.883	-0.009		0.007	253.047		214.139	0.009		0.009
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	1284.229	***	307.603	0.026	***	0.009	1225.191	***	299.381	0.030	**	0.012
Between 1986 and 1991	534.515		516.696	0.025	*	0.015	849.786	*	488.748	0.039	**	0.019
Between 1991 and 1996	-119.643		742.364	0.039	*	0.022	814.501		716.969	0.074	***	0.028
After 1996	-1361.657		1037.91	0.020		0.030	682.472		1012.263	0.062	*	0.039
Age at school completion	877.550	***	82.358	-0.001		0.002	766.590	***	834.795	0.010	***	0.003
Number of kids at t	1175.862	***	97.964	0.014	***	0.003	-2103.802	***	88.876	-0.048	***	0.004
Fraction of time spent at work 1 year before diploma	-2229.414	***	321.634	-0.016		0.012	-5460.331	***	534.594	-0.097	***	0.018
Constant at $t = 5$	-5800.698	*	3115.307	0.904	***	0.075	3117.294		3120.362	0.866	***	0.100
Constant at $t = 10$	-2846.612		3065.073	0.832	***	0.076	4030.952		3139.494	0.796	***	0.101
Constant at $t = 15$	-723.747		3105.204	0.823	***	0.077	3690.866		3148.441	0.784	***	0.102
Constant at $t = 20$	1320.226		3065.818	0.797	***	0.077	6377.144	**	3217.662	0.806	***	0.104
Constant at $t = 25$	1625.225		3108.922	0.780	***	0.079	8085.320	**	3207.738	0.842	***	0.105
$\ln(\sigma^2)$	0.533	***	0.006	-2.151	***	0.015	0.128	***	0.006	-1.950	***	0.019

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.
We estimated the model using labor earnings divided by 10,000 to reduce numerical problems. Then, we multiplied all the estimated coefficients by 10,000 before reporting results, apart from the natural logarithms of the variances of the underlying normal distributions. Hence, the latter must be interpreted as the log of the variance of the normal distribution of labor earnings divided by 10,000, i.e. $\ln(\sigma_t^2 \cdot 10,000)$.

Table B.2: Estimated coefficients of the measurement equations without unobserved heterogeneity

	Number of siblings at 14 (Men)			Employment 1 year before school completion (Men)			Number of siblings at 14 (Women)			Employment 1 year before school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	-0.013	***	0.003	0.000		0.001	-0.016	***	0.003	-0.001		0.001
Mother's age at respondent's birth is missing	0.273	**	0.107	0.041	**	0.019	-0.381	***	0.105	-0.007		0.018
Respondent's father has at least secondary education	-0.024		0.040	-0.028	***	0.008	-0.122	***	0.041	-0.010		0.007
Respondent's mother has at least secondary education	-0.104	**	0.045	-0.026	***	0.012	-0.088	*	0.046	-0.005		0.008
Mother's employment at 14	-0.136	***	0.040	-0.003		0.007	-0.089	**	0.038	-0.011	*	0.007
Father's employment at 14	0.301	***	0.049	-0.041	***	0.009	0.221	***	0.056	0.005		0.011
Respondent lived with both parents at 14	-0.073		0.066	0.038	***	0.014	0.169	**	0.085	-0.009		0.014
Number of siblings at 14 if IT-SILC wave is 2005	–		–	0.004		0.003	–		–	0.005	*	0.003
Number of siblings at 14 if IT-SILC wave is 2011	–		–	0.012	**	0.004	–		–	0.016	***	0.003
Quarter of birth - Reference category: October, November, December												
January, February, March	-0.028		0.045	-0.008		0.009	0.118	**	0.047	0.014	*	0.008
April, May, June	-0.073		0.047	-0.012		0.009	0.168	***	0.048	0.017	**	0.008
July, August, September	-0.020		0.044	-0.005		0.009	0.078	*	0.048	0.013		0.008
Year of birth/10 (normalized to its minimum)	0.116		0.083	-0.028	*	0.016	-0.105		0.086	-0.025	*	0.014
Geographical area at birth - Reference category: North-West												
North-East	0.127	**	0.052	0.031	***	0.008	0.162	***	0.049	0.022	***	0.007
Center	-0.007		0.059	-0.013		0.011	-0.047		0.061	0.000		0.009
South	0.602	***	0.072	-0.011		0.015	0.712	***	0.076	-0.004		0.015
Islands	0.511	***	0.093	0.013		0.019	0.663	***	0.098	0.003		0.021
Regional unemployment rate at birth	-0.035	**	0.016	-0.010	***	0.003	-0.057	***	0.016	-0.009	***	0.002
Regional employment rate at birth	-0.027	***	0.007	-0.002		0.001	-0.028	***	0.006	-0.001		0.001
Regional growth rate at birth	-1.804	**	0.781	-0.281	*	0.163	-1.047		0.830	-0.195		0.169
IT-SILC wave 2011	-0.498	***	0.036	-0.014		0.010	-0.535	***	0.037	-0.012		0.008
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	-0.173	***	0.061	0.042	***	0.012	-0.073		0.061	-0.011		0.011
Between 1986 and 1991	-0.404	***	0.097	0.051	**	0.020	-0.084		0.094	0.022		0.016
Between 1991 and 1996	-0.527	***	0.132	0.050	*	0.027	-0.193		0.138	0.029		0.023
After 1996	-0.571	***	0.181	0.118	***	0.035	-0.069		0.181	0.066	**	0.030
Constant	3.426	***	0.460	0.239	***	0.089	3.554	***	0.448	0.184	**	0.071
ln(σ^2)	0.179	***	0.010	-3.064	***	0.022	0.140	***	0.014	-3.516	***	0.020

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.3: Estimated coefficients of the treatment equation without unobserved heterogeneity

	Days (%) of nonemployment during the first 3 years after school completion (Men)			Days (%) of nonemployment during the first 3 years after school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	0.001		0.001	0.002	**	0.001
Mother's age at respondent's birth is missing	0.023		0.025	0.054	*	0.029
Respondent's father has at least secondary education	0.045	***	0.010	0.027	**	0.011
Respondent's mother has at least secondary education	0.038	***	0.010	0.056	***	0.012
Mother's employment at 14	0.021	**	0.009	0.008		0.010
Father's employment at 14	-0.014		0.015	-0.014		0.017
Respondent lived with both parents at 14	-0.012		0.021	-0.006		0.023
Number of siblings at 14 if IT-SILC wave is 2005	0.001		0.005	-0.003		0.005
Number of siblings at 14 if IT-SILC wave is 2011	-0.005		0.006	-0.014	**	0.006
Quarter of birth - Reference category: October, November, December						
January, February, March	-0.020	*	0.011	-0.012		0.013
April, May, June	-0.018		0.011	-0.005		0.013
July, August, September	-0.001		0.011	0.004		0.013
Year of birth/10 (normalized to its minimum)	0.007		0.025	0.049	*	0.028
Geographical area at birth - Reference category: North-West						
North-East	-0.031	***	0.011	-0.061	***	0.012
Center	0.040	***	0.012	0.076	***	0.013
South	0.024		0.017	0.071	***	0.019
Islands	-0.020		0.023	0.039		0.029
Average regional unemployment rate 3 years after diploma	0.009	***	0.002	0.014	***	0.003
Average regional employment rate 3 years after diploma	-0.008	***	0.001	-0.007	***	0.002
Average regional growth rate 3 years after diploma	0.142		0.310	0.644	*	0.349
IT-SILC wave 2011	0.023	*	0.013	0.030	**	0.014
Calendar year of t - Reference category: before 1981						
Between 1981 and 1986	-0.011		0.020	-0.050	**	0.021
Between 1986 and 1991	0.033		0.029	-0.044		0.031
Between 1991 and 1996	0.009		0.040	-0.064		0.044
After 1996	-0.027		0.054	-0.096	*	0.061
Average number of kids 3 years after diploma	-0.160	**	0.061	0.028		0.027
Age at school completion	-0.006		0.004	-0.022	***	0.050
Fraction of time spent at work 1 year before diploma	-0.338	***	0.021	-0.390	***	0.030
Constant	1.085	***	0.123	1.195	***	0.141
ln(σ^2)	-2.521	***	0.030	-2.435	***	0.032

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

C. Full set of estimation results with unobserved heterogeneity

In this section we briefly discuss the estimated coefficients associated with the other covariates entering the equations for the yearly labor earnings and the fraction of days spent in employment, but also the selection into treatment and the two equations for the selection-free measurements. Tables C.1–C.5 shows estimated parameters of the model with time-constant unobserved heterogeneity (5 points of support). Tables from C.6 to C.10 display instead the results of the model with time-varying unobserved heterogeneity (10 support points).

Table C.6 shows that parents' educational attainment and their employment status when the individual was 14 years old are positively associated with labor earnings. For both men and women, we find that regions matter in explaining earnings variation: individuals in North-West earn more, in particular with respect those in the Center, as well as those working in regions with lower unemployment rates. Labor earnings are increasing in the age at which the diploma was obtained, while the number of kids increases earnings for men but reduces those for women. Having worked before the diploma determines lower labor earnings but increases the participation in the labor market. As concern the fraction of days in employment, individuals living in regions with lower unemployment rates have a larger labor market participation. However, results also suggest that individuals in the South or living in the Islands spend more time in the labor market.

Table C.7 reports the estimated parameters for selection-free measurements. We find that the probability of having worked in the year before high school diploma is larger if the number of siblings is higher and for individuals born in the North-East. The number of siblings is smaller if respondent's mother was employed and attained higher education levels, and is higher in the Center and in the Southern regions.

Finally, in Table C.8 we report the estimated coefficients of the selection into treatment equation. Our findings suggest that parents' education is statistically significant in explaining early nonemployment. Individuals born in the North-East are the least likely to experience early nonemployment, while individuals born in the Center or in the South are significantly more likely. Average regional unemployment rate 3 years after school completion is a further strong predictor of the selection into treatment, whereas the more the individual worked during year before the diploma, the lower the probability of experiencing early nonemployment. Finally, the average number of kids 3 years after graduation is negatively associated to nonemployment only for men.

Table C.9 contains the estimated discrete distribution of the time-varying unobserved heterogeneity with 10 support points once constrained $\theta^h_{20} = \theta^h_{25}$ for each $h = 1, ..., H$. The last columns report the resulting probabilities p^h for each support point and the 9 weights for the probability masses. Table C.10 shows the loading factors connecting the distribution of the latent factor θ and the error terms of the 13 equations included in our framework. More in detail, we estimated 2 loading factors for the measurement equations, 1 for the treatment intensity, and 4 for the equations of the participation in the labor market (they would have been 5 without the constraint of time-varying unobserved heterogeneity for the last 2 periods). The loading factors entering the yearly labor earnings equations are normalized to 1: the support points of θ are in 2014 Euro.

Table C.1: Estimated coefficients of the covariates of the labor market outcome equations with time-constant unobserved heterogeneity

	Yearly labor earnings (Men)			Yearly fraction of days spent at work (Men)			Yearly labor earnings (Women)			Yearly fraction of days spent at work (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	-14.146		21.385	0.001	**	0.000	29.796		18.775	0.000		0.001
Mother's age at respondent's birth is missing	-1008.754		696.388	-0.031	**	0.014	1072.730	*	618.425	0.003		0.017
Respondent's father has at least secondary education	543.159	**	262.219	-0.028	***	0.005	300.084		239.568	-0.018		0.007
Respondent's mother has at least secondary education	-931.101	***	278.276	-0.042	***	0.006	292.566		251.339	-0.003		0.008
Mother's employment at 14	-35.153		228.535	0.000		0.005	351.824		214.264	0.000		0.006
Father's employment at 14	443.752		368.615	0.016	**	0.007	15.072		392.799	0.001		0.010
Respondent lived with both parents at 14	191.037		543.657	0.001		0.010	118.952		510.779	0.018		0.014
Number of siblings at 14 if IT-SILC wave is 2005	-2.565		137.107	0.001		0.002	118.745		138.756	0.003		0.003
Number of siblings at 14 if IT-SILC wave is 2011	-143.024		171.147	-0.001		0.003	346.211	**	159.092	0.001		0.004
Quarter of birth - Reference category: October, November, December												
January, February, March	417.834		292.347	0.004		0.006	-458.132	*	268.451	-0.005		0.008
April, May, June	-51.141		295.902	0.000		0.006	-202.408		281.788	-0.013	*	0.008
July, August, September	83.657		291.587	0.006		0.006	9.249		273.508	0.003		0.008
Year of birth/10 (normalized to its minimum)	617.716		651.431	0.029	**	0.013	-941.106		626.503	0.026		0.017
Geographical area at t - Reference category: North-West												
North-East	-838.572	***	267.465	-0.013	**	0.006	-349.477		240.217	-0.003		0.007
Center	-1541.361	***	284.853	0.007		0.006	-1427.770	***	248.982	-0.018	**	0.007
South	-1536.664	***	484.407	-0.020	**	0.010	-1594.797	***	442.087	-0.037	***	0.012
Islands	-485.220	***	651.284	0.021		0.013	-428.115		629.941	-0.012		0.017
Regional unemployment rate at t	-207.836	***	43.432	-0.009	***	0.001	-316.111	***	417.891	-0.018	***	0.001
Regional employment rate at t	263.789	***	30.884	0.004	***	0.001	119.069	***	28.887	0.001		0.001
Regional growth rate at t	-4028.908		2670.057	0.024		0.084	-2344.243		2645.202	-0.035		0.101
IT-SILC wave 2011	246.732		332.791	-0.012	*	0.007	-153.359		307.608	-0.001		0.009
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	1441.680	***	453.798	0.031	***	0.009	1838.093	***	412.516	0.044	***	0.012
Between 1986 and 1991	854.756		731.313	0.030	**	0.015	1936.745	***	689.412	0.065	***	0.019
Between 1991 and 1996	193.692		1031.498	0.047	**	0.021	2149.440	**	992.597	0.106	***	0.028
After 1996	-1480.031		1386.918	0.022		0.029	1959.121		1338.022	0.091	**	0.038
Age at school completion	7450.237	***	1139.143	-0.003		0.002	566.074	***	115.719	0.005		0.003
Number of kids at t	885.457	***	112.791	0.011	***	0.003	-2699.539	***	95.848	-0.061	***	0.003
Fraction of time spent at work 1 year before diploma	975.960	*	588.968	0.038	***	0.012	-2690.928	***	747.287	-0.026		0.020
Constant at $t = 5$	-1553.102		3132.122	1.077	***	0.070	3974.224		3077.591	0.897	***	0.087
Constant at $t = 10$	5835.035	*	3137.120	1.045	***	0.070	5339.772	*	3106.162	0.836	***	0.088
Constant at $t = 15$	11244.890	***	3192.380	1.017	***	0.072	5171.108	*	3133.992	0.825	***	0.089
Constant at $t = 20$	15905.060	***	3187.798	0.954	***	0.072	7676.434	**	3173.279	0.839	***	0.090
Constant at $t = 25$	17136.460	***	3234.930	0.907	***	0.074	9026.959	***	3190.162	0.870	***	0.091
$\ln(\sigma^2)$	-0.095	***	0.006	-2.347	***	0.014	-0.474	***	0.006	-2.217	***	0.016

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.
We estimated the model using labor earnings divided by 10,000 to reduce numerical problems. Then, we multiplied all the estimated coefficients by 10,000 before reporting results, apart from the natural logarithms of the variances of the underlying normal distributions. Hence, the latter must be interpreted as the log of the variance of the normal distribution of labor earnings divided by 10,000, i.e. $\ln(\sigma_t^2 \cdot 10,000)$.

Table C.2: Estimated coefficients of the measurement equations with time-constant unobserved heterogeneity

	Number of siblings at 14 (Men)			Employment 1 year before school completion (Men)			Number of siblings at 14 (Women)			Employment 1 year before school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	-0.012	***	0.003	0.000		0.001	-0.016	***	0.003	-0.001		0.001
Mother's age at respondent's birth is missing	-0.263	**	0.107	0.042	**	0.019	-0.381	***	0.106	-0.008		0.018
Respondent's father has at least secondary education	-0.022		0.040	-0.028	***	0.008	-0.118	***	0.041	-0.009		0.007
Respondent's mother has at least secondary education	-0.099	**	0.046	-0.025	***	0.009	-0.089	*	0.046	-0.006		0.008
Mother's employment at 14	-0.140	***	0.041	-0.004		0.007	-0.088	**	0.038	-0.011	*	0.007
Father's employment at 14	0.310	***	0.049	-0.040	***	0.009	0.221	***	0.056	0.005		0.011
Respondent lived with both parents at 14	-0.087		0.067	0.037	***	0.014	0.172	*	0.085	-0.009		0.014
Number of siblings at 14 if IT-SILC wave is 2005	–		–	0.004		0.003	–		–	0.004		0.003
Number of siblings at 14 if IT-SILC wave is 2011	–		–	0.011	***	0.004	–		–	0.016	***	0.003
Quarter of birth - Reference category: October, November, December												
January, February, March	-0.028		0.045	-0.008		0.009	0.119	**	0.047	0.014	*	0.008
April, May, June	-0.074		0.047	-0.013		0.009	0.168	***	0.048	0.017	**	0.008
July, August, September	-0.022		0.045	-0.006		0.009	0.079		0.048	0.013		0.009
Year of birth/10 (normalized to its minimum)	0.110		0.083	-0.030	*	0.016	-0.112		0.087	-0.025	*	0.014
Geographical area at birth - Reference category: North-West												
North-East	0.126	**	0.052	0.031	***	0.008	0.159	***	0.049	0.022	***	0.007
Center	-0.016		0.059	-0.015		0.011	-0.047		0.061	0.000		0.009
South	0.591	***	0.072	-0.012		0.015	0.717	***	0.076	-0.004		0.015
Islands	0.504	***	0.094	0.012		0.019	0.670	***	0.098	0.003		0.021
Regional unemployment rate at birth	-0.035	**	0.016	-0.010	***	0.003	-0.058	***	0.016	-0.009	***	0.003
Regional employment rate at birth	-0.027	***	0.007	-0.002		0.001	-0.027	***	0.006	-0.001		0.001
Regional growth rate at birth	-1.766	**	0.788	-0.277	*	0.012	1.005		0.833	-0.193		0.172
IT-SILC wave 2011	-0.498	***	0.037	-0.014		0.010	-0.533	***	0.037	-0.012		0.008
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	-0.174	***	0.062	0.042	***	0.012	-0.074		0.060	-0.011		0.011
Between 1986 and 1991	-0.405	***	0.098	0.050	***	0.020	-0.086		0.095	0.022		0.016
Between 1991 and 1996	-0.527	***	0.133	0.050	*	0.027	-0.195		0.138	0.029		0.024
After 1996	-0.567	***	0.182	0.119	***	0.035	-0.062		0.182	0.066	**	0.030
Constant	3.337	***	0.464	0.219	**	0.090	3.530	***	0.447	0.184	***	0.071
$\ln(\sigma^2)$	0.183	***	0.010	-3.068	***	0.022	0.138	***	0.014	-3.518	***	0.021

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table C.3: Estimated coefficients of the treatment equation with time-constant unobserved heterogeneity

	Days (%) of nonemployment during the first 3 years after school completion (Men)			Days (%) of nonemployment during the first 3 years after school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	0.001		0.001	0.002	**	0.001
Mother's age at respondent's birth is missing	0.025		0.025	0.051	*	0.028
Respondent's father has at least secondary education	0.045	***	0.010	0.030	***	0.011
Respondent's mother has at least secondary education	0.040	***	0.010	0.055	***	0.011
Mother's employment at 14	0.019	**	0.009	0.008		0.010
Father's employment at 14	-0.012		0.015	-0.013		0.017
Respondent lived with both parents at 14	-0.013		0.021	-0.005		0.023
Number of siblings at 14 if IT-SILC wave is 2005	0.000		0.005	-0.005		0.005
Number of siblings at 14 if IT-SILC wave is 2011	-0.006		0.006	-0.017	**	0.006
Quarter of birth - Reference category: October, November, December						
January, February, March	-0.021	*	0.011	-0.012		0.013
April, May, June	-0.018		0.011	-0.005		0.013
July, August, September	-0.002		0.011	0.004		0.013
Year of birth/10 (normalized to its minimum)	0.004		0.025	0.047		0.028
Geographical area at birth - Reference category: North-West						
North-East	-0.030	***	0.011	-0.062	***	0.012
Center	0.036	***	0.012	0.074	***	0.013
South	0.020		0.017	0.072	***	0.019
Islands	-0.021		0.023	0.041		0.029
Average regional unemployment rate 3 years after diploma	0.009	***	0.002	0.013	***	0.002
Average regional employment rate 3 years after diploma	-0.008	***	0.001	-0.007	***	0.001
Average regional growth rate 3 years after diploma	0.132		0.311	0.624	*	0.341
IT-SILC wave 2011	0.023	*	0.013	0.031	**	0.014
Calendar year of t - Reference category: before 1981						
Between 1981 and 1986	-0.012		0.019	-0.050	**	0.021
Between 1986 and 1991	0.032		0.029	-0.047		0.031
Between 1991 and 1996	0.008		0.040	-0.066		0.044
After 1996	-0.026		0.054	-0.096		0.060
Average number of kids 3 years after diploma	-0.168	***	0.060	0.034		0.027
Age at school completion	-0.006		0.004	-0.021	***	0.005
Fraction of time spent at work 1 year before diploma	-0.345	***	0.021	-0.397	***	0.031
Constant	1.056	***	0.122	1.194	***	0.140
ln(σ^2)	-2.530	***	0.029	-2.453	***	0.032

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table C.4: Estimated distribution of the discrete time-constant unobserved heterogeneity with $H = 5$ support points

	Location of the mass			Logistic weight of the probability masses (p^h)			Resulting probabilities (p^h)
	Coeff.		Std. Error	Coeff.		Std. Error	
a) Men							
θ^1	0.00		–	2.151	***	0.191	0.132
θ^2	-13268.00	***	854.94	1.774	***	0.253	0.091
θ^3	-4629.90	***	308.79	3.397	***	0.209	0.460
θ^4	-8334.58	***	542.71	2.978	***	0.216	0.302
θ^5	6033.00	***	432.65	–		–	0.015
b) Women							
θ^1	0.00		–	2.959	***	0.193	0.437
θ^2	-19597.73	***	500.62	1.476	***	0.227	0.099
θ^3	-9867.77	***	295.17	2.603	***	0.195	0.306
θ^4	10241.62	***	305.16	1.794	***	0.188	0.136
θ^5	24080.07	***	546.42	–		–	0.023

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%. Since the loading factor of one earnings equation is normalized to 1 for both genders, all the figures are in 2014 Euro.

Table C.5: Estimated loading factors with time-constant unobserved heterogeneity (discrete distribution with $H = 5$ support points)

Equations	Men			Women		
	Loading factor		Std. Error	Loading factor		Std. Error
a) Measurement equations						
Number of siblings when 14 years old	-0.142	**	0.058	-0.074	***	0.026
Employment 1 year before school completion	-0.033	***	0.011	-0.006	*	0.005
b) Selection into treatment equation						
Days (%) of nonemployment 3 years after school completion	-0.069	***	0.017	-0.043	***	0.007
c) Labor market outcomes						
Yearly labor earnings 5 years after school completion	1.000		–	0.380	***	0.024
Yearly labor earnings 10 years after school completion	1.879	***	0.144	0.680	***	0.021
Yearly labor earnings 15 years after school completion	2.569	***	0.168	0.884	***	0.023
Yearly labor earnings 20 years after school completion	3.217	***	0.210	1.000		–
Yearly labor earnings 25 years after school completion	3.439	***	0.221	0.973	***	0.024
Yearly fraction of days spent at work 5 years after school completion	0.366	***	0.039	0.152	***	0.009
Yearly fraction of days spent at work 10 years after school completion	0.439	***	0.031	0.220	***	0.010
Yearly fraction of days spent at work 15 years after school completion	0.406	***	0.033	0.239	***	0.010
Yearly fraction of days spent at work 20 years after school completion	0.334	***	0.030	0.204	***	0.011
Yearly fraction of days spent at work 25 years after school completion	0.277	***	0.030	0.150	***	0.011

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table C.6: Estimated coefficients of the covariates of the labor market outcome equations with time-varying unobserved heterogeneity

	Yearly labor earnings (Men)			Yearly fraction of days spent at work (Men)			Yearly labor earnings (Women)			Yearly fraction of days spent at work (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	20.806	*	11.245	0.000		0.000	9.113		8.950	0.000		0.000
Mother's age at respondent's birth is missing	329.345		358.722	-0.008		0.008	792.190	***	286.44	0.002		0.010
Respondent's father has at least secondary education	1445.685	***	132.032	0.000		0.003	902.926	***	106.394	0.001		0.004
Respondent's mother has at least secondary education	532.359	***	142.303	-0.002		0.003	446.787	***	113.122	0.003		0.004
Mother's employment at 14	-393.146	***	119.783	-0.003		0.003	364.577	***	98.355	-0.001		0.004
Father's employment at 14	494.609	***	191.530	0.004	**	0.004	123.384		179.471	0.005		0.006
Respondent lived with both parents at 14	-44.886		267.468	-0.004		0.006	-132.891		235.879	0.000		0.008
Number of siblings at 14 if IT-SILC wave is 2005	-256.002	***	66.715	0.001		0.001	161.295	***	52.917	-0.002		0.002
Number of siblings at 14 if IT-SILC wave is 2011	-445.398	***	79.238	-0.001		0.002	-4.512		66.883	0.001		0.002
Quarter of birth - Reference category: October, November, December												
January, February, March	7.548		149.086	-0.003		0.004	-391.449	***	127.477	0.000		0.004
April, May, June	-278.014	*	151.806	0.000		0.004	10.587		129.874	0.001		0.004
July, August, September	-474.224	***	148.496	-0.002		0.004	55.382		127.500	0.001		0.004
Year of birth/10 (normalized to its minimum)	-241.181		349.994	-0.013		0.008	-1525.899	***	295.127	-0.016		0.010
Geographical area at t - Reference category: North-West												
North-East	-619.835	***	137.398	-0.004		0.004	-665.015	***	117.967	-0.006		0.004
Center	-2546.118	***	151.540	0.002		0.004	-946.969	***	123.743	0.009	**	0.004
South	-1688.532	***	338.974	0.013	**	0.006	-362.773		274.421	0.022	***	0.008
Islands	-848.629	**	430.689	0.032	***	0.007	624.539		384.740	0.030	***	0.009
Regional unemployment rate at t	-113.750	**	45.115	-0.004	***	0.001	-134.470	***	40.576	-0.006	***	0.001
Regional employment rate at t	155.359	***	27.135	0.000		0.000	50.148	**	24.209	-0.007		0.001
Regional growth rate at t	-582.076		2423.789	-0.036		0.038	-1855.768		2252.019	-0.088	*	0.046
IT-SILC wave 2011	638.596	***	169.251	0.000		0.004	1.807		138.049	-0.003		0.005
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	561.075	**	223.859	0.004		0.006	834.730	***	192.126	0.008		0.006
Between 1986 and 1991	-252.934		375.067	0.004		0.010	233.212		314.834	0.004		0.011
Between 1991 and 1996	-1201.755	**	539.341	0.008		0.013	-217.472		461.812	0.009		0.016
After 1996	-2228.168	***	753.382	0.006		0.018	40.012		651.958	0.014		0.023
Age at school completion	941.353	***	59.829	-0.002		0.001	534.276	***	540.557	-0.002		0.002
Number of kids at t	950.919	***	71.227	0.004	**	0.002	-1385.903	***	57.741	-0.011	***	0.002
Fraction of time spent at work 1 year before diploma	-1868.949	***	234.217	-0.003		0.006	-4002.103	***	342.061	-0.021	**	0.009
Constant at $t = 5$	-19367.220	***	2499.585	0.188	***	0.043	-3153.973		2132.559	0.344	***	0.048
Constant at $t = 10$	-17571.980	***	2361.651	0.221	***	0.040	-4395.957	**	2161.705	0.222	***	0.050
Constant at $t = 15$	-19284.120	***	2404.844	0.124	***	0.044	-4897.454	**	2117.043	0.247	***	0.049
Constant at $t = 20$	-16297.360	***	2298.743	0.320	***	0.040	-4928.042	**	2127.937	0.342	***	0.048
Constant at $t = 25$	-16129.820	***	2330.063	0.296	***	0.040	-3663.224	*	2130.286	0.354	***	0.049
ln(σ^2)	0.206	***	0.004	-3.786	***	0.008	-0.318	***	0.004	-3.508	***	0.009

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.
We estimated the model using labor earnings divided by 10,000 to reduce numerical problems. Then, we multiplied all the estimated coefficients by 10,000 before reporting results, apart from the natural logarithms of the variances of the underlying normal distributions. Hence, the latter must be interpreted as the log of the variance of the normal distribution of labor earnings divided by 10,000, i.e. $\ln(\sigma_t^2 \cdot 10,000)$.

Table C.7: Estimated coefficients of the measurement equations with time-varying unobserved heterogeneity

	Number of siblings at 14 (Men)			Employment 1 year before school completion (Men)			Number of siblings at 14 (Women)			Employment 1 year before school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	-0.013	***	0.003	0.000		0.001	-0.016	***	0.003	-0.001		0.001
Mother's age at respondent's birth is missing	-0.271	**	0.108	0.042	**	0.019	-0.380	***	0.106	-0.006		0.018
Respondent's father has at least secondary education	-0.027		0.041	-0.026	***	0.008	-0.122	***	0.041	-0.009		0.007
Respondent's mother has at least secondary education	-0.108	**	0.046	-0.023	**	0.009	-0.089	*	0.046	-0.004		0.008
Mother's employment at 14	-0.138	***	0.041	-0.001		0.007	-0.088	**	0.038	-0.011	*	0.007
Father's employment at 14	0.306	***	0.050	-0.043	***	0.009	0.221	***	0.056	0.004		0.011
Respondent lived with both parents at 14	-0.082		0.067	0.039	***	0.014	0.169	**	0.086	-0.010		0.014
Number of siblings at 14 if IT-SILC wave is 2005	–		–	0.005		0.003	–		–	0.005	*	0.003
Number of siblings at 14 if IT-SILC wave is 2011	–		–	0.012	***	0.004	–		–	0.016	***	0.003
Quarter of birth - Reference category: October, November, December												
January, February, March	-0.026		0.045	-0.009		0.009	0.118	**	0.047	0.015	*	0.008
April, May, June	-0.074		0.047	-0.012		0.009	0.169	***	0.049	0.017	**	0.008
July, August, September	-0.020		0.045	-0.005		0.009	0.079		0.048	0.013		0.009
Year of birth/10 (normalized to its minimum)	0.119		0.084	-0.029	*	0.017	-0.105		0.087	-0.025	*	0.014
Geographical area at birth - Reference category: North-West												
North-East	0.128	**	0.053	0.028	***	0.008	0.163	***	0.049	0.022	***	0.007
Center	-0.010		0.059	-0.011		0.011	-0.048		0.062	0.002		0.009
South	0.592	***	0.073	-0.001		0.016	0.710	***	0.077	0.001		0.015
Islands	0.505	***	0.094	0.018		0.020	0.661	***	0.099	0.007		0.021
Regional unemployment rate at birth	-0.035	**	0.016	-0.010	***	0.003	-0.058	***	0.016	-0.008	***	0.003
Regional employment rate at birth	-0.026	***	0.007	-0.002	*	0.001	-0.028	***	0.006	-0.001		0.001
Regional growth rate at birth	-1.814	**	0.791	-0.261		0.164	-1.046		0.836	-0.206		0.169
IT-SILC wave 2011	-0.500	***	0.037	-0.012		0.010	-0.536	***	0.037	-0.012		0.008
Calendar year of t - Reference category: before 1981												
Between 1981 and 1986	-0.171	***	0.062	0.038	***	0.012	-0.073		0.060	-0.013		0.011
Between 1986 and 1991	-0.403	***	0.098	0.048	**	0.020	-0.084		0.095	0.020		0.016
Between 1991 and 1996	-0.522	***	0.133	0.043		0.027	-0.193		0.139	0.024		0.024
After 1996	-0.565	***	0.183	0.109	***	0.035	-0.068		0.183	0.059	**	0.030
Constant	3.433	***	0.465	0.235	***	0.089	3.556	***	0.451	0.184	***	0.071
ln(σ^2)	0.184	***	0.010	-3.073	***	0.022	0.142	***	0.014	-3.520	***	0.021

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table C.8: Estimated coefficients of the treatment equation with time-varying unobserved heterogeneity

	Days (%) of nonemployment during the first 3 years after school completion (Men)			Days (%) of nonemployment during the first 3 years after school completion (Women)		
	Coeff.		Std. Error	Coeff.		Std. Error
Mother's age at respondent's birth	0.001		0.001	0.002	**	0.001
Mother's age at respondent's birth is missing	0.015		0.024	0.040		0.027
Respondent's father has at least secondary education	0.034	***	0.010	0.023	**	0.010
Respondent's mother has at least secondary education	0.022	**	0.010	0.045	***	0.011
Mother's employment at 14	0.015	*	0.009	0.006		0.009
Father's employment at 14	-0.005		0.014	-0.009		0.016
Respondent lived with both parents at 14	-0.013		0.020	-0.003		0.022
Number of siblings at 14 if IT-SILC wave is 2005	-0.001		0.005	-0.003		0.005
Number of siblings at 14 if IT-SILC wave is 2011	-0.005		0.005	-0.015	**	0.006
Quarter of birth - Reference category: October, November, December						
January, February, March	-0.016		0.011	-0.014		0.012
April, May, June	-0.018		0.011	-0.007		0.012
July, August, September	-0.004		0.011	0.004		0.012
Year of birth/10 (normalized to its minimum)	0.021		0.024	0.063	**	0.027
Geographical area at birth - Reference category: North-West						
North-East	-0.022	**	0.011	-0.060	***	0.011
Center	0.029	**	0.011	0.052	***	0.012
South	-0.006		0.016	0.035	*	0.018
Islands	-0.035		0.022	0.012		0.026
Average regional unemployment rate 3 years after diploma	0.007	***	0.002	0.010	***	0.002
Average regional employment rate 3 years after diploma	-0.006	***	0.001	-0.005	***	0.002
Average regional growth rate 3 years after diploma	-0.006		0.291	0.762	**	0.328
IT-SILC wave 2011	0.014		0.012	0.027	**	0.013
Calendar year of t - Reference category: before 1981						
Between 1981 and 1986	0.011		0.018	-0.033	*	0.020
Between 1986 and 1991	0.039		0.027	-0.034		0.030
Between 1991 and 1996	0.026		0.037	-0.037		0.042
After 1996	-0.018		0.050	-0.082		0.057
Average number of kids 3 years after diploma	-0.131	**	0.056	-0.002		0.024
Age at school completion	-0.003		0.004	-0.017	***	0.005
Fraction of time spent at work 1 year before diploma	-0.298	***	0.020	-0.350	***	0.028
Constant	1.083	***	0.115	1.153	***	0.132
$\ln(\sigma^2)$	-2.643	***	0.026	-2.573	***	0.029

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%.

Table C.9: Estimated distribution of the discrete time-varying unobserved heterogeneity with $H = 10$ support points

	Location of the mass				Logistic weight of the probability masses (p^h)			Resulting probabilities (p^h)
	$t = 5$	$t = 10$	$t = 15$	$t = 20/25$	Coeff.		Std. Error	
a) Men								
θ^1	0.00	0.00	0.00	0.00	0.890	***	0.133	0.045
θ^2	16123.09***	18555.35***	22615.87***	22180.61***	3.325	***	0.126	0.510
	(1026.68)	(828.50)	(909.56)	(510.55)				
θ^3	-5.114	-1583.01***	22103.38***	21996.60***	1.277	***	0.138	0.066
	(363.15)	(279.69)	(941.49)	(543.72)				
θ^4	387.92	18243.65***	22913.90***	21316.69***	2.307	***	0.126	0.184
	(302.67)	(829.60)	(912.61)	(507.13)				
θ^5	10745.48***	18276.38***	21379.39***	1856.64***	0.888	***	0.134	0.045
	(719.71)	(852.88)	(896.74)	(196.62)				
θ^6	248.43	6101.99***	445.38	19926.73***	0.957	***	0.131	0.048
	(349.94)	(307.07)	(510.41)	(512.03)				
θ^7	15517.97***	-1032.95***	18628.75***	19900.97***	0.653	***	0.141	0.035
	(1017.95)	(303.78)	(796.93)	(505.18)				
θ^8	332.38	-1279.99***	21592.88***	4927.54***	0.136		0.157	0.021
	(434.07)	(396.06)	(995.74)	(254.27)				
θ^9	15267.27***	18282.33***	1514.03***	18937.44***	0.453	**	0.145	0.008
	(993.91)	(903.88)	(501.95)	(496.73)				
θ^{10}	15839.88***	3500.28***	1411.94***	-955.01***	–		–	0.018
	(1052.84)	(244.84)	(498.58)	(244.73)				
b) Women								
θ^1	0.00	0.00	0.00	0.00	0.144		0.099	0.084
θ^2	13487.72***	16263.15***	19280.14***	12546.85***	1.694	***	0.069	0.396
	(755.95)	(740.81)	(443.27)	(748.39)				
θ^3	12546.85***	649.54**	15931.55***	16666.54***	-0.445	***	0.099	0.047
	(748.39)	(308.87)	(701.10)	(437.11)				
θ^4	-673.88***	15779.45***	16377.12***	18977.70***	0.629	***	0.077	0.136
	(185.44)	(738.52)	(660.36)	(458.99)				
θ^5	13129.48***	15789.42***	14937.07***	2700.26***	-0.370	***	0.110	0.050
	(806.24)	(767.28)	(632.06)	(202.16)				
θ^6	12943.14***	100.16	-574.51	13821.84***	-0.789	***	0.113	0.033
	(811.48)	(359.54)	(409.04)	(376.11)				
θ^7	-969.87**	14615.73***	14353.83***	3174.40***	-0.860	***	0.131	0.031
	(480.61)	(719.57)	(620.67)	(239.93)				
θ^8	-1180.99***	-156.62	16141.49***	17041.98***	0.194	**	0.084	0.088
	(300.18)	(283.82)	(668.55)	(426.95)				
θ^9	8739.69***	15626.11***	-268.93	12113.33***	-0.166		0.103	0.062
	(507.47)	(767.91)	(312.78)	(330.65)				
θ^{10}	-1145.74***	-439.08	-760.73**	17147.36***	–		–	0.073
	(327.83)	(341.63)	(350.53)	(425.63)				

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%. Since the loading factors of the earnings equations are normalized to 1, all the figures are in 2014 Euro. The normalisation $\theta^1 = 0$ is innocuous: all the support points are indeed in deviation from the time-varying constant terms displayed in the last part of Table C.6.

Table C.10: Estimated loading factors with time-varying unobserved heterogeneity (discrete distribution with $H = 10$ support points)

	Men			Women		
Equations	Loading factor		Std. Error	Loading factor		Std. Error
a) Measurement equations						
Number of siblings when 14 years old	-0.029		0.023	-0.006		0.026
Employment 1 year before school completion	0.030	***	0.006	0.019	***	0.005
b) Selection into treatment equation						
Days (%) of nonemployment 3 years after school completion	-0.138	***	0.011	-0.170	***	0.011
c) Labor market outcomes						
Yearly labor earnings 5 years after school completion	1.000		–	1.000		–
Yearly labor earnings 10 years after school completion	1.000		–	1.000		–
Yearly labor earnings 15 years after school completion	1.000		–	1.000		–
Yearly labor earnings 20 years after school completion	1.000		–	1.000		–
Yearly labor earnings 25 years after school completion	1.000		–	1.000		–
Yearly fraction of days spent at work 5 years after school completion	0.558	***	0.036	0.610	***	0.038
Yearly fraction of days spent at work 10 years after school completion	0.462	***	0.022	0.558	***	0.027
Yearly fraction of days spent at work 15 years after school completion	0.420	***	0.017	0.527	***	0.023
Yearly fraction of days spent at work 20 or 25 years after school completion	0.333	***	0.009	0.401	***	0.011

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%. The loading factors of the yearly labor earnings equations are normalized to 1.

D. Sensitivity analysis

Table D.1: Impact of early nonemployment or unpaid internship/stage/training on labor market outcomes with time-varying unobserved heterogeneity

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment or unpaid internship/stage/training during the first 3 years after school completion (men)	-4526.72*** (1067.79)	-3914.81*** (772.27)	-4045.99*** (720.25)	-4084.16*** (675.11)	-2122.72*** (625.39)
Nonemployment or unpaid internship/stage/training during the first 3 years after school completion (women)	-5292.39*** (725.68)	-3596.06*** (550.48)	-1619.49*** (499.82)	-1997.51*** (494.46)	-412.97 (481.90)
b) Yearly fraction of days spent at work					
Nonemployment or unpaid internship/stage/training during the first 3 years after school completion (men)	-0.090*** (0.011)	-0.005 (0.010)	-0.003 (0.014)	-0.022** (0.009)	0.014 (0.010)
Nonemployment or unpaid internship/stage/training during the firs3 years after school completion (women)	-0.112*** (0.011)	-0.004 (0.017)	-0.001 (0.014)	-0.000 (0.008)	0.033*** (0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.2: Impact of early nonemployment during the first 2 years after school completion on labor market outcomes with time-varying unobserved heterogeneity

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-3017.37***	-3338.88***	-2896.27***	-3090.98***	-940.90
2 years after school completion (men)	(984.62)	(717.11)	(683.97)	(613.93)	(582.34)
Nonemployment during the first	-4254.46***	-3082.40***	-1697.36***	-2242.27***	-1109.14***
2 years after school completion (women)	(683.26)	(524.82)	(471.96)	(463.27)	(451.11)
b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.048***	-0.008	-0.001	0.000	0.039***
2 years after school completion (men)	(0.010)	(0.009)	(0.013)	(0.008)	(0.008)
Nonemployment during the first	-0.075***	-0.003	-0.001	-0.000	0.033***
during the firs3 years after school completion (women)	(0.011)	(0.016)	(0.013)	(0.008)	(0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.3: Impact of early nonemployment during the first 4 years after school completion on labor market outcomes with time-varying unobserved heterogeneity

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-5041.78***	-5066.98***	-4812.33***	-5569.02***	-3715.05***
4 years after school completion (men)	(1120.76)	(776.44)	(705.03)	(654.41)	(622.90)
Nonemployment during the first	-6116.17***	-4252.87***	-2492.40***	-3345.95***	-1867.65***
4 years after school completion (women)	(770.08)	(565.10)	(501.91)	(499.20)	(475.19)
b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.098***	-0.018**	-0.002	-0.010	0.042***
4 years after school completion (men)	(0.010)	(0.009)	(0.014)	(0.008)	(0.009)
Nonemployment during the first	-0.134***	-0.011	-0.003	-0.018**	0.034***
4 years after school completion (women)	(0.016)	(0.017)	(0.015)	(0.009)	(0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.4: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity by including geographical area at birth and regional rates at birth in the outcome and treatment equations

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-3852.39***	-4255.17***	-4035.90***	-4502.19***	-2269.94***
3 years after school completion (males)	(1050.95)	(758.34)	(702.87)	(647.58)	(618.07)
Nonemployment during the first	-4965.48***	-3660.18***	-1901.50***	-2753.99***	-1361.83***
3 years after school completion (females)	(723.10)	(548.34)	(487.52)	(489.39)	(476.16)
(b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.065***	-0.012	-0.003	-0.005	0.043***
3 years after school completion (males)	(0.010)	(0.009)	(0.013)	(0.008)	(0.009)
Nonemployment during the first	-0.101***	-0.006	-0.005	-0.014	0.030***
3 years after school completion (females)	(0.011)	(0.016)	(0.014)	(0.008)	(0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.5: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity by including geographical area at birth, regional rates at birth and average regional rates across 3 years after school completion in the outcome equations

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-4001.40***	-4394.44***	-4136.76***	-4551.30***	-2329.76***
3 years after school completion (males)	(1050.16)	(757.81)	(702.55)	(646.73)	(618.08)
Nonemployment during the first	-4984.55***	-3672.19***	-1890.95***	-2743.19***	-1353.11***
3 years after school completion (females)	(723.56)	(548.74)	(489.54)	(489.94)	(477.29)
(b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.067***	-0.015	-0.005	-0.007	0.043***
3 years after school completion (males)	(0.010)	(0.009)	(0.013)	(0.008)	(0.009)
Nonemployment during the first	-0.101***	-0.006	-0.005	-0.014*	0.030***
3 years after school completion (females)	(0.011)	(0.016)	(0.014)	(0.008)	(0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.6: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using only individuals born in 1960s

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-3612.84***	-3952.90***	-3429.31***	-4958.71***	-2000.35**
3 years after school completion (males)	(1950.23)	(1470.90)	(1193.26)	(919.97)	(791.84)
Nonemployment during the first	-4373.17***	-3431.93***	-1892.24***	-2834.94***	-1638.87***
3 years after school completion (females)	(1181.81)	(935.12)	(746.15)	(679.62)	(586.33)
(b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.095***	-0.013	0.003	0.004	0.053***
3 years after school completion (males)	(0.012)	(0.017)	(0.031)	(0.011)	(0.011)
Nonemployment during the first	-0.099***	-0.002	-0.001	0.001	0.028***
3 years after school completion (females)	(0.018)	(0.025)	(0.021)	(0.011)	(0.012)
Observations (men)	2724	2717	2706	2674	2571
Observations (women)	2570	2491	2400	2310	2188

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.7: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using only individuals born in 1970s-1980s

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-4987.74***	-4672.43***	-4362.71***	-2239.73***	-2522.86
3 years after school completion (males)	(1122.23)	(792.34)	(810.93)	(936.45)	(2318.14)
Nonemployment during the first	-5891.23***	-3985.04***	-1700.73***	-2815.37***	-2432.92
3 years after school completion (females)	(833.28)	(612.94)	(612.38)	(703.74)	(1810.72)
(b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.066***	-0.003	0.008	0.006	0.018
3 years after school completion (males)	(0.012)	(0.014)	(0.015)	(0.012)	(0.023)
Nonemployment during the first	-0.099***	-0.013	-0.004	-0.054***	0.056***
3 years after school completion (females)	(0.013)	(0.018)	(0.017)	(0.014)	(0.021)
Observations (men)	2672	2593	2158	1273	221
Observations (women)	2329	2231	1835	1073	235

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.8: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using only individuals we follow up to 25 years later

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first 3 years after school completion (males)	-3369.32 (2096.02)	-3487.70** (1497.57)	-3105.83*** (1194.46)	-4220.93*** (917.24)	-1822.05** (773.47)
Nonemployment during the first 3 years after school completion (females)	-3885.86*** (1250.19)	-3073.97*** (975.09)	-1455.63*** (778.74)	-2707.29*** (683.06)	-1502.73*** (595.14)
(b) Yearly fraction of days spent at work					
Nonemployment during the first 3 years after school completion (males)	-0.085*** (0.013)	-0.014 (0.017)	0.005 (0.032)	0.006 (0.010)	0.051*** (0.010)
Nonemployment during the first 3 years after school completion (females)	-0.082*** (0.020)	-0.002 (0.032)	-0.003 (0.019)	-0.010 (0.012)	0.035*** (0.011)
Observations (men)	2792	2792	2792	2792	2792
Observations (women)	2423	2423	2423	2423	2423

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.9: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using only individuals born and graduated in Central or Northern Italy

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first	-5486.99***	-4632.72***	-3703.93***	-3329.53***	-1665.45***
3 years after school completion (males)	(1334.70)	(954.99)	(906.23)	(851.74)	(772.62)
Nonemployment during the first	-4982.19***	-3573.52***	-1476.99**	-1518.21***	-607.70
3 years after school completion (females)	(906.35)	(675.16)	(615.76)	(600.17)	(580.89)
(b) Yearly fraction of days spent at work					
Nonemployment during the first	-0.085***	-0.013	-0.002	-0.014	0.009
3 years after school completion (males)	(0.011)	(0.011)	(0.015)	(0.009)	(0.010)
Nonemployment during the first	-0.079***	-0.010	0.005	0.008	0.024**
3 years after school completion (females)	(0.015)	(0.018)	(0.013)	(0.009)	(0.010)
Observations (men)	3739	3693	3429	2807	2000
Observations (women)	3552	3466	3176	2581	1854

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.10: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using only individuals born and graduated in Southern Italy or Islands

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first 3 years after school completion (males)	-3740.46** (1861.58)	-2691.44* (1509.31)	-4783.19*** (1418.20)	-3813.67*** (1297.11)	-1243.61 (1448.55)
Nonemployment during the first 3 years after school completion (females)	-3199.77** (1415.13)	-2811.95** (1285.06)	-681.14 (1224.82)	-4019.22*** (1299.04)	334.50 (1404.07)
(b) Yearly fraction of days spent at work					
Nonemployment during the first 3 years after school completion (males)	-0.106*** (0.035)	0.018 (0.031)	-0.017 (0.038)	-0.016 (0.030)	0.003 (0.034)
Nonemployment during the first 3 years after school completion (females)	-0.107*** (0.036)	0.009 (0.052)	0.002 (0.038)	0.005 (0.030)	0.017 (0.029)
Observations (men)	1657	1617	1435	1140	792
Observations (women)	1347	1256	1059	802	569

Notes: Labor earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.

Table D.11: Impact of early nonemployment on labor market outcomes with time-varying unobserved heterogeneity using daily earnings as outcome variable

	Years since school completion				
	$t = 5$	$t = 10$	$t = 15$	$t = 20$	$t = 25$
a) Yearly labor earnings (€)					
Nonemployment during the first 3 years after school completion (males)	-8.75*** (2.41)	-10.55*** (1.90)	-11.02*** (1.72)	-13.44*** (1.66)	-8.14*** (1.66)
Nonemployment during the first 3 years after school completion (females)	-11.70*** (1.70)	-9.40*** (1.40)	-6.50*** (1.30)	-8.58*** (1.31)	-5.84*** (1.36)
(b) Yearly fraction of days spent at work					
Nonemployment during the first 3 years after school completion (males)	-0.065*** (0.010)	-0.014 (0.009)	0.001 (0.013)	-0.010 (0.008)	0.040*** (0.009)
Nonemployment during the first 3 years after school completion (females)	-0.073*** (0.013)	-0.006 (0.016)	-0.002 (0.012)	-0.014* (0.008)	0.029*** (0.009)
Observations (men)	5396	5310	4864	3947	2792
Observations (women)	4899	4722	4235	3383	2423

Notes: Labor daily earnings are in 2014 prices and deflated by the ISTAT consumer price index.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors are reported in parentheses.