The effect of adverse labor market entry conditions on wage mobility: a transition matrix approach.

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Abstract

We use Italian administrative data to study the effect of adverse labor market entry conditions on wage mobility of young males. We compare wage transition matrices between individuals who entered the labor market in the higher unemployment period 1986-1988 and those who entered in the lower unemployment period 1990-1992. We use a new nonparametric testing procedure in the context of conditional transition probabilities. We find that individuals who enter during the high unemployment period face a worse long run income mobility and in particular have significantly lower probabilities of reaching the top class of the wage distribution. We argue that Italy has a static labor market with a high cost of changing job. This reduces the opportunity of individuals to improve their working status, leading to a negative persistent effect of adverse entry conditions.

Keywords: wage mobility, entry conditions, nonparametric testing.

JEL classification: C14, D31, J01.

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1 Introduction

Due to the economic crisis, the youth unemployment rate around Europe, and in particular in the southern countries, exploded. There is an increasing concern on how the actual economic conditions will affect the future career of young workers who are entering the labor market. Among European countries, Italy is one of those with the highest youth unemployment rate, which reached above 42% in January 2014, and the public debate on the urgency of making reforms to help young workers entering the labor market is particularly strong.

We enter the debate studying the effect of high unemployment entry conditions on the wage mobility of young males in Italy. Our focus is to determine if individuals who enter the labor market in different economic phases have the same possibilities to improve their social condition; where social condition means the class of the wage distribution they belong to. The analysis is based on a transition matrix approach and a nonparametric testing methodology that was never used before in the context of wage mobility. We use Italian administrative data and compare wage mobility between young males (14-26 years old) who enter the labor market in a period of high unemployment (1986-1988) and in a period of low unemployment (1990-1992). The analysis is run on different time horizons: we consider the first four years of potential experience, the first ten years and from the fourth year of potential experience to the tenth. We use 3-by-3 transition matrices and account for individuals' demographic characteristics that could affect wage mobility such as age at first spell, education, geographic area of the first spell and first type of occupation. We show that individuals who entered the labor market between 1986 and 1988 face a less favorable wage mobility compared to individuals that entered between 1990 and 1992 in the first ten years of potential experience. In particular, there is a clear disadvantage in the probabilities of reaching the top class of the wage distribution. There is also evidence of a rigid labor market in terms of job mobility. We argue that individuals who enter during the high unemployment period remain "trapped" in worse jobs and cannot reach those occupations that would allow them to move to the top class of the wage distribution. The estimated average loss of entering in the period 86-88 over the first ten years of potential experience is more than 17,600 euros. This amount is equivalent to around 79% of the median tenth year income of individuals who entered in the period 1986-1988.

The effect of entering the labor market in adverse economic conditions on future labor outcomes is topic of a growing literature.[1] Labor outcomes such as the probability of being employed after a certain period, actual experience, job mobility and full time worker status are studied in the literature, but usually the main focus is on wages. Labor market entry conditions are often summarized in terms of unemployment.[2] Works such as Kahn (2010), Genda et al. (2010), Oreopoulos et al. (2012) among others, find a negative persistent effect of adverse market conditions on future wages. This type of analysis is usually undertaken by means of parametric models in which the dependent variable is the logarithm of wages and the parameters of interest are the coefficients of the covariate that summarizes the entry conditions and its interactions with other elements of interest (e.g. experience or measure of skills). These models allow to control for several covariates and to determine causality, but they do not allow to capture how adverse entry conditions affect the individuals wage dynamics in relation to the rest of the population they live in. For example, with a parametric approach of the type we just described, we would eventually find a significant negative effect of entering in period 86-88 on the future expected wages. In our approach we can indicate that this negative effect is mainly concentrated in the probabilities of reaching the top of the wage distribution and it is not constant among classes. Our wage mobility approach gives a different and complementary set

[1] See Oreopoulos et al. (2012) for an excellent review of the literature and of the possible explanations for the persistence of the effect of entry labor market conditions.

[2] For example, Kahn (2010) divides college graduates in low, medium and high unemployment groups; Oreopoulos et al. (2012) define a recession as an increase of 5 percentage points in unemployment rate, Genda et al. (2010) use unemployment rate.

of insights to the previous parametric approaches used in literature.

In order to compare the transition matrices between the two groups of individuals, we use the nonparametric testing methodology introduced in the context of conditional transition probabilities by Risi (2013). We use a two-sided test to study the hypothesis of equal conditional transition probabilities between two samples. A nonparametric test allows to not assume any functional form for the transition probabilities and it is more appropriate than a parametric model such as the probit from a theoretical point of view.[3] Bhattacharya and Mazumder (2011) highlight that to use a parametric model such as the probit in the context of transition probabilities would be problematic because "..., it is unclear what type of joint distribution of errors will imply a probit form for transition probabilities; in particular, a bivariate normal error distribution will not,..". Besides, they show that a probit leads to qualitative misleading conclusions in their empirical analysis.

We are not aware of any previous work that tried to determine the effect of adverse entry conditions for the Italian case. Several works study Italian wage mobility and the evolution of young individuals careers from different perspectives. Among others, Cappellari (2007) studies wage mobility in and out the low paid class of the Italian population, Bigard et al. (1998) use a transition matrix approach to compare Italian and French earnings mobility, Del Bono and Vuri (2011) use administrative data to investigate gender differences in job mobility and wages, Contini and Grand (2010) study the effect of the first job length and wage on the individuals survival rate in the labor market, Rosolia and Torrini (2007) study the evolution of age-earnings profiles comparing different cohorts since the '70s.

The rest of the paper is structured as follows: in section 2 we describe in detail our analysis, in section 3 we present the testing methodology, in section 4 we talk about the data we use, in

[3] In Risi (2013), the Monte Carlo simulation shows that if the transition probability is generated by a probit model, the nonparametric test performs properly. Hence, the test has the advantage of being more general maintaining good performances.

section 5 and 6 we present the results of our analysis and in section 7 we conclude.

2 Analysis description

We compare weekly wage mobility between individuals who entered the job market with age 14-26 in the periods 1986-1988 and 1990-1992. In between these two periods, young males unemployment rate passed from 27.47% in 1987 to 22.62% in 1990, a 5 percentage points decrease.[4] We consider individuals who entered the job market around the peak of 1987 and those who entered in the successive years to 1990, when the unemployment stabilized around 23%. The average young male unemployment rate of period 86-88 is 26.62%; the one of period 90-92 is 22.94%.[5] Figure 1 presents the evolution of young males unemployment and starting real average weekly wages between 1985 and 2004. The figure shows the negative relation between unemployment rate and real starting wages and highlights how the initial wage of group 86-88 is lower than for group 90-92 (in the rest of the paper we use the term group to distinguish between individuals who entered the job market in different periods, thus group 86-88 are those individuals who entered in period 86-88).

We compare wage mobility in terms of potential experience: before we run the analysis on a short run period of four years (periods 1989-1993 and 1993-97 for groups 86-88 and 90-92 respectively), successively we study a long run period with the first ten years (1989-1999 and 1993-2003 respectively), finally we consider a period that starts from the fifth year and goes up to the tenth (1993-1999 and 1997-2003 respectively). Considering three periods allows us both to see the persistence of the unemployment effect on wage mobility and to determine dynamically when it arises. To start the analysis in year 1989 for group 86-88 and year 1993 for group 90-92 allows all individuals from each group to have at least one whole first year of

[4]Unemployment rate data are from the Italian national statistics institute (Istat) and available at www.istat.it.

[5]We run the analysis on periods 87-89 and 91-93 as robustness check.

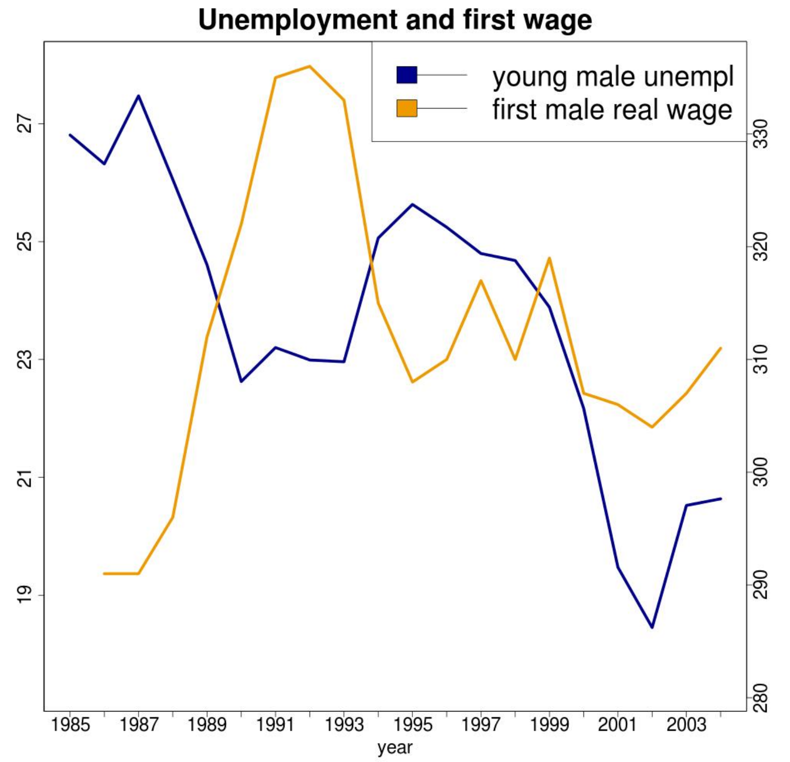

Figure 1: Sources: Young males unemployment rate from ISTAT (www.istat.it), first real weekly wages time series is Authors' calculation. Base year: 2012.

potential experience.

As it is set up, the analysis could be affected by a problem of self selection: for example, most able individuals could decide to not enter the labor market and to continue to study during the high unemployment period; or they could migrate abroad to look for better opportunities. If this happens, the two groups differ in terms of unobservable ability and the comparison between them, without taking this into account, will give biased results. We discuss this issue in details when presenting the results and show that they are robust to self selection.

We study wage mobility by means of 3X3 transition matrices. Class boundaries are taken as the quantiles corresponding to probabilities 1/3 and 2/3 of the national wage distribution and are considered as exogenous.[6]

[6]For each year of analysis, the national wage distribution is estimated using all the individuals available from the administrative data that we describe in section 4. For example, in the study of wage mobility for

We compare the probability for each transition between the two groups. We focus our analysis on the upward transition probabilities from class one of the wage distribution and on the transition probabilities from class two (in the rest of the paper we define the first class as the lowest class of wage mobility and the third class as the top class). This choice follows the fact that young males are most likely to enter in the first class of the wage distribution when they start working, eventually the second. Joining the two groups, we find that around 85% of individuals are in the first or second class when they enter the job market.

The comparison of the transition probabilities between the two groups of individuals is done by means of the conditional and unconditional tests we introduce next section. If the transition probability depends on a covariate, we call it conditional and test it with our conditional test. If the probability does not depend on any covariate, we perform the unconditional test.

We define the conditional transition probability $p^{(s)}(C_0, C_1, x) = Pr[Y_1^{(s)} \in C_1 | Y_0^{(s)} \in C_0, X^{(s)} = x]$ as the probability of the random variable $Y^{(s)}$, in group s, to pass from a determined state C_0 in period zero to another state C_1 in period one, given to be in state C_0 in the first period and the covariate $X^{(s)} = x$. In our application, variable $Y^{(s)}$ is the weekly wage, states C_0 and C_1 are the classes of the wage distribution at the beginning and at the end of the period of analysis, $X^{(s)}$ is a covariate of interest such as age at first spell.

We test the null hypothesis of equality of conditional transition probabilities on the common support I of covariate X:

$$H_0 : p^{(1)}(C_0, C_1, x) = p^{(2)}(C_0, C_1, x) \quad for \ \ all \ \ x \in I; \tag{1}$$

group 86-88 for period 1989-1993, we use all the individuals available in the data for year 1989 to estimate the national wage distribution and the quantiles of that year; while we use all available individuals for year 1993 to estimate the national wage distribution and the quantiles of that year. Each of our groups of analysis is around 8% of an annual sample. Since the proportion is small, we consider class boundaries as exogenous. The relation between the total sample size and the number of new male workers for each year can be seen in Table 1 in the Complementary Material.

against the alternative H_1 of the negation of the null.
The equivalent unconditional probability is $p^{(s)}(C_0, C_1) = Pr[Y_1^{(s)} \in C_1 | Y_0^{(s)} \in C_0]$ and we test the null hypothesis:

$$H_0 : p^{(1)}(C_0, C_1) - p^{(2)}(C_0, C_1) = 0, \tag{2}$$

against the alternative:

$$H_1 : p^{(1)}(C_0, C_1) - p^{(2)}(C_0, C_1) \neq 0;$$

We perform the analysis on different sub-samples of the panels. Which test is used and the sub-samples considered will depend on the possibility to determine the causal effect of entry conditions on wage mobility. We explain this in detail in the following demographic analysis.

3 Testing methodology

3.1 The conditional test

We consider two independent samples of iid observations and size n_1 and n_2 respectively. Each observation is the realization of a triple of random variables $\left\{Y_{i0}^{(s)}, Y_{i1}^{(s)}, X_i^{(s)}\right\}$, where $s = 1, 2$, is the sample index and $i = 1, ..., n_s$ is the unit index.
The conditional probability can be written:

$$p^{(s)}(C_0, C_1, x) = \frac{\Pi^{(s)}(C_0, C_1, x)}{\Pi^{(s)}(C_0, x)},$$

where $\Pi^{(s)}(C_0, C_1, x) = Pr[Y_1^{(s)} \in C_1, Y_0^{(s)} \in C_0 | X^{(s)} = x]$ is the joint probability of variable $Y^{(s)}$ to be in state C_0 in period zero and in state C_1 in period one given $X = x$ and $\Pi^{(s)}(C_0, x) = Pr[Y_0^{(s)} \in C_0 | X^{(s)} = x]$ is the probability of $Y^{(s)}$ being in state C_0 given $X^{(s)} = x$.
We allow $X^{(s)}$ to be distributed differently in the two samples following densities $f^{(s)}(x)$ for $s = 1, 2$. We assume $f^{(s)}(x)$ to be differentiable of order two and bounded away from zero

on the common support I for $s = 1, 2$. We also assume $\Pi^{(s)}(C_0, C_1, x)$ and $\Pi^{(s)}(C_0, x)$ to be differentiable functions of X. The classes C_0 and C_1 are exogenously determined.

The null hypothesis (1) can be characterized as:

$$p^{(1)}(C_0, C_1, x) = p^{(2)}(C_0, C_1, x) \ a.s. \ \Leftrightarrow \gamma(x) = 0 \ \forall x \ .$$

where $\gamma(x)$ is:

$$\gamma(x) = \int_{-\infty}^{x} \left(\Pi^{(1)}(C_0, C_1, \overline{x})\Pi^{(2)}(C_0, \overline{x}) - \Pi^{(2)}(C_0, C_1, \overline{x})\Pi^{(1)}(C_0, \overline{x})\right) f^{(1)}(\overline{x}) f^{(2)}(\overline{x}) d\overline{x},$$

and can be estimated by:

$$\begin{aligned}\gamma_{n_1 n_2}(x) =& \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \Big[1\{Y_{i0}^{(1)} \in C_0\} 1\{Y_{i1}^{(1)} \in C_1\} 1\{Y_{j0}^{(2)} \in C_0\} \\ & -1\{Y_{j0}^{(2)} \in C_0\} 1\{Y_{j1}^{(2)} \in C_1\} 1\{Y_{i0}^{(1)} \in C_0\} \Big] \times \frac{1}{h} k \left(\frac{X_i^{(1)} - X_j^{(2)}}{h} \right) 1\{X_i^{(1)} \leq x\} 1\{X_j^{(2)} \leq x\}.\end{aligned}$$

where k is symmetric kernel satisfying standard conditions.

$\gamma_{n_1 n_2}(x)$ is a U-process indexed by x and we can get the test statistics for the null hypothesis by considering a continuous functional of $\gamma_{n_1 n_2}$. A Kolmogorov-Smirnov type test statistic is:

$$t_{n_1 n_2} = \sqrt{\frac{n_1 n_2}{n_1 + n_2}} sup_{x \in I} \left| \gamma_{n_1 n_2}(x) \right| .$$

In Risi (2013) we state that, under some standard assumptions in the literature (see the Appendix), under H_0:

$$t_{n_1 n_2} = sup_{x \in I} \left| \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \gamma_{n_1 n_2}(x) \right| \xrightarrow{d} sup_{x \in I} \left| G(x) \right| ,$$

where $\{G(x)\}_{x\in\mathbb{R}}$ is a centered Gaussian process with a defined covariance structure.
Since the test statistics does not have a pivotal distribution, we estimate the critical values by means of a multiplicative bootstrap.
We describe the bootstrap in details in Section 8.2 in the Appendix.
In the empirical analysis we use the Epanechnikov kernel and following Neumeyer and Dette (2003) and Srihera and Stute (2010), we take the bandwidth

$$h = \left(\frac{n_1\hat{\sigma}_1^2 + n_2\hat{\sigma}_2^2}{(n_1+n_2)^2}\right)^{\frac{7}{24}}, \tag{3}$$

for the estimation of $\gamma_{n_1n_2}(C_0, C_1; x)$. The bandwidth satisfies the assumptions mentioned above. We take $\hat{\sigma}_s$ as the standard deviation in sample s of covariate X, and use 200 bootstrap iterations to estimate the test p-values.

3.2 The unconditional test

Assuming sample independence and $n_1/N \to \rho \in (0,1)$ as $N \to \infty$, it can be shown that under the null hypothesis (2):

$$\sqrt{\frac{n_1n_2}{n1+n2}}\left(\hat{p}^{(1)}(C_0,C_1) - \hat{p}^{(2)}(C_0,C_1)\right) \xrightarrow{d} N(0,\sigma^2),$$

with

$$\begin{aligned}\sigma^2 =&(1-\rho)\ \left[\left(\frac{1}{\Pi^{(1)}(C_0)}\right)^2 \Pi^{(1)}(C_0,C_1)(1-\Pi^{(1)}(C_0,C_1)) + \left(\frac{\Pi^{(1)}(C_0,C_1)}{(\Pi^{(1)}(C_0))^2}\right)^2\right.\\ &\left.\times\Pi^{(1)}(C_0)(1-\Pi^{(1)}(C_0,C_1)) + \frac{2}{\Pi^{(1)}(C_0)}\frac{\Pi^{(1)}(C_0,C_1)}{(\Pi^{(1)}(C_0))^2}\Pi^{(1)}(C_0,C_1)(1-\Pi^{(1)}(C_0))\right]\\ &+\rho\ \left[\left(\frac{1}{\Pi^{(2)}(C_0)}\right)^2 \Pi^{(2)}(C_0,C_1)(1-\Pi^{(2)}(C_0,C_1)) + \left(\frac{\Pi^{(2)}(C_0,C_1)}{(\Pi^{(2)}(C_0))^2}\right)^2\right.,\end{aligned}$$

where $\Pi^{(s)}(C_0, C_1)$ is the joint probability of variable $Y^{(s)}$ to be in state C_0 in period zero and in state C_1 in period one and $\Pi^{(s)}(C_0)$ is the probability of $Y^{(s)}$ being in state C_0.
The unconditional t-statistic is:

$$t_u = \frac{\hat{p}^{(1)}(C_0, C_1) - \hat{p}^{(2)}(C_0, C_1)}{\hat{\sigma}/\sqrt{\frac{n_1 n_2}{n_1+n_2}}}, \tag{4}$$

and we can use the standard normal density to obtain the test p-values.
We estimate $\hat{\sigma}^2$ with:

$$\begin{aligned}
\hat{\Pi}^{(s)}(C_0) &= \frac{1}{n_s}\sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)} \in C_0\} \\
\hat{\Pi}^{(s)}(C_0, C_1) &= \frac{1}{n_s}\sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)} \in C_0\}1\{Y_{j1}^{(s)} \in C_1\} \\
\hat{p}^{(s)}(C_0, C_1) &= \frac{\hat{\Pi}^{(s)}(C_0, C_1)}{\hat{\Pi}^{(s)}(C_0)}.
\end{aligned}$$

4 The Data

We use the Italian administrative data (INPS) distributed by Fondazione Rodolfo Debenedetti. The data concern non-agricultural private employees born the 10th of March, June, September, and December of each year, and cover period 1985-2004. The original data contain from 150,000 to 190,000 records for each year. Every record corresponds to an employment spell and there could be several per individual. We summarize the information in order to obtain one record per person.
In the original data, for each spell, we can find information on the number of months, weeks, days worked in the year, the end date, a string of zeros and ones showing in which months

the individual works, if the spell is part-time, the sum of gross monthly wages, the eventual lump-sum wages, eventual special wages[7] and the geographic area where the spell takes place. Also demographic information on individuals such as sex and year of birth is available. Since we do not have information on education, we assign low education to individuals who entered the job market less than 19 years old and high education to those that entered at 19 or more. Thus, category high education includes both secondary and tertiary education.This is a common choice when dealing with Italian administrative data (e.g. Del Bono and Vuri (2011) consider the same definition of education and show that it is a reasonable one using the Survey on Households Income and Wealth database by Bank of Italy).[8]

We summarize the original data and for each individual compute the number of weeks worked per year (using the number of weeks used for determining the contribution period for old age benefits for part time workers), the year total wage as sum of the gross wages and lump-sum wages, the year weekly gross wage, the main occupation of the individual in that year, the area of the main occupation. Further, we obtain the year of individuals' first spell, the individual first occupation and working area and the age at the first spell.

The first spell is defined as the first non-seasonal spell that lasts at least 13 weeks (we consider a spell to be seasonal if it lasts less than 17 weeks and ends in September or October).[9] The main spell of the year is the one that lasted the most full time weeks in the year. In case of two spells with the same length, we choose the last spell had and eventually we prefer a full-time

[7]Special wages refer to specific type of workers. They are defined by law.

[8]We expect individuals with tertiary education to be a small proportion of the sample. From the World Development Indicators database by the World Bank it can be seen that the gross male enrollment rate in tertiary education in period 1980-1991 reached a maximum of 32% (see Figure 4 in the Appendix). Besides, in Del Bono and Vuri (2011) they find, using the SHIW, that the proportion of individuals that entered the labor market with tertiary education in period 1989-1998, with age 15-25, is less than 3%.

[9]The nature of the data does not allow to be certain about the identification of the first spell. We can observe the first spell in the non-agricultural private sector, but there is the possibility that some worker had previous job spells in the public and agricultural sectors before, and the probability of this happening increases with age at first spell. We take this into account running a robustness check and showing that this does not seem to be a problem in our analysis.

over a part-time spell. Those individuals for whom it was not possible to determine a unique main spell are removed from the sample (around 700 individuals out of more than 100000). Finally, we trim top and bottom 1% of the weekly wage distribution, exclude negative wages or wages equal to zero, remove individuals with special wages (around 3,000 individuals out of more than 100,000).

The final panels for the short run analysis include 4,744 and 4,426 individuals for groups 86-88 and 90-92 respectively, while for the long run they include 3,992 and 4,087 individuals respectively. The panels for the analysis on the second six years of potential experience have 4,155 and 3,864 for groups 86-88 and 90-92 respectively[10]. The higher attrition in group 86-88 could be a consequence of the less favorable entry conditions: if the unemployment has a negative persistent effect on individuals' career in terms of job stability, and the cost of searching for a job increases over time, there will be a higher proportion of individuals exiting the labor market among those who entered in the high unemployment period. We consider attrition when we interpret the results of our analysis.

5 Demographic analysis

Wage mobility of young workers may be affected by their demographic characteristics at the beginning of the working career, and we need to consider them in the analysis to give a causal interpretation to the effect of unemployment on wage mobility.

For example, if the low unemployment group has a higher proportion of individuals with high education and a better wage mobility than the high unemployment group, it is not possible to

[10]We consider all individuals that start to work in periods 86-88 and 90-92 respectively and are present in the panel after four and ten years of career. We obtain a slightly different panel than the one for the ten year analysis. The objective is to have the maximum number of observations.

determine if the better wage mobility is caused by the labor market entry conditions or by the different distribution of education. To solve the problem, we need to compare wage mobility between the subgroup of individuals with high/low education from the high unemployment group and the correspondent subgroup from the low unemployment group, for both categories. On the other hand, if the two groups are similar in terms of demographic characteristics, and we assume that their effect on wage mobility is the same in the two groups, we do not need to take them into account in the comparison. For instance, if the probability distribution of education is the same in the two groups, then education is not going to be the cause of the different wage mobility.

With discrete covariates, we test the null hypothesis of the equality of the probability distributions between two samples by means of the Pearson's χ^2 test of independence. The null hypothesis is the independence between the covariate of interest and a binary variable that represent the group the individuals belong to. With continuous covariates we use the two-sample Kolmogorov-Smirnov test.

We investigate if education, first type of occupation, first area of work and age at first spell have the same probability distribution in the two groups, 86-88 and 90-92, using the panels from the four years analysis. If this happens for some of the covariates, we ignore it when comparing wage transition probabilities. If the probability distribution differs, we need to take it into account. If the covariate is categorical, we split the group into its categories and compare the transition probabilities between each subgroup. If it is continuous, we account for it using our conditional test.

The demographic analysis shows that we need to consider first area of work, education and age at first spell to determine causality. The subgroups on which we run the analysis on wage mobility are: individuals from overall Italy with low education, from the South with high education, from the Center with high education and from the North with high education.

	Italy whole		North high		Center high		South high		Italy low	
	86-88	90-92	86-88	90-92	86-88	90-92	86-88	90-92	86-88	90-92
Apprentices	0.36	0.32	0.07	0.06	0.06	0.05	0.05	0.06	0.85	0.86
Blue collars	0.47	0.47	0.64	0.62	0.62	0.60	0.77	0.70	0.14	0.14
Man. & White col.	0.16	0.21	0.29	0.32	0.32	0.35	0.18	0.25	0.01	0.00
Others	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
North	0.55	0.64							0.65	0.68
Center	0.17	0.19							0.16	0.17
South	0.28	0.17							0.19	0.15
Low educ.	0.38	0.33								
High educ.	0.62	0.67								
Obs.	4743	4426	1436	1852	526	577	962	554	1819	1443

Table 1: Comparison of the proportion of the different types of first occupation, education, first area of work in the two groups, and sample sizes.

In Table 1 we present the probability distribution of the demographic characteristics in the whole groups and in the four sub-groups we consider in our analysis. In column "Italy whole" the proportion of "managers and white collar" is 5 percentage points higher in group 90-92 than in group 86-88 while the proportion of "blue collar" is 5 points lower. Besides, the proportion of individuals from the North of Italy in group 90-92 is 9 points higher than in group 86-88 while the proportion from the South is 11 points lower. Finally, the percentage of high educated workers is 5 points higher. Nevertheless, the demographic differences between the two groups tend to disappear in the subgroups.

We run the Pearson's χ^2 test of independence for first type of occupation, education and first area of work and run the Kolmogorov-Smirnov test for age at entry. We run the tests on different subgroups and for the three initial income classes.[11] Since "Apprentices" is rather a temporary working condition than a type of occupation, we test independence in three different ways: at first we consider "Apprentices" as a different type of occupation; then we remove from the sample those individuals with "Apprentices" as first occupation; finally we attribute to

[11] To determine the effect of the entry conditions on the transition probability from class 1 to 2, we need individuals in class 1 at the beginning of the period to be similar between the two groups in terms of demographic characteristics.

these individuals the second occupation they held.[12] We investigate independence in all three cases. In Table 2 we report the p-values of the tests; the null hypothesis is the equality of the covariate' s probability distribution in the two sub-groups. More details on the covariates' frequency distribution for each sub-group we use in the analysis and test statistics can be found in the Complementary Material of the paper.

In Table 2, column of Italy, low education, the null hypothesis is never rejected at 5% for any demographic covariate (the χ^2 p-value of class 2 for first area of work is border line). We do not need to take into account neither age nor education nor area of work to determine the causality of unemployment in this subgroup. To run the unconditional test is adequate.

In column Center, high education, type of occupation is equally distributed in the two subgroups while the p-value of age is border line for class 2 and 3. We run our conditional test on age in order to get causality.

In column South, high education, we reject the null hypothesis for occupation at 5% in class 2. We run a χ^2 test on occupation dividing the samples in age classes and we see in Tables 5-10 in the Appendix that once we account for age, we overall do not reject the null hypothesis.[13] Running our conditional test on age we can limit the effect of this change in the occupation distribution in the two periods.

A similar reasoning can be done on the occupation distribution of subsample North, high education, although the rejection of the null hypothesis at 5% is not clear in this case. Tables 11-16 in the Appendix show the results of the test on occupation when age is considered. In this case, the use of our test is also required by the rejection of the null of equality of the age distribution in the two groups.

[12] We compute the second occupation following the same criteria we used for the first.

[13] Considering age classes reduces the sample size on which the test is run and thus its power. We cannot determine to what extent the lack of rejection of the null is due to a correlation between occupation and age or to a lack of power of the test.

	Starting Class	North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	1	0.000	0.332	0.521	0.988	0.363	0.459	0.052	0.514	0.121	0.060	0.710	0.075
Occupation	2	0.001	0.120	0.093	0.397	0.260	0.193	0.047	0.611	0.057	0.001	0.320	0.006
	3	0.194	0.737	0.352	0.348	0.404	0.037	0.365	1.000	0.568	0.429	0.215	0.592
Occupation	1	0.420		0.453	1.000	0.639	0.775	0.089	0.412	0.051	0.026	0.616	0.092
no	2	0.088	0.166	0.063	0.224	1.000	0.268	0.016	1.000	0.020	0.004	0.184	0.002
Apprentices	3	0.173	1.000	0.209	0.357		0.306	0.630		0.588	0.828	0.409	0.837
Occupation	1	0.057	0.301	0.407	0.170	0.251	0.515	0.260	0.430	0.115	0.016	0.189	0.109
replaced	2	0.016	0.340	0.039	0.215	1.000	0.221	0.020	1.000	0.038	0.000	0.505	0.001
Apprentices	3	0.159	0.568	0.217	0.344		0.340	0.615		0.595	0.794	0.542	0.844
	1	0.000	0.900	0.005	0.201	0.773	0.924	0.241	0.371	0.959	0.107	0.512	0.139
Age	2	0.000	0.354	0.000	0.060	0.761	0.082	0.908	1.000	0.981	0.000	0.867	0.000
	3	0.027	0.921	0.074	0.045	0.100	0.046	0.751	0.979	0.986	0.001	0.268	0.008
	1	0.000			0.180			0.044			0.099		
Education	2	0.005			0.583			0.186			0.007		
	3	0.042			1.000			0.147			0.011		
	1										0.000	0.114	0.000
Region	2										0.000	0.056	0.000
	3										0.000	0.212	0.000

Table 2: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

We argue that using the right testing methodology we are able to obtain results on the effect of unemployment on wage mobility that are not significantly affected by the demographic characteristics we considered.

6 Comparison of wage mobility and other labor market outcomes

Figure 2 compares the evolution of the real mean weekly wages and of the probabilities of being in the three income classes over the potential experience for the two groups of analysis. We can see that the mean real weekly wage of group 90-92 is higher at the beginning of the working career (346 euros group 86-88, 369 group 90-92) and continues to be higher in the long run. Individuals who enter in the high unemployment period seem to have an initial lower weekly wage and they cannot close the gap with group 90-92 in the first 10 years of potential experience.[14] From the second sub-figure we can see that the probabilities of being in the three classes of the wage distribution evolve similarly at the beginning of the working careers, but successively the differences between the two groups widen: group 90-92 have higher probability of being in class 3, group 86-88 have higher probability of being in class 2, the probability of being in class 1 keeps being higher for group 86-88. The social condition of individuals entered in period 86-88 seems to worsen compared to those entered in period 90-92.

We summarize the results of our comparison of wage mobility in Table 3. We focus on the upward probabilities from class 1 and on the up and downward probabilities from class 2.[15]

[14]The crossing between the two lines from the second to the fourth year of potential experience could be due to the different economic conditions in periods 91-93 and 95-97, with the first being of lower unemployment and higher wages. This would imply that the economic conditions in the years successive to the beginning of the career have an effect on wage mobility. We will consider this in details when discussing the results.

[15]The complete transition matrices for the two groups, their differences, the unconditional and conditional tests' p-values can be found the Complementary Material of the paper.

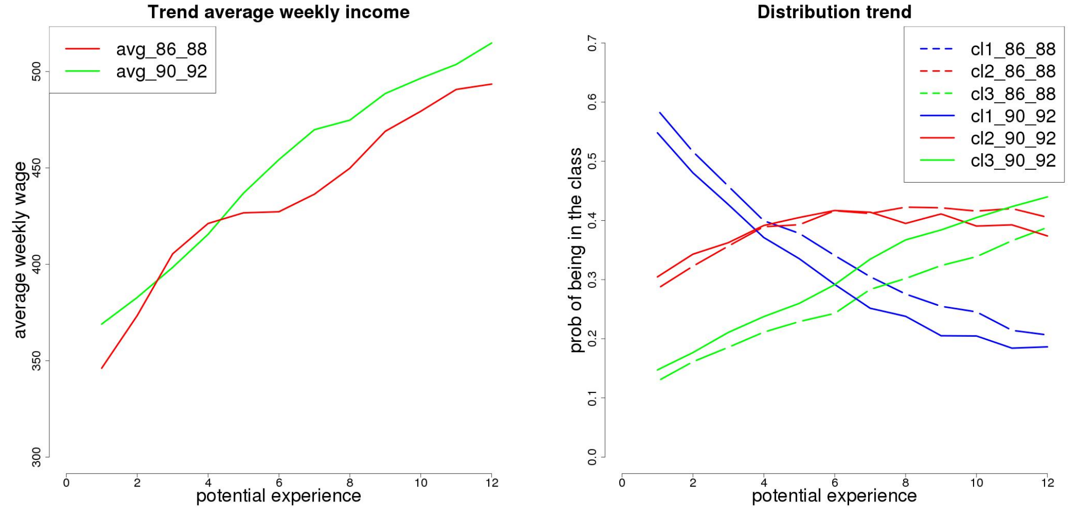

Figure 2: Evolution of the real mean weekly wages and of the probabilities of being in the three income classes over the potential experience.
Sources: Authors' calculation.

The subsamples considered are North, Center, South with high education and the whole Italy with low education.

Table 3 contains the differences between the transition probabilities of individuals who entered the labor market during the high unemployment period (86-88) minus those of individuals who entered in the low unemployment period (90-92). For each difference, we report the p-value from our conditional test considering age for the high education subgroups and from the unconditional test for the low education one. The null hypothesis of the tests is the equality of the transition probabilities between the two groups of individuals 86-88 and 90-92. The conditional test results are robust to bandwidth selection.[16]

We find that individuals that entered in period 86-88 (high unemployment) have a worse long run wage mobility than individuals that entered in period 90-92. The difference seems to arise after the first four years of potential experience and it is particularly clear for the transition probabilities of reaching the top class of the wage distribution.

[16]We multiply the bandwidths by a weight from 1 to 6. With weight from 1 to 4 the results we obtain are almost identical, with weights 5 and 6 we overall reject less, but the results do not change qualitatively.

A better wage mobility for group 90-92 implies that the starting weekly wage disadvantage of group 86-88 caused by entering the job market during the high unemployment period tends to increase over time, mainly in the long run. These findings are in line with the theory that during a high unemployment period individuals find worse jobs than those that would be the right match with their skills. This initial mismatch delays the creation of specialized human capital and increases the time the individuals take to find a better job.

In Table 3, 21 out of 36 upward probabilities (probabilities of improving the individual's social position passing to a higher class of wage) present a negative difference: they are higher for group 90-92 than for group 86-88. Out of 21, 16 are statistically different from zero. Overall the table, 8 upward probabilities have a positive difference, with 3 significant. For what concerns the downward probabilities, 9 out of 12 have a positive sign in the difference and 8 out of 9 are significant. These results depict a situation in which individuals from period 86-88 have lower probabilities to improve their wage position and higher probabilities to worsen it.

The results in the short run subtable do not offer a clear image of the difference between the two groups' wage mobility. There is not a clear path in the signs nor in the significance level of the differences. The disadvantage of group 86-88 becomes evident in the subtables of the long run and successive years analyses. In the long run subtable, 9 out of 12 upward transition probabilities have a negative difference and 7 out of 9 are statistically significant. All 4 downwards probabilities have a positive difference and 3 are statistically significant. Similar results are found in the successive years analysis subtable. These findings indicate that there is a significant difference in the long run wage mobility between the two groups and that the differences mainly arise after the first four years of potential experience.[17]

[17] The lack of a significantly different wage mobility between the two groups in the first four years of experience could be partially explained by the better economic conditions in period 1989-1993 compared to period 1993-1997. The initial disadvantage of the high unemployment group could be partially compensated by the more positive economic situation during the first years of career. We discuss the consequences of analyzing wage mobility on two different periods shortly.

The results are overall similar in the four subgroups, indicating a lack of strong regional effects. Finally, we can see a clear difference in the long run probabilities to reach the top class of the wage distribution in the two groups: 7 out of 8 long run upward transition probabilities to the third class are higher for group 90-92 and are all significant. If we observe the magnitude of the differences, we see that those from class 2 to 3 of the long run table have the highest (above 8 percentage points). This suggests that the biggest difference between the two groups' wage mobility lays in the probabilities of reaching the top class of the wage distribution and in particular to pass from class 2 to 3.

In the data description we pointed out that there is some attrition in our panels, with group 86-88 that looses more observations than group 90-92 between the four and ten years analyses. If those individuals who exit the job market because of the higher unemployment entry condition are the less skilled, then our results are strengthen by the attrition: 86-88 is a more selective group of individuals and still they have a worse wage mobility than group 90-92. Another possible explanation for the attrition could be an higher migration abroad of individuals that entered during the higher unemployment period. If the individuals who migrate are the most skilled, then our results could overestimate the effect of the labor market entry conditions. However, from the International Migration Database by OECD it can be seen that the number of Italian individuals who migrate from Italy in period 1994-1999 is similar to the number that migrate in period 1998-2003.[18] This excludes a significant effect of migration on our results. Also the timing of the two periods, high unemployment before low unemployment, strengthens our results. If those individuals who find an occupation in the high unemployment period are the most skilled, there could be a number of low skilled workers entering the sample of group 90-92 because they remained unemployed before (they could even pass age 19 and figure in the

[18]From the International Migration Database by OECD we estimated that the total number of Italians who migrated abroad in period 1994-1999 is 368,202 while those who migrated in period 1998-2003 are 339,411. The difference is 28,791 over the whole Italian population.

(a) Short run: periods 89-93 and 93-97 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob. diff	0.014	-0.024	0.034**	-0.036**
	p-value	0.170	0.120	0.045	0.048
class 1 to 3	Prob. diff	0.002	0.002*	-0.000	0.000
	p-value	0.290	0.080	0.185	0.955
class 2 to 1	Prob. diff	0.029*	-0.004*	0.044**	0.003
	p-value	0.000	0.095	0.005	0.951
class 2 to 3	Prob. diff	-0.031**	0.114**	-0.001	0.009
	p-value	0.005	0.000	0.225	0.812

(b) Long run: periods 89-99 and 93-03 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob. diff	-0.035	0.079**	-0.014	0.050**
	p-value	0.285	0.025	0.285	0.014
class 1 to 3	Prob. diff	-0.037**	-0.114**	-0.034**	-0.037**
	p-value	0.005	0.000	0.000	0.026
class 2 to 1	Prob. diff	0.029**	0.085**	0.053**	0.027
	p-value	0.000	0.000	0.000	0.396
class 2 to 3	Prob. diff	-0.081**	-0.094**	0.010	-0.086*
	p-value	0.000	0.005	0.210	0.099

(c) Successive years: periods 93-99 and 97-03 respectively

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob. diff	-0.068**	0.057**	-0.008	0.066**
	p-value	0.000	0.020	0.190	0.017
class 1 to 3	Prob. diff	-0.016	-0.078**	-0.016*	-0.031*
	p-value	0.135	0.010	0.085	0.099
class 2 to 1	Prob. diff	0.026**	0.051**	0.078**	0.002
	p-value	0.000	0.000	0.000	0.929
class 2 to 3	Prob. diff	-0.046**	-0.088**	-0.051**	-0.054**
	p-value	0.000	0.000	0.000	0.053

Table 3: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment). The p-values for high education columns are from the conditional test considering age, the ones for low education are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

high education class although they are not). This flow of low skilled workers would lead to underestimate the positive effect of entering in the low unemployment period. Still we find a positive significant effect.

On the other side, if the most able individuals decide to continue to study during the high unemployment period, waiting for better opportunities, and enter the labor market during the low unemployment period, then we would overestimate the effect of the entry conditions on wage mobility. Nevertheless, Figure 4 in the Appendix does not show any discontinuity in the trend of secondary and tertiary school enrollment rate for males during the high unemployment period. Thus we exclude that this type of self selection affects our results.

The groups of analysis are composed by individuals entering the labor market in three consecutive years: e.g. 1986, 1987, 1988 for the high unemployment group. This implies that the potential experience of the individuals in the year we start the analysis (e.g. 1989) ranges between 1 and 3. A different distribution of the potential experience at start could affect the results of the analysis on the first four years of career. We report in Table 17 in the Appendix the distribution of experience at start in the two groups for the subgroups of analysis. Although there are some differences, they are not large. We run the same type of testing than in the demographic analysis above to check the equality in probability distribution of the potential experience at start. Table 18 in the Appendix shows that we do not reject the null hypothesis of independence at 1% significance level in all subgroups except for the North, high education. This result should be considered when interpreting the results of the analysis on the first four years of career of the latter subgroup. Intuitively, small differences in the potential experience at start, although significant, should not affect the results of the analysis on the first ten years of career (i.e. to have 12 or 10 years of potential experience should not make a significant difference in terms of wage mobility). This intuition is confirmed by the robustness check run on individuals who entered the labor market in periods 1987-1988 and 1991-1992 that we present next subsection.

Comparing wage mobility between the two groups in terms of potential experience leads to compare different periods with a shift of four years between them. For example, when we compare wage mobility of period 1989-1999 for group 86-88 with that of period 1993-2003 for group 90-92, the two periods of analysis overlap from 1993 to 1999 and do not overlap from 1989 to 1992 and from 2000 to 2003. It could be argued that our results are affected by the different economic conditions the two groups face in these non-overlapping intervals; in particular that group 90-92 enjoys a better wage mobility in the long run because it faces a low unemployment period in years 2001-2003. However, looking at the two non-overlapping periods 1989-1992 and 2000-2003 in Figure 1, we see that both periods are characterized by low unemployment with the difference that the first is at the beginning of group 86-88 working career while the second is after 8 years of potential experience for group 90-92. Although the drop in young males unemployment is larger in 2001-2003, we assert that its positive effect on the wage mobility of group 90-92 is not more relevant than the one of period 1990-1992 on the wage mobility of group 86-88 because of the different timing. It has been shown in literature that economic conditions affect more new workers than experienced workers: e.g. Oreopoulos et al. (2012) show that the effect of regional unemployment on wages is not significant for individuals with five or more years of experience. In conclusion, our results should not be significantly affected by the difference in the economic conditions of the periods of analysis.

Finally we argue that the abolition of the wage index mechanism ('scala mobile') in 1992 does not affect our results. Manacorda (2004) argues that 'scala mobile' actuated as an equalizing factor in the Italian earnings distribution until the beginning of the '80s, but then this effect faded away. Although the dispersion of the earnings distribution could theoretically affect transition probabilities, our periods of analysis do not belong to the period affected by 'scala mobile'. Besides, we do not notice any effect on the level of entry wages nor on the average cumulative income of the first four years.

6.1 Robustness Checks

We summarize in here the main robustness checks outcomes, while we report all the details in Section 8.7 of the Appendix.

The results are robust to a different definition of first spell. In our analysis, an individual enters the labor market with a first spell of at least 13 weeks outside periods characterized by seasonal work. If we reduce the number of weeks to 4 the results both of the demographic and wage mobility analyses do not change.

To control if the results are driven by the selection of the groups, we delay the analysis of one year considering the individuals who enter the labor market between 1987 and 1989 as high unemployment group and those who enter between 1991 and 1993 as low unemployment group. The results are overall robust to the change. Group 91-93 faces a more positive wage mobility. It seems the differences between the two groups is clear since the beginning of the career, while in the original analysis it is not. This difference could be due to the fact that when individuals enter in 91-93 the low unemployment period has already started since one year and their initial entry conditions are even more positive than for group 90-92 (figure 2 shows they have higher wages). The results on the difference in the upward probabilities of reaching the top class of the wage distribution are confirmed.

We study mobility using 5X5 transition matrices to verify if the results are robust to the definition and the number of classes. The analysis confirms our conclusions in terms of the sign and the magnitude in the differences between the transition probabilities, for all periods. As expected, passing from three to five classes decreases the number of observations available in each transition, reducing the power of the tests. For this reason we reject overall less the null hypothesis of equality of transition probabilities.

In the original analysis we include individuals up to 26 years old. We now restrict the sample to individuals up to 22 years old. With such as restriction we limit the possibility of including in the sample workers who became non-agricultural private employees from another type of occupation.[19] The restriction on the age reduces considerably the sample size and lowers the power of our tests; however the analysis does not contradict our results (the signs are as expected but overall we reject less the null hypothesis of equality) and confirms the findings on the upward probabilities of reaching the top class of the wage distribution.

To see if the results differ when more homogeneous groups are considered, both in terms of demographic characteristics and potential experience at start, we select as higher unemployment group those individuals that enter the labor market in period 1987-1988 and as lower unemployment group those that enter in period 1991-1992. In the new groups, the lack of rejection of the null of equality in probability distribution is stronger than in the original analysis, for all the discrete demographic characteristics and for all subgroups. Also the difference in potential experience at start is removed. The results of the analysis on wage mobility are similar to those of the original in terms of the signs and the magnitudes of the differences between transition probabilities, in any period considered. As expected, since we loose around one third of the panels, the power of the tests reduces and we reject overall less the null hypothesis of equality of transition probabilities. In conclusion, the original results are not affected by the eventual heterogeneity that we introduce by gathering in one group individuals who enter the labor market in three successive years; instead, considering the larger groups increases significantly the power of the tests.

We study wage mobility on the common period 2000-2004 to support the argument that the results of the original analysis are not affected by the fact that we compare wage mobility on different time intervals. In this comparison, group 86-88 have four years of potential experience more than group 90-92. We choose period 2000-2004, the last four-year interval available, in

[19]We also exclude individuals with a college degree.

order to reduce the effect of the difference in potential experience on wage mobility (11 years for group 86-88, 7 for group 90-92), that we expect to be decreasing over time. We find that group 90-92 still enjoys a more positive wage mobility in the period. In particular the results on the transition probabilities from the second class confirm those of the original analysis. Thus, even considering a common period we find evidence of a better wage mobility for the low unemployment group. Besides, this outcome importantly strengthens the finding of a persistent negative effect of adverse entry conditions.

To show that our results are not driven by the low unemployment phase between 2001 and 2003, we study wage mobility on the first 7 years of potential experience: on periods 1989-1996 and 1993-2000 for groups 86-88 and 90-92 respectively. The results of the original long run analysis are confirmed.

Although it would be useful, we cannot run an analysis similar to the original in which we compare the low unemployment period 1990-1992 with another successive high unemployment period. The next and only high unemployment period available in our database is 1994-1997. This period is characterized by an average increase of unemployment of just 3% does not allow us to analyze the 10 years wage mobility because the panel stops in 2004, and individuals that enter this period face a reform in 1997 with the aim of increasing the labor market flexibility (Treu, Law 197/1997). These differences make hard to compare an analysis that includes this period with the original.

We run anyway a robustness check studying groups 91-93 as low unemployment and 95-97 as high unemployment. The objective is to find some evidence in support of the causality of entry conditions on wage mobility. We exploit the regional variations in unemployment rate and choose the groups in such as way there is an increase of around 4% in the subgroup South.[20]

[20]The evolution of the young male unemployment rate in the three areas is presented in Figure 3 in the Appendix.

We find that in subgroup South, high education, there is a better six years wage mobility for group 91-03. Besides, we find that for subgroup North high education, where the unemployment remains stable between the two groups, there is a similar wage mobility. Comparing these results with the analysis on groups 87-89 and 91-93, we state that there is some evidence in support of the causality of the entry conditions.

6.2 Other labor market outcomes

We extend our analysis to other labor market outcomes that could be affected by the unemployment entry conditions. For the two groups considered in the wage mobility analysis for the short and long run periods respectively, we report in Table 4 descriptive statistics on individuals' number of spells, actual individuals' experience, cumulative income and weekly wage volatility.

From the table we can see that the average number of spells held by the individuals is similar in the two different groups: around 2.5 in the short run and 4 in the long run. The average actual experience is around 3.5 years in the short run and 8 years in the long run in both groups. These two results together also suggest that the average spell length is similar between the two groups. The median individual from group 90-92 earns around 4,000 euros more in the first four years of career and more than 17,600 in the first 10 years. We estimate from our sample that the annual median real income for an individual of group 86-88 after ten years of potential experience (in year 1999) is around 22,300 euros. The loss in cumulated income for the median individual of group 86-88 is equivalent to around 79% of the yearly income at the tenth years of potential experience. Finally the average weekly wage standard deviation seems similar between the two groups and quite small compared to the average mean weekly wages (e.g. less than one third).

Unemployment at entry does not seem to affect job mobility, while it would be reasonable

			Short run	Long run
Number of spells	86_88	avg	2.5	4.1
		avg_sd	0.0	0.1
		med	2.0	3.0
		med_sd	0.0	0.0
		sd	1.5	3.8
	90_92	avg	2.4	4.1
		avg_sd	0.0	0.0
		med	2.0	3.0
		med_sd	0.0	0.2
		sd	1.4	2.5
Actual experience	86_88	avg	38.9	94.0
		avg_sd	0.2	0.5
		med	45.0	107.0
		med_sd	0.4	0.6
		sd	11.7	29.6
	90_92	avg	39.6	95.4
		avg_sd	0.2	0.5
		med	47.0	108.0
		med_sd	0.2	0.1
		sd	11.8	29.2
Cumulative Income	86_88	avg	78201.3	230598.4
		avg_sd	547.6	1843.0
		med	74266.1	213487.4
		med_sd	531.4	1864.5
		sd	33553.7	83505.6
	90_92	avg	80907.4	244580.9
		avg_sd	536.2	1786.7
		med	78527.6	231163.3
		med_sd	596.2	1699.6
		sd	32064.7	84146.1
Wage volatility	86_88	avg avg	412.9	441.0
		avg sd	80.2	123.0
	90_92	avg avg	417.3	458.6
		avg sd	74.6	127.2

Table 4: Number of spells is in units, the actual experience is in months, cumulative income is in euros, weekly wage volatility is in euro. The standard deviation of the median is obtained bootstrapping.

to expect group 86-88 to have a higher average number of job spells, indicating individuals' attempt to improve their working condition by searching for better jobs. This outcome could suggest that the Italian job market is too rigid and does not allow individuals to change job at an affordable cost. Another signal of the rigidity of the job market is that in our sample the median individual changes job only twice during the first four years and 3 times in the first ten (in Topel and Ward (1992) the median number of job spells for young American males in the first ten years of career is 7).

The lack of flexibility of the labor market could explain the persistence of the entry conditions effect. If the first jobs held determine future wage growth and mobility, a reduction of works with good wage prospective during the high unemployment period will have a persistent effect on new workers.

7 Concluding remarks

We investigated the effect of adverse entry conditions on young males' wage mobility in Italy. We compared the wage mobility of two groups of individuals who entered the labor market in a higher (86-88) and in a lower unemployment period (90-92). We showed that individuals who entered in period 86-88 face a worse long run wage mobility, in particular they have significant lower probabilities of reaching the top class of the wage distribution. We attribute the cause of the persistence of the negative effect of high unemployment at entry to the rigidity of Italian labor market where individuals struggle to improve their working status by changing job.

Our analysis could be used for policy evaluation purposes. In 1997 a labor market reform (Treu, Law 197/1997) took place in Italy with the objective to increase the flexibility of the labor market "mainly introducing temporary contracts and providing incentives for part-time job" (Schindler (2009)). This was the most important reform of the Italian labor market in the last two decades.[21] With our analysis, and when data will be available, we could study if the Treu's reform removed the persistence of the effect of adverse entry conditions on young males' wage mobility. In fact, we could run the same analysis we undertook between individuals that entered the labor market in periods 1998-1999 and 2001-2003 and compare the results to those obtained in this paper.

[21]Another reform was introduced in 2003 (Legge Biagi, law 30/2003); however Barbieri and Scherer (2009) claim that this reform "left the situation of the Italian labour market de facto unaltered".

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8 Appendix

8.1 Assumptions for the asymptotic properties of the test

For the pointwise asymptotic unbiasedness of $\gamma_{n_1 n_2}(x)$, we need to assume:

- $N = n_1 + n_2$, $\frac{n_1}{N} \to \rho \in (0, 1)$ and $h \to 0$ as $N \to \infty$;
- k be symmetric about 0, $\int k(u)^2 du < \infty$, $\int u^2 k(u)^2 du = \tau^2 < \infty$;
- $f^{(1)}(X)$ and $f^{(2)}(X)$ be two times differentiable;

For the weakly convergence, besides the assumptions above, we need to assume:

- $Nh^2 \to 0$

8.2 The Bootstrap

We apply the proposal of Delgado and Gonazález-Manteiga (2001) and run the bootstrap on the Hoeffding decomposition of $\gamma_{n_1 n_2}(x)$ under the null.
Considering the two independent samples $\zeta_1, ..., \zeta_{n_1}$ and $\xi_1, ..., \xi_{n_2}$ where $\zeta_i = (X_i^{(1)}, Y_{i0}^{(1)}, Y_{i1}^{(1)})$ and $\xi_j = (X_j^{(2)}, Y_{j0}^{(2)}, Y_{j1}^{(2)})$, under the null hypothesis, the bootstrap test statistics is:

$$\hat{t}^*_{n_1 n_2} = \sqrt{\frac{n_1 n_2}{n_1 + n_2}}\, sup_{x \in I} \left| \hat{\gamma}^*_{n_1 n_2}(x) \right|,$$

where:

$$\hat{\gamma}^*_{n_1 n_2}(x) = \frac{1}{n_1} \sum_{i=1}^{n_1} \hat{E}[\gamma_{n_1 n_2}(x)|\zeta_i] V_i^{(1)} + \frac{1}{n_2} \sum_{j=1}^{n_2} \hat{E}[\gamma_{n_1 n_2}(x)|\xi_j] V_j^{(2)}.$$

Under standard assumptions, $\hat{t}^*_{n_1 n_2} \xrightarrow{d} t_{n_1 n_2}$.
It can be shown that

$$E[\gamma_{n_1 n_2}(x)|\zeta_i] = \left[\Pi^{(2)}(C_0, X_i^{(1)})1\{Y_{i1}^{(1)} \in C_1\} - \Pi^{(2)}(C_0, C_1, X_i^{(1)})\right] 1\{Y_{i0}^{(1)} \in C_0\} f^{(2)}(X_i^{(1)}) 1\{X_i^{(1)} \leq x\},$$
$$E[\gamma_{n_1 n_2}(x)|\xi_j] = \left[\Pi^{(1)}(C_0, C_1, X_j^{(2)}) - \Pi^{(1)}(C_0, X_j^{(2)})1\{Y_{j1}^{(2)} \in C_1\}\right] 1\{Y_{j0}^{(2)} \in C_0\} f^{(1)}(X_j^{(2)}) 1\{X_j^{(2)} \leq x\}.$$

and $V^{(1)}$, $V^{(2)}$ are random vectors of values drawn from a distribution with mean zero and variance equal 1.

We estimate $\hat{E}[\gamma_{n_1 n_2}(x)|\zeta_i]$, $\hat{E}[\gamma_{n_1 n_2}(x)|\xi_j]$ using:

$$\hat{f}^{(s)}(z) = \frac{1}{n_s h^{(s)}} \sum_{j=1}^{n_s} K\left(\frac{z - X_j^{(s)}}{h^{(s)}}\right) \tag{5}$$

$$\hat{\Pi}^{(s)}(C_0, z) = \frac{1}{n_s h^{(s)} \hat{f}^{(s)}(z)} \sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)} \in C_0\} K\left(\frac{z - X_j^{(s)}}{h^{(s)}}\right) \tag{6}$$

$$\hat{\Pi}^{(s)}(C_0, C_1, z) = \frac{1}{n_s h^{(s)} \hat{f}^{(s)}(z)} \sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)} \in C_0\} 1\{Y_{j1}^{(s)} \in C_1\} K\left(\frac{z - X_j^{(s)}}{h^{(s)}}\right), \tag{7}$$

with $s = 1, 2$ and $h^{(s)}$ satisfy Nadaraya Watson estimator assumptions.

For $V^{(1)}$, $V^{(2)}$ we use the popular proposal introduced by Mammen (1993) with the distribution characterized by two density points: $-(\sqrt{5}-1)/2$ with probability $(\sqrt{5}+1)/2\sqrt{5}$ and $(\sqrt{5}+1)/2$ with probability $1 - (\sqrt{5}+1)/2\sqrt{5}$.

We use the Epanechnikov kernel and the bandwidths

$$h^{(s)} = \left(\frac{\hat{\sigma}_s^2}{n_s}\right)^{\frac{1}{5}},$$

for the estimation of $f^{(s)}(x)$, $\Pi^{(s)}(C_0, x)$, $\Pi^{(s)}(C_0, C_1, x)$, for $s = 1, 2$. These bandwidths satisfy the assumptions mentioned above. We take $\hat{\sigma}_s$ as the standard deviation in sample s of covariate X.

The bootstrap is implemented with the following steps:

- For each $\zeta_1, \zeta_2, ..., \zeta_{n_1}$ and $\xi_1, \xi_2, ..., \xi_{n_2}$, using (5), (6) and (7), we estimate respectively:

$$\hat{E}[\gamma_{n_1 n_2}|\zeta_i] = \left[\hat{\Pi}^{(2)}(C_0, X_i^{(1)})1\{Y_{i1}^{(1)} \in C_1\} - \hat{\Pi}^{(2)}(C_0, C_1, X_i^{(1)})\right] 1\{Y_{i0}^{(1)} \in C_0\}\hat{f}^{(2)}(X_i^{(1)}),$$
$$\hat{E}[\gamma_{n_1 n_2}|\xi_j] = \left[\hat{\Pi}^{(1)}(C_0, C_1, X_j^{(2)}) - \hat{\Pi}^{(1)}(C_0, X_j^{(2)})1\{Y_{j1}^{(2)} \in C_1\}\right] 1\{Y_{j0}^{(2)} \in C_0\}\hat{f}^{(1)}(X_j^{(2)});$$

- For $B = 200$ iterations:

- Withdraw the random vectors $V^{(1)}$ and $V^{(2)}$ and obtain the vectors $\left(\hat{E}[\gamma_{n_1 n_2}|\zeta_i]V_i^{(1)}\right)_{i=1,...,n_1}$ and $\left(\hat{E}[\gamma_{n_1 n_2}|\xi_j]V_j^{(2)}\right)_{j=1,...,n_2}$;
- For each $x \in I$ estimate

$$\hat{\gamma}^{*(b)}_{n_1 n_2}(x) = \frac{1}{n_1}\sum_{i=1}^{n_1} \hat{E}[\gamma_{n_1 n_2}|\zeta_i]V_i^{(1)}1\{X_i^{(1)} \leq x\} + \frac{1}{n_2}\sum_{j=1}^{n_2} \hat{E}[\gamma_{n_1 n_2}(x)|\xi_j]V_j^{(2)}1\{X_j^{(2)} \leq x\},$$

and obtain $\hat{t}^{*(b)}_{n_1 n_2}$;

- Use the quantiles of the distribution of $\hat{t}^{*}_{n_1 n_2}$ as critical values for $t_{n_1 n_2}$.

8.3 Demographic analysis

age	cl1	cl2	cl3	all cl.
19	0.693	0.485	0.585	0.073
20	0.183	0.089	0.200	0.076
21	0.062	0.504	0.351	0.165
22	0.731	0.325	0.512	0.154
23	0.512	0.702	1.000	0.074
24	0.892	0.352	0.900	0.080
25	1.000	0.036	0.602	0.032
26	0.440	0.379	0.397	0.926

Table 5: Chi-squared test on occupation for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	0.583	0.440	0.500	0.054
20	0.787	0.024	0.098	0.074
21	0.035	0.259	0.730	0.066
22	0.441	0.238	0.642	0.076
23	0.826	0.926	1.000	0.334
24	0.702	0.140	0.905	0.030
25	1.000	0.040	0.587	0.025
26	0.435	0.147	0.384	0.857

Table 6: Chi-squared test on occupation without apprentices for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	0.830	0.655	0.382	0.156
20	0.819	0.090	0.054	0.108
21	0.075	0.203	0.859	0.133
22	0.687	0.168	0.798	0.096
23	0.754	0.922	1.000	0.328
24	0.724	0.140	0.911	0.035
25	1.000	0.041	0.615	0.033
26	0.411	0.143	0.396	0.866

Table 7: Chi-squared test on occupation replacing apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.517	0.401	0.553	0.882
21	22	0.075	0.161	0.186	0.021
23	24	0.561	0.440	0.715	0.053
25	26	0.684	0.015	0.558	0.300

Table 8: Chi-squared test on occupation for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.213	0.333	0.664
21	22	0.039	0.064	0.867	0.006
23	24	0.535	0.289	0.867	0.066
25	26	0.683	0.011	0.584	0.175

Table 9: Chi-squared test on occupation without apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.524	0.369	0.362	0.374
21	22	0.087	0.068	0.766	0.012
23	24	0.541	0.289	0.829	0.064
25	26	0.674	0.010	0.559	0.166

Table 10: Chi-squared test on occupation replacing apprentices for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	0.705	0.513	0.590	0.063
20	0.171	0.085	0.189	0.092
21	0.067	0.492	0.341	0.164
22	0.747	0.319	0.525	0.138
23	0.536	0.705	1.000	0.058
24	0.878	0.323	0.890	0.079
25	1.000	0.042	0.582	0.033
26	0.439	0.396	0.388	0.931

Table 11: Chi-squared test on occupation for age classes, North, high education

age	cl1	cl2	cl3	all cl.
19	0.565	0.471	0.488	0.064
20	0.775	0.029	0.088	0.070
21	0.028	0.240	0.724	0.066
22	0.439	0.202	0.631	0.083
23	0.824	0.908	1.000	0.341
24	0.727	0.137	0.905	0.030
25	1.000	0.032	0.581	0.025
26	0.419	0.124	0.382	0.853

Table 12: Chi-squared test on occupation without apprentices for age classes, North, high education

age	cl1	cl2	cl3	all cl.
19	0.832	0.593	0.357	0.136
20	0.819	0.105	0.063	0.100
21	0.077	0.206	0.858	0.123
22	0.689	0.174	0.805	0.083
23	0.749	0.927	1.000	0.338
24	0.693	0.150	0.907	0.034
25	1.000	0.043	0.583	0.032
26	0.430	0.140	0.378	0.859

Table 13: Chi-squared test on occupation replacing apprentices for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.529	0.397	0.544	0.877
21	22	0.077	0.161	0.184	0.021
23	24	0.555	0.433	0.684	0.050
25	26	0.688	0.018	0.590	0.311

Table 14: Chi-squared test on occupation for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.237	0.344	0.674
21	22	0.028	0.063	0.854	0.009
23	24	0.541	0.282	0.857	0.078
25	26	0.695	0.009	0.559	0.157

Table 15: Chi-squared test on occupation without apprentices for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.514	0.388	0.356	0.373
21	22	0.091	0.060	0.757	0.009
23	24	0.564	0.287	0.823	0.068
25	26	0.661	0.010	0.571	0.162

Table 16: Chi-squared test on occupation replacing apprentices for age classes, North, high education

8.4 Potential experience

	Italy whole		North high		Center high		South high		Italy low	
starting exper.	86-88	90-92	86-88	90-92	86-88	90-92	86-88	90-92	86-88	90-92
1	0.34	0.34	0.33	0.35	0.31	0.33	0.30	0.36	0.37	0.32
2	0.31	0.34	0.27	0.34	0.29	0.32	0.33	0.31	0.33	0.36
3	0.36	0.32	0.39	0.31	0.40	0.34	0.37	0.33	0.31	0.33

Table 17: Starting experience distribution in the subgroups of analysis

	North high	Center high	South high	Italy low
cl1	0.007	0.786	0.029	0.016
cl2	0.000	0.042	0.307	0.807
cl3	0.344	0.279	1.000	0.508
all cl.	0.000	0.150	0.031	0.009

Table 18: P-values of χ^2 test for the independence of potential experience at start. The null hypothesis is independence.

8.5 Regional Unemployment Rates

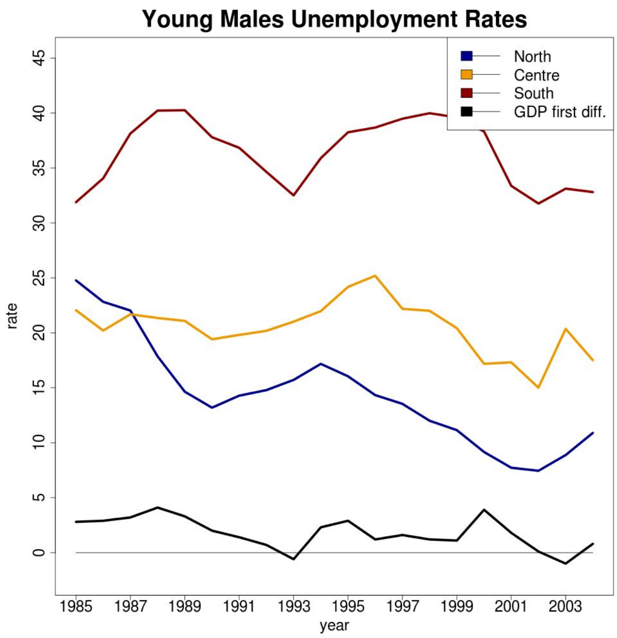

Figure 3: Sources: Young males unemployment rate from ISTAT (www.istat.it).

8.6 Schools Enrollment Rates

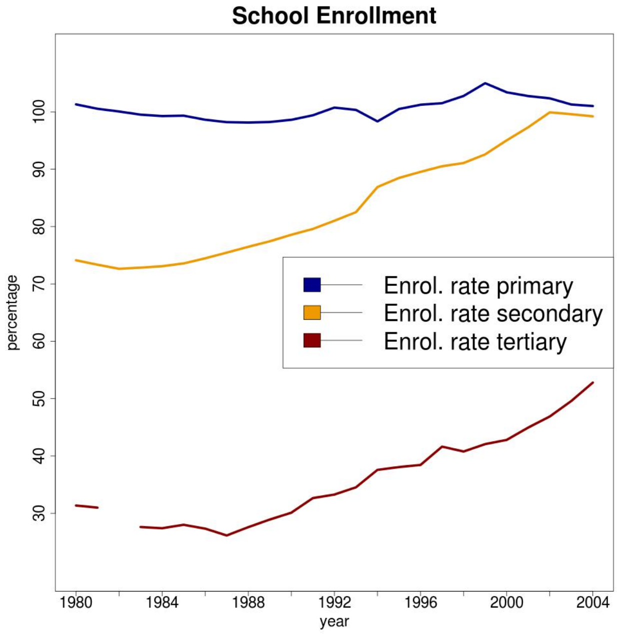

Figure 4: Primary, secondary and tertiary education gross enrollment rates for males in Italy. Source: World Development Indicators database by the World Bank (http://data.worldbank.org/).

8.7 Robustness checks

8.7.1 Changing the first spell definition

We control if the results are robust to our definition of first spell. In our analysis, an individual enters the labor market with a first spell of at least 12 weeks outside periods characterized by seasonal work. Now we reduce the number of weeks to 4; we include all the possible spells that are not strictly seasonal[22].

Our results are robust to the different definition of first spell.

From Table 19 and from Tables 20-25 we see that the demographic analysis results are close to those obtained in the original and we can investigate wage mobility on the same sub-panels we use above, running the unconditional test on the subgroups with high education and the unconditional on the subgroup with low education.

We report the results of the comparison between the two groups transition probabilities in Table 26. The signs of the differences and their significance level are similar to those in the main analysis.

age	cl1	cl2	cl3	all cl.
19	0.862	0.543	1.000	0.398
20	0.842	1.000	1.000	0.950
21	0.031	0.529	0.591	0.045
22	0.759	0.159	0.684	0.427
23	0.909	1.000	0.112	0.630
24	0.013	0.371	0.744	0.051

Table 20: Chi-squared test on occupation for age classes, South, high education

[22] This choice is also done by Del Bono and Vuri (2011)

	Starting Class	North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	1	0.000	0.692	0.445	0.666	0.519	0.406	0.024	0.538	0.096	0.090	0.509	0.123
Occupation	2	0.014	0.306	0.315	0.150	0.297	0.091	0.020	0.225	0.035	0.003	0.226	0.007
	3	0.166	0.736	0.209	0.803	0.407	0.375	0.741	1.000	0.427	0.781	0.317	0.930
Occupation	1	0.508	0.462	0.295	0.492	0.328	0.589	0.069	0.480	0.034	0.035	0.473	0.214
no	2	0.295	0.217	0.257	0.059	0.566	0.060	0.007	1.000	0.010	0.000	0.158	0.003
Apprentices	3	0.098	1.000	0.112	0.582		0.451	0.657		0.620	0.641	1.000	0.814
Occupation	1	0.101	0.286	0.155	0.079	0.189	0.389	0.197	0.410	0.063	0.024	0.193	0.207
replaced	2	0.068	0.648	0.139	0.064	1.000	0.070	0.012	1.000	0.017	0.001	0.539	0.003
Apprentices	3	0.076	0.562	0.126	0.452		0.410	0.648		0.597	0.642	0.538	0.876
	1	0.000	0.997	0.020	0.148	0.351	0.984	0.206	0.284	0.995	0.079	0.551	0.448
Age	2	0.000	0.804	0.000	0.102	0.952	0.172	0.555	1.000	0.663	0.000	0.986	0.000
	3	0.074	0.936	0.169	0.019	0.518	0.019	0.971	0.979	0.991	0.004	0.425	0.017
	1	0.000			0.334			0.050			0.115		
Education	2	0.003			0.413			0.347			0.004		
	3	0.075			1.000			0.179			0.024		
	1										0.000	0.050	0.000
Region	2										0.000	0.164	0.000
	3										0.000	0.207	0.000

Table 19: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

age	cl1	cl2	cl3	all cl.
19	1.000	1.000	1.000	0.324
20	0.655	1.000	1.000	1.000
21	0.049	1.000	0.574	0.089
22	0.746	0.070	0.665	0.203
23	0.886	1.000	0.131	0.494
24	0.012	0.257	0.744	0.015

Table 21: Chi-squared test on occupation without apprentices for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	1.000	0.625	1.000	0.325
20	0.666	1.000	1.000	1.000
21	0.113	1.000	0.601	0.132
22	0.759	0.073	0.665	0.202
23	0.876	1.000	0.124	0.436
24	0.007	0.411	0.741	0.022

Table 22: Chi-squared test on occupation replacing apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.814	1.000	0.652
21	22	0.097	0.372	1.000	0.046
23	24	0.060	0.581	0.155	0.047

Table 23: Chi-squared test on occupation for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	1.000	1.000	0.644
21	22	0.109	0.158	1.000	0.023
23	24	0.022	0.345	0.184	0.025

Table 24: Chi-squared test on occupation without apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.487	1.000	0.371
21	22	0.192	0.249	1.000	0.045
23	24	0.021	0.449	0.166	0.023

Table 25: Chi-squared test on occupation replacing apprentices for age classes, South, high education

(a) Short run: periods 89-93 and 93-97 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	0.013**	-0.021	0.040**	-0.036**
	p-value	0.025	0.160	0.020	0.048
class 1 to 3	Prob diff	0.014	0.018**	0.007	-0.002
	p-value	0.645	0.040	0.555	0.802
class 2 to 1	Prob diff	0.025**	-0.010**	0.038*	0.000
	p-value	0.010	0.045	0.075	0.991
class 2 to 3	Prob diff	-0.038**	0.142**	-0.005	0.001
	p-value	0.005	0.000	0.110	0.970

(b) Long run: periods 89-99 and 93-03 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.032	0.052	-0.010	0.045**
	p-value	0.455	0.160	0.555	0.023
class 1 to 3	Prob diff	-0.041**	-0.104**	-0.049**	-0.034**
	p-value	0.000	0.000	0.000	0.043
class 2 to 1	Prob diff	0.030**	0.094**	0.056**	0.023
	p-value	0.000	0.000	0.005	0.457
class 2 to 3	Prob diff	-0.066**	-0.095**	0.001	-0.095*
	p-value	0.000	0.000	0.375	0.061

(c) Successive years: periods 93-99 and 97-03 respectively

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.076**	0.072**	-0.034**	0.062**
	p-value	0.000	0.010	0.025	0.021
class 1 to 3	Prob diff	-0.025	-0.085**	-0.027**	-0.024
	p-value	0.160	0.005	0.015	0.191
class 2 to 1	Prob diff	0.016**	0.071**	0.073**	0.004
	p-value	0.040	0.000	0.000	0.817
class 2 to 3	Prob diff	-0.048**	-0.079**	-0.100**	-0.051*
	p-value	0.000	0.045	0.000	0.066

Table 26: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for high education columns are from the conditional test considering age the ones for low education are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.2 Analysis on five classes of income

We run the analysis considering five classes of income to check if the results are robust to the choice of 3 classes of income and to the definition of the class boundaries.

We focus the analysis on the individuals that entered in the first three classes of the wage distribution, who are around 80% of the total sample.

The results of the demographic analysis are presented in Table 27 and suggest to use the conditional test only for the sub-group North, high education. The null hypothesis of the equality of probability distributions is not rejected for occupation overall the subgroups and for age in the other sub-groups than North, high education.

The signs and amplitude of the differences between transition probabilities are similar to those of the original analysis. However, increasing the number of classes implies a reduction of observations available for each transition and the power of the tests decreases considerably making the p-values not comparable. While there is not a clear pattern between the two groups in the first four years of career, the wage mobility of the low unemployment group 90-92 becomes clearly more positive in the first ten years of career and from the fifth to the tenth year.

Table 28 reports the results of the short run analysis. Out of 36 upward probabilities 13 differences are higher for group 86-88, with 2 significant at least at 10%, and 13 are for group 90-92, with 5 significant. The others are lower than 0.01. Out of 12 downwards probabilities, 6 are higher for group 86-88, with 2 significant and 2 for group 90-92, with none significant. We report the results for the first ten years of career in Table 29. In the table, 21 out of 36 upwards probabilities are higher for the low unemployment group 90-92, with 5 significant. Only 7 are higher for the high unemployment group, with 2 significant. Focusing on the probabilities of reaching class 4 and 5 of the wage distribution, 20 out of 24 probabilities are higher for group

90-92, with 5 significant, and 2 are higher for group 86-88, with none significant. Also the magnitude of the differences is important, reaching 5% or above in 9 out of 20 probabilities. For what concerns downwards probabilities, 8 out of 12 are higher in group 86-88, with 3 significant, and none is higher for group 90-92. Similar results can be found in Table 30, where the results of the analysis from year five to ten of career are reported.

In conclusion, the analysis on five classes of wage mobility confirms the results of the original on three classes. As expected, taking five classes reduces the power of the tests and the results are statistically less significant than the previous analysis.

		North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	cl1	0.002	0.192	0.509	0.543	0.404	0.577	0.477	0.532	0.774	0.297	0.441	0.065
	cl2	0.001	0.620	0.289	0.338	0.278	0.610	0.030	0.910	0.061	0.031	0.714	0.085
Occupation	cl3	0.005	0.094	0.204	0.337	0.809	0.118	0.086	1.000	0.129	0.002	0.488	0.012
	cl4	0.504	0.739	0.441	0.672	1.000	0.581	0.024	1.000	0.038	0.064	0.697	0.066
	cl5	0.151	0.296	0.153	0.518	0.266	0.064	0.234	0.234	0.091	0.588	0.026	0.091
	cl1	0.431		0.313	0.495	1.000	0.338	0.734	0.401	0.919	0.179	0.253	0.734
Occupation	cl2	0.395	0.492	0.467	0.280	0.301	0.441	0.047	1.000	0.021	0.026	0.634	0.033
no	cl3	0.199	0.663	0.140	0.159	1.000	0.161	0.026		0.057	0.011	0.692	0.010
Apprentices	cl4	0.538	1.000	0.599	0.716		0.720	0.012		0.018	0.048	1.000	0.069
	cl5	0.145		0.201	0.273		0.189	0.164		0.101	0.725		0.552
	cl1	0.431	0.508	0.160	0.144	0.280	0.306	0.709	0.454	0.828	0.110	0.229	0.305
Occupation	cl2	0.217	1.000	0.474	0.399	1.000	0.551	0.103	0.512	0.032	0.039	0.825	0.048
replaced	cl3	0.059	0.513	0.088	0.218	0.485	0.154	0.053		0.087	0.001	0.382	0.006
Apprentices	cl4	0.441	0.597	0.568	0.610		0.678	0.006		0.006	0.029	0.561	0.049
	cl5	0.096	1.000	0.208	0.153	0.153	0.228	0.232	0.232	0.087	0.738	1.000	0.577
	cl1	0.005	0.617	0.543	0.107	0.956	1.000	0.913	0.620	0.481	0.219	0.389	0.820
	cl2	0.000	1.000	0.003	0.049	0.769	0.138	0.311	0.656	0.871	0.003	0.983	0.010
Age	cl3	0.000	0.291	0.000	0.398	1.000	0.333	0.998	1.000	0.960	0.000	0.528	0.000
	cl4	0.000	0.999	0.000	0.010	0.996	0.012	0.175	0.847	0.247	0.000	1.000	0.000
	cl5	0.000	0.291	0.000	0.398	1.000	0.333	0.998	1.000	0.960	0.000	0.528	0.000
	cl1	0.000			0.048			0.293			0.297		
	cl2	0.000			0.136			0.086			0.042		
Education	cl3	0.061			1.000			0.268			0.098		
	cl4	0.418			0.885			0.619			0.222		
	cl5	0.018			0.612			0.431			0.053		
	cl1										0.000	0.032	0.000
Region	cl2										0.000	0.681	0.000
	cl3										0.000	0.075	0.000
	cl4										0.001	0.512	0.002
	cl5										0.001	0.071	0.000

Table 27: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	-0.093**	-0.091	0.001	0.028
	p-value	0.015	0.217	0.976	0.165
class 1 to 3	diff	0.013	-0.037	-0.010	-0.006
	p-value	0.865	0.553	0.762	0.717
class 1 to 4	diff	0.039	-0.042	-0.007	-0.002
	p-value	0.175	0.321	0.728	0.846
class 1 to 5	diff	0.017**	0.010	0.008	-0.004
	p-value	0.000	0.743	0.580	0.254
class 2 to 1	diff	0.008*	0.049	0.016	-0.009
	p-value	0.060	0.185	0.682	0.735
class 2 to 3	diff	0.002	0.017	-0.024	-0.105**
	p-value	0.185	0.745	0.564	0.006
class 2 to 4	diff	-0.034**	-0.014	0.005	0.029
	p-value	0.000	0.709	0.842	0.266
class 2 to 5	diff	-0.005	0.018	0.001	0.012
	p-value	0.100	0.499	0.942	0.178
class 3 to 1	diff	0.013**	0.044	0.007	-0.037
	p-value	0.005	0.129	0.872	0.264
class 3 to 2	diff	0.039**	-0.045	-0.008	0.013
	p-value	0.000	0.288	0.860	0.807
class 3 to 4	diff	-0.094**	0.027	0.025	-0.073
	p-value	0.000	0.639	0.630	0.243
class 3 to 5	diff	-0.028**	0.018	-0.012	0.010
	p-value	0.000	0.583	0.673	0.701

Table 28: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for sub-panel North high education are from the conditional test considering age the others are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	0.059	0.016	0.074	-0.000
	p-value	0.140	0.812	0.089	0.993
class 1 to 3	diff	-0.002	0.058	-0.028	0.049**
	p-value	0.030	0.422	0.518	0.016
class 1 to 4	diff	-0.027**	-0.112*	-0.011	-0.006
	p-value	0.000	0.067	0.752	0.734
class 1 to 5	diff	-0.057	-0.023	-0.018	-0.024**
	p-value	0.260	0.605	0.370	0.037
class 2 to 1	diff	-0.005	0.007	0.088**	0.011
	p-value	0.650	0.814	0.009	0.578
class 2 to 3	diff	0.028**	0.026	0.011	-0.006
	p-value	0.005	0.666	0.819	0.869
class 2 to 4	diff	-0.004	-0.058	-0.012	-0.031
	p-value	0.580	0.258	0.750	0.436
class 2 to 5	diff	-0.049**	-0.048	-0.037	-0.017
	p-value	0.000	0.237	0.111	0.516
class 3 to 1	diff	0.035**	0.040	0.002	0.010
	p-value	0.000	0.171	0.949	0.741
class 3 to 2	diff	0.042**	0.031	0.035	-0.004
	p-value	0.000	0.449	0.453	0.933
class 3 to 4	diff	-0.018	-0.049	-0.015	-0.078
	p-value	0.240	0.427	0.806	0.247
class 3 to 5	diff	-0.094**	-0.071	0.049	0.013
	p-value	0.000	0.200	0.261	0.810

Table 29: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for sub-panel North high education are from the conditional test considering age the others are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	0.043**	0.024	-0.038	0.056
	p-value	0.050	0.809	0.487	0.158
class 1 to 3	diff	-0.016	0.021	-0.021	0.030
	p-value	0.285	0.796	0.661	0.392
class 1 to 4	diff	-0.008	0.006	0.024	-0.011
	p-value	0.250	0.931	0.523	0.707
class 1 to 5	diff	0.005	-0.003	-0.005	0.003
	p-value	0.295	0.924	0.819	0.799
class 2 to 1	diff	0.007	-0.011	0.039**	0.011**
	p-value	0.260	0.620	0.020	0.000
class 2 to 3	diff	0.011*	0.056	0.035	0.020
	p-value	0.075	0.394	0.494	0.520
class 2 to 4	diff	-0.076**	-0.067	-0.091**	-0.008
	p-value	0.000	0.204	0.022	0.755
class 2 to 5	diff	-0.014**	-0.020	-0.001	-0.042**
	p-value	0.025	0.515	0.962	0.005
class 3 to 1	diff	0.003**	0.011	0.035	0.003
	p-value	0.035	0.596	0.147	0.827
class 3 to 2	diff	-0.000	0.066*	0.065	-0.010
	p-value	0.015	0.065	0.151	0.689
class 3 to 4	diff	-0.012	-0.114**	-0.060	-0.038
	p-value	0.500	0.058	0.266	0.306
class 3 to 5	diff	-0.016**	-0.036	0.025	-0.015
	p-value	0.050	0.370	0.357	0.542

Table 30: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for sub-panel North high education are from the conditional test considering age the others are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.3 Select adjacent periods

To check if the results of our analysis depend on the two groups selection, we replicate the analysis using period 87-89 as high unemployment and period 91-93 as low unemployment.
The results confirm those obtained with the original periods: the lower unemployment group enjoys a more positive income mobility, mainly for what concerns reaching the top class of the wage distribution. However there is one main distinction: the difference in the wage mobility seems to be clear since the first four years of potential experience, while with periods 86-88 and 90-92 it was not. This difference in timing could be due to the fact that when individuals enter in 91-93 the low unemployment period has already started since one year and their initial entry conditions are even more positive than for group 90-92 (figure 2 shows they have higher wages).
Table 31 and Tables 32-43 show the results of the demographic analysis. They are similar to those obtained with the original groups, except that we do not need to use the conditional test for comparing the transition probabilities in the subgroup Center, high education. The results on the wage mobility analysis are reported in Table 44. In the short run subtable, 8 out of 12 upward probabilities have a negative difference, of which 6 are statistically significant. All 4 downward probabilities have a positive sign and 3 are significant. The results of the long run analysis are similar to those of the original periods. Finally we obtain less significantly different transition probabilities in the years of potential experience successive to the first four compared to the original analysis.

	Starting Class	North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	1	0.000	0.190	0.731	0.125	0.904	0.193	0.093	0.954	0.103	0.022	0.336	0.240
Occupation	2	0.000	0.170	0.023	0.154	1.000	0.096	0.016	0.771	0.001	0.000	0.471	0.000
	3	0.148	0.743	0.032	0.626	0.412	0.788	0.853	1.000	0.960	0.339	0.294	0.120
Occupation	1	1.000	0.211	0.921	0.069	0.774	0.073	0.086	0.793	0.047	0.353	0.193	0.516
no	2	0.004	0.339	0.010	0.067	1.000	0.076	0.017	1.000	0.029	0.001	0.693	0.001
Apprentices	3	0.162		0.120	1.000		0.893	0.919	1.000	0.920	0.199	1.000	0.153
Occupation	1	0.790	0.851	0.911	0.121	0.233	0.302	0.295	0.670	0.101	0.348	0.335	0.468
replaced	2	0.002	0.766	0.009	0.064	0.537	0.200	0.016	0.580	0.022	0.000	0.357	0.000
Apprentices	3	0.564	0.562	0.205	0.942		0.883	0.919	1.000	1.000	0.303	1.000	0.248
	1	0.000	0.486	0.582	0.583	1.000	0.502	0.815	0.584	0.919	0.000	0.445	0.058
Age	2	0.010	0.311	0.112	0.110	1.000	0.177	0.194	0.912	0.177	0.006	0.421	0.023
	3	0.235	0.795	0.338	0.498	1.000	0.553	0.768	1.000	0.846	0.452	0.994	0.546
	1	0.000			0.224			0.371			0.000		
Education	2	0.000			0.096			0.901			0.000		
	3	0.529			0.919			0.712			0.686		
	1										0.000	0.334	0.000
Region	2										0.000	0.344	0.000
	3										0.019	0.799	0.017

Table 31: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

age	cl1	cl2	cl3	all cl.
19	0.211	0.921	0.012	0.477
20	0.437	0.032	1.000	0.019
21	0.809	0.834	0.477	0.493
22	0.133	0.247	0.007	0.711
23	0.886	0.011	0.303	0.521
24	0.468	0.831	0.570	0.885

Table 32: Chi-squared test on occupation for age classes, North, high education

age	cl1	cl2	cl3	all cl.
19	0.299	0.762	0.146	0.636
20	0.371	0.118	1.000	0.037
21	1.000	1.000	0.456	0.431
22	0.184	0.287	0.006	0.607
23	0.784	0.025	0.331	0.634
24	1.000	0.679	0.565	1.000

Table 33: Chi-squared test on occupation without apprentices for age classes, North, high education

age	cl1	cl2	cl3	all cl.
19	0.204	0.918	0.014	0.478
20	0.451	0.036	1.000	0.016
21	0.793	0.845	0.469	0.532
22	0.128	0.219	0.006	0.704
23	0.885	0.009	0.352	0.529
24	0.448	0.843	0.586	0.874

Table 34: Chi-squared test on occupation replacing apprentices for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.765	0.098	0.236	0.318
21	22	0.579	0.336	0.004	0.499
23	24	1.000	0.046	0.944	0.445

Table 35: Chi-squared test on occupation for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.116	0.595	0.180
21	22	0.331	0.372	0.010	0.291
23	24	1.000	0.071	0.955	0.532

Table 36: Chi-squared test on occupation without apprentices for age classes, North, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	0.784	0.112	0.235	0.325
21	22	0.599	0.313	0.003	0.509
23	24	1.000	0.044	0.957	0.442

Table 37: Chi-squared test on occupation replacing apprentices for age classes, North, high education

age	cl1	cl2	cl3	all cl.
19	1.000	0.541	1.000	0.639
20	0.719	0.499	0.430	0.381
21	0.620	0.259	0.634	0.408
22	0.271	0.110	1.000	0.062
23	0.533	0.821	1.000	0.742
24	0.068	0.192	0.736	0.017

Table 38: Chi-squared test on occupation for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	1.000	1.000	1.000	0.403
20	0.241	0.255	0.369	0.361
21	1.000	0.684	1.000	0.647
22	0.292	0.284	1.000	0.144
23	0.348	0.809	1.000	0.631
24	0.058	0.192	0.718	0.016

Table 39: Chi-squared test on occupation without apprentices for age classes, South, high education

age	cl1	cl2	cl3	all cl.
19	1.000	0.547	1.000	0.645
20	0.718	0.477	0.425	0.353
21	0.630	0.250	0.631	0.406
22	0.303	0.095	1.000	0.064
23	0.553	0.825	1.000	0.755
24	0.059	0.200	0.730	0.011

Table 40: Chi-squared test on occupation replacing apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.645	1.000	0.865
21	22	0.223	0.030	1.000	0.058
23	24	0.057	0.407	0.872	0.055

Table 41: Chi-squared test on occupation for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.680	1.000	1.000
21	22	0.326	0.283	1.000	0.145
23	24	0.050	0.408	0.870	0.029

Table 42: Chi-squared test on occupation without apprentices for age classes, South, high education

age_l	age_h	cl1	cl2	cl3	all cl.
19	20	1.000	0.629	1.000	0.843
21	22	0.208	0.027	1.000	0.056
23	24	0.064	0.395	0.874	0.050

Table 43: Chi-squared test on occupation replacing apprentices for age classes, South, high education

(a) Short run: periods 90-94 and 94-98 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.011	0.067	-0.067**	-0.038**
	p-value	0.670	0.231	0.000	0.053
class 1 to 3	Prob diff	-0.066**	-0.043	-0.020**	0.004
	p-value	0.000	0.211	0.000	0.652
class 2 to 1	Prob diff	0.055**	0.061*	0.080**	0.022
	p-value	0.000	0.064	0.000	0.566
class 2 to 3	Prob diff	-0.070**	0.009	-0.095**	0.002
	p-value	0.000	0.837	0.000	0.966

(b) Long run: periods 90-00 and 94-04 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.043*	0.079	-0.039**	0.050**
	p-value	0.110	0.181	0.035	0.017
class 1 to 3	Prob diff	-0.053**	-0.023	-0.066**	-0.037**
	p-value	0.005	0.666	0.000	0.042
class 2 to 1	Prob diff	0.030**	0.027	0.092**	-0.032
	p-value	0.000	0.411	0.000	0.365
class 2 to 3	Prob diff	-0.117**	-0.079*	-0.089**	-0.028
	p-value	0.000	0.115	0.005	0.603

(c) Successive years: periods 94-00 and 98-04 respectively

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.045*	0.051	-0.025*	0.055*
	p-value	0.065	0.481	0.055	0.056
class 1 to 3	Prob diff	0.026	-0.107**	-0.018	-0.019
	p-value	0.265	0.025	0.200	0.370
class 2 to 1	Prob diff	0.005	-0.031	0.085**	-0.002
	p-value	0.220	0.292	0.000	0.928
class 2 to 3	Prob diff	-0.032**	-0.050	-0.047**	-0.078**
	p-value	0.030	0.316	0.040	0.009

Table 44: The tables present the difference between the transition probabilities from group 87-89 (high unemployment) minus group 91-93 (low unemployment). The p-values for high education North and South are from the conditional test considering age the ones for high education Center and low education are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.4 Age up to 22

We restrict the sample to individuals up to 22 years old. With such as restriction we exclude individuals with a degree and limit the possibility of observing individuals who became private non-agricultural employees from another type of work.

The restriction on the age reduces the samples size considerably and lower significantly the power of the tests for comparing transition probabilities. The results on the long run upwards probability to class three are confirmed by the analysis; the others are not contradicted (the signs are as expected, but we reject less the null of equality).

In Table 45 we present the demographic analysis on those subgroups that are affected by the sampling restriction. We never reject the null of independence between the two groups and we can use the unconditional test in order to compare transition probabilities. We report the results of the analysis in Table 46. From the table, we can see that the sign of the differences between group 86-88 and 90-92 are overall in line with those of the original analysis. We reject the hypothesis of equality for 3 of the upwards probabilities to the top class in the long run analysis and for 4 in the analysis on the successive periods.

	Starting Class	North low & high	North high	Center low & high	Center high	South low & high	South high	Italy low & high	Italy high
	1	0.064	0.509	0.740	0.330	0.141	0.162	0.104	0.017
Occupation	2	0.712	0.976	0.836	0.756	0.286	0.388	0.930	0.784
	3	0.941	0.805	1.000	0.223	0.437	1.000	0.745	0.666
Occupation	1	0.317	0.375	0.890	1.000	0.303	0.112	0.085	0.121
no	2	0.617	1.000	0.868	0.855	0.168	0.219	0.719	0.514
Apprentices	3	0.905	0.681	1.000	1.000	1.000	1.000	0.967	0.586
Occupation	1	0.091	0.638	0.154	0.920	0.356	0.207	0.044	0.360
replaced	2	0.873	0.937	0.881	0.852	0.101	0.158	0.590	0.386
Apprentices	3	0.899	0.506	0.833	0.843	0.775	1.000	0.925	0.438
	1	0.088	0.431	0.606	0.596	0.271	1.000	0.645	0.063
Age	2	0.638	0.425	0.997	1.000	0.923	0.574	0.385	0.160
	3	0.483	0.085	0.957	0.906	0.708	0.995	0.700	0.099
	1	0.003		0.643		0.053		0.889	
Education	2	1.000		0.872		0.238		0.881	
	3	0.135		1.000		0.139		0.054	
	1							0.000	0.000
Region	2							0.016	0.171
	3							0.061	0.108

Table 45: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

(a) Short run: periods 89-93 and 93-97 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	0.028	-0.074	0.023	-0.036**
	p-value	0.532	0.303	0.618	0.048
class 1 to 3	Prob diff	-0.016	0.048	-0.016	0.000
	p-value	0.568	0.226	0.432	0.955
class 2 to 1	Prob diff	0.007	-0.023	0.007	0.003
	p-value	0.738	0.673	0.923	0.951
class 2 to 3	Prob diff	-0.012	0.066	-0.002	0.009
	p-value	0.731	0.344	0.970	0.812

(b) Long run: periods 89-99 and 93-03 respectively.

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.011	0.034	0.005	0.050**
	p-value	0.815	0.635	0.929	0.014
class 1 to 3	Prob diff	-0.049	-0.079	-0.054	-0.037**
	p-value	0.267	0.205	0.164	0.026
class 2 to 1	Prob diff	0.031	-0.011	0.078	0.027
	p-value	0.131	0.839	0.163	0.396
class 2 to 3	Prob diff	-0.080**	-0.071	-0.083	-0.086*
	p-value	0.030	0.371	0.267	0.099

(c) Successive years: periods 93-99 and 97-03 respectively

		High educ.			Low Education
		North	Centre	South	Italy
class 1 to 2	Prob diff	-0.080	0.055	-0.006	0.066**
	p-value	0.202	0.540	0.926	0.017
class 1 to 3	Prob diff	-0.022	-0.045	-0.006	-0.031**
	p-value	0.658	0.522	0.852	0.099
class 2 to 1	Prob diff	0.026	0.049	0.059	0.002
	p-value	0.160	0.262	0.234	0.929
class 2 to 3	Prob diff	-0.079**	-0.068	-0.168**	-0.054**
	p-value	0.036	0.324	0.006	0.053

Table 46: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with individuals maximum 22 years old. The p-values for high education columns are from the conditional test considering age the ones for low education are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.5 Considering groups 87-88 and 91-92

We redefine our groups of analysis: individuals who enter the labor market in years 1987 and 1988 belong to the higher unemployment group, while those who enter in years 1991 and 1992 belong to the lower unemployment group. The objective of the sample reduction is to obtain more homogeneous groups of analysis in terms of demographic characteristics and potential experience at start. The results of the demographic analysis in Table 48 and of the potential starting experience in Table 49 confirm the equality of the probability distribution for all covariates; with the exception of age at entry for sub-panel North high education.

With this sample reduction, we loose around one third of the panels size: 1,686 and 1,431 individuals from the higher and the lower unemployment groups respectively. This loss of observations reduces the power in testing.

We present the results of the analysis on wage mobility in Table 50. The periods of analysis are the same than in the original. Following the results of the demographic analysis in Table 48, we apply our conditional test only to the subgroup North, high education. The unconditional test is used for all the other subgroups. The results are similar to those of our original analysis in terms of the signs and the magnitudes of the differences between transition probabilities, in any period considered. As expected, the power of the tests reduces and we reject overall less the null hypothesis of equality of transition probabilities.

In conclusion, our results are not affected by the eventual heterogeneity that we introduce by gathering in one group individuals who enter the labor market in three successive years, both in terms of the demographic characteristics and potential experience at start. Instead, considering larger samples increases significantly the power of the tests.

	Italy whole		North high		Center high		South high		Italy low	
	87-88	90-91	87-88	90-91	87-88	90-91	87-88	90-91	87-88	90-91
Apprentices	0.39	0.31	0.08	0.06	0.05	0.05	0.04	0.05	0.86	0.85
Blue collars	0.45	0.48	0.62	0.63	0.60	0.61	0.77	0.71	0.14	0.15
Executives	0.00	0.00	0.00	0.00			0.00	0.00	0.00	0.00
Managers & white collars	0.16	0.21	0.30	0.31	0.35	0.34	0.19	0.25	0.00	0.00
Others	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Low	0.41	0.34								
High	0.59	0.66								
North	0.56	0.65							0.67	0.68
Center	0.16	0.18							0.15	0.16
South	0.28	0.17							0.19	0.16
Obs.	3058	2995	871	1272	316	379	608	371	1263	973

Table 47: Descriptive statistics groups 87-88 91-92

	North high	Center high	South high	Italy low
cl1	0.614	1.000	0.075	0.009
cl2	0.097	0.139	0.162	0.554
cl3	0.333	0.167	1.000	0.372

Table 49: P-values of the independence test for the potential experience at start. The null hypothesis is independence.

	Starting Class	North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	1	0.000	0.069	0.035	0.465	0.504	0.186	0.199	0.890	0.178	0.002	0.691	0.281
Occupation	2	0.004	0.367	0.296	0.849	0.075	1.000	0.232	0.760	0.095	0.020	0.900	0.236
	3	0.073	0.074	0.127	0.128		0.245	1.000		0.841	0.817	0.045	0.663
Occupation	1	0.103		0.140	0.272	0.631	0.161	0.105	1.000	0.073	0.051	1.000	0.136
no	2	0.317	0.686	0.376	0.809		1.000	0.101	1.000	0.095	0.083	0.693	0.118
Apprentices	3	0.191	1.000	0.166	0.623		0.569	1.000		0.822	0.714	1.000	0.464
Occupation	1	0.052	0.477	0.358	0.157	0.655	0.163	0.081	0.795	0.071	0.021	0.309	0.189
replaced	2	0.119	0.444	0.278	0.821	1.000	1.000	0.076	1.000	0.105	0.028	0.743	0.077
Apprentices	3	0.174	1.000	0.146	0.739		0.622	1.000		0.834	0.706	1.000	0.436
	1	0.000	0.085	0.157	0.307	0.987	0.839	0.840	0.916	0.998	0.002	0.107	0.936
Age	2	0.000	0.772	0.009	0.806	0.756	0.808	0.584	0.518	0.876	0.005	0.834	0.031
	3	0.784	0.441	0.615	0.455		0.609	0.991		0.945	0.367	0.576	0.659
	1	0.000			0.148			0.228			0.001		
Education	2	0.005			0.899			0.189			0.003		
	3	0.681			0.388			0.111			0.034		
	1										0.000	0.460	0.000
Region	2										0.000	0.078	0.000
	3										0.000	0.097	0.001

Table 48: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

(a) Short run: periods 89-93 and 93-97 respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	0.024**	-0.068	0.008	-0.019
	p-value	0.005	0.285	0.827	0.382
class 1 to 3	diff	0.005	0.044	0.007	0.003
	p-value	0.195	0.253	0.725	0.742
class 2 to 1	diff	0.020	-0.009	0.096	-0.017
	p-value	0.215	0.827	0.053	0.781
class 2 to 3	diff	0.023	0.110**	0.023	-0.037
	p-value	0.105	0.042	0.665	0.486

(b) Long run: periods 89-99 and 93-03 respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	-0.026	0.046	-0.044	0.075
	p-value	0.755	0.495	0.327	0.002
class 1 to 3	diff	-0.049**	-0.117**	-0.022	-0.033
	p-value	0.035	0.041	0.484	0.098*
class 2 to 1	diff	0.009	0.111**	0.047	0.020
	p-value	0.190	0.013	0.270	0.654
class 2 to 3	diff	-0.062**	-0.120**	0.092	-0.112
	p-value	0.000	0.060	0.134	0.119

(c) Successive years: periods 93-99 and 97-03 respectively

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	-0.062**	-0.002	-0.043	0.097**
	p-value	0.025	0.981	0.424	0.003
class 1 to 3	diff	-0.035**	-0.071	-0.007	-0.030
	p-value	0.005	0.185	0.831	0.200
class 2 to 1	diff	0.029**	0.058	0.078**	0.011
	p-value	0.005	0.104	0.067	0.618
class 2 to 3	diff	-0.046**	-0.096	0.005	-0.077**
	p-value	0.000	0.117	0.917	0.028

Table 50: The tables present the difference between the transition probabilities from group 87-88 (high unemployment) minus group 91-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for sub-panel North high education are from the conditional test considering age the others are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively. Grey cells are those for which we could lack of power.

8.7.6 Analyzing wage mobility on the same period

In our analysis we compare wage mobility between the two groups in terms of potential experience. As consequence, we compare the wage mobility over different periods with a shift of four years between them. For example, when we compare wage mobility of period 1989-1999 for group 86-88 with that of period 1993-2003 for group 90-92, the two periods of analysis overlap from 1993 to 1999 and do not overlap from 1989 to 1992 and from 2000 to 2003. The results of our analysis could be affected by the different economic conditions the two groups face in these different periods. We argued above that this should not be a relevant problem for our analysis. We run a robustness check to support our argument: we compare wage mobility between the two groups on the common period 2000-2004. Since we are comparing the two groups on the same period, we should consider that group 86-88 will have four years of potential experience more than group 90-92. This difference in potential experience would most probably affect the results at the beginning of the working career where wage mobility is higher, but we can expect a decreasing effect in time. We choose period 2000-2004, the last four years period available, in order to reduce the effect of the difference in potential experience on wage mobility (11 years for group 86-88, 7 for group 90-92).

We present the results in Table 51. We can see from the Table that group 90-92 has a more positive wage mobility in the period. In particular the results on the transition probabilities from the second class are in line with those from our analysis. We can conclude that also when considering a common period, it seems that the group of individuals who enter during the high unemployment phase faces a worse wage mobility.

This outcome importantly strengthen the finding of a persistent negative effect of adverse entry conditions.

(a) Period 00-04.

Prob		High educ. North	Centre	South	Low Education Italy
class 1 to 2	diff	-0.048**	-0.063	-0.001	0.001
	p-value	0.050	0.220	0.735	0.969
class 1 to 3	diff	0.002	0.065**	-0.033**	0.009
	p-value	0.065	0.030	0.015	0.653
class 2 to 1	diff	0.023**	0.015	0.007	0.013
	p-value	0.035	0.400	0.390	0.415
class 2 to 3	diff	-0.040**	-0.106**	-0.032**	0.001
	p-value	0.000	0.000	0.055	0.974

Table 51: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for high education columns are from the conditional test considering age the ones for low education are from the unconditional test. The null hypothesis is the equality of transition probabilities. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.7 Excluding low unemployment period 2001-2003

To show that our results are not driven by the low unemployment phase between 2001 and 2003, we study wage mobility on the first 7 years of potential experience: on periods 1989-1996 and 1993-2000 for groups 86-88 and 90-92 respectively.

The results in Table 52 are similar to those of the long run original analysis in terms of the signs and the significance of the differences between the two groups transition probabilities.

(a) Middle run: periods 89-96 and 93-00 respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	0.012	0.001	0.003	0.025
	p-value	0.335	0.430	0.415	0.211
class 1 to 3	diff	-0.067**	-0.027	-0.044**	-0.027**
	p-value	0.000	0.420	0.000	0.050
class 2 to 1	diff	0.038**	0.051**	0.041**	0.038
	p-value	0.000	0.000	0.015	0.294
class 2 to 3	diff	-0.090**	0.028*	-0.026**	-0.092*
	p-value	0.000	0.075	0.020	0.064

Table 52: The tables present the difference between the transition probabilities from group 86-88 (high unemployment) minus group 90-92 (low unemployment) for the analysis with a different definition of first spell. The p-values for high education columns are from the conditional test considering age the ones for low education are from the unconditional test. The null hypothesis is the equality of transition probabilities. Differences marked * or ** are significant around 10% and at 5% respectively.

8.7.8 Investigating a different period of high unemployment

We run the analysis comparing the wage mobility of the low unemployment group with the next higher unemployment group available. Since in the data there is not an increase of the national unemployment rate comparable to the decrease of the original analysis (4%), we consider the unemployment rate in the single geographic areas and take group 91-93 as the low unemployment one and group 95-97 as the high. In this way subgroup South has a comparable increase of unemployment: the average rate passes from 34.66% to 38.80%. In the Centre it passes from 20.33% to 23.85%, while in the North it remains stable in the two periods (from 14.92% to 14.63%).[23]

It should be noticed that a reform of the labor market (Treu) took place in 1997. The aim of the reform was to increase the flexibility of the labor market introducing temporary contracts and internships. Since the wage mobility of group 95-97 is probably affected by the different institutional framework, the results between this and the original analysis are not completely comparable. Still we can obtain some evidence to support the causality of unemployment at entry on different wage mobility.

In Table 53 it can be seen that there is a lower proportion of Managers and White Collars in group 95-97 than 91-93 and a higher proportion of Apprentices. The demographic analysis in Table 54 rejects the null of equality in distribution of occupation in all subgroups, except Italy, low education. We find similar results both in the original analysis and in the analysis on groups 87-89 and 91-93 above. In both cases conditioning on age reduces the inequalities, so we use our conditional test for all high education subgroups.

We also run the demographic analysis between groups 87-89 and 95-97 to check to what extent we can compare the results with those of the analysis on groups 87-89 and 91-93. Tables 55

[23]The evolution of the young male unemployment rate in the three areas is presented in Figure 3 in the Appendix.

and 56 show similar demographic characteristics between the two groups for subgroups North and South high education. Instead, Center high education seems to have a different occupation distribution in the two groups and Italy low education to have a different age and regional structure, besides an increase in unemployment of just 2.17%. For these reasons the results of subgroups North and South, high education are more comparable to the previous, and we focus on them in our analysis.

We can consider maximum six years of potential experience in the analysis on wage mobility. The results are reported in Table 57. In subgroup South, high education, as expected, we find a better six year wage mobility for the low unemployment group 91-93: all the upward probabilities of the analysis have a negative sign and 2 out of 3 are significant at 5%. The differences in the transition probabilities for subgroup North, high education are small in magnitude and not significant at 5% except the one from class 1 to 3. This result seems to strengthen the causality of the entry conditions in the analysis of groups 87-89 and 91-93: with a similar group to 87-89, the lack of a variation in the unemployment rate coincides with no difference in the income mobility.

In conclusion the analysis with groups 91-93 and 95-97 gives some evidence that the difference in wage mobility we find in the original analysis is caused by the labor market entry conditions. However, when taking into account these results, it should be considered that the institutional framework changes in 1997, that the increase in unemployment rate that we are using is not national and that we cannot perform the ten years analysis.

	Italy whole		North high		Center high		South high		Italy low	
	95-97	91-93	95-97	91-93	91-93	91-93	95-97	91-93	95-97	91-93
Apprentices	0.38	0.33	0.15	0.07	0.15	0.08	0.12	0.05	0.90	0.86
Blue collars	0.48	0.47	0.62	0.63	0.67	0.59	0.74	0.69	0.09	0.13
Managers & white collars	0.14	0.20	0.23	0.30	0.18	0.33	0.14	0.26	0.01	0.01
Low	0.31	0.32								
High	0.69	0.68								
North	0.68	0.66							0.71	0.69
Center	0.17	0.18							0.15	0.17
South	0.15	0.16							0.13	0.14
Obs.	3174	3727	1434	1630	388	454	356	435	996	1208

Table 53: Descriptive statistics groups 95-97 91-93

	Italy whole		North high		Center high		South high		Italy low	
	87-89	95-97	87-89	95-97	87-89	95-97	87-89	95-97	87-89	95-97
Apprentices	0.38	0.38	0.07	0.15	0.07	0.15	0.03	0.12	0.87	0.90
Blue collars	0.45	0.48	0.62	0.62	0.60	0.67	0.77	0.74	0.12	0.09
Managers & white collars	0.17	0.14	0.31	0.23	0.33	0.18	0.20	0.14	0.01	0.01
Low	0.40	0.31								
High	0.60	0.69								
North	0.58	0.68							0.68	0.71
Center	0.18	0.17							0.16	0.15
South	0.25	0.15							0.16	0.13
Obs.	4482.00	3174.00	1381.00	1434.00	503.00	388.00	819.00	356.00	1779.00	996.00

Table 55: Descriptive statistics groups 87-89 95-97

(a) Long run: periods 98-04 and 94-00 respectively.

		High educ.			Low Education
Prob		North	Centre	South	Italy
class 1 to 2	diff	-0.014*	0.190**	-0.076**	-0.010
	p-value	0.095	0.000	0.005	0.657
class 1 to 3	diff	0.054**	-0.033	-0.010	0.012
	p-value	0.005	0.115	0.705	0.457
class 2 to 1	diff	-0.002	-0.033	-0.038	-0.075*
	p-value	0.435	0.105	0.140	0.081
class 2 to 3	diff	0.003	0.081**	-0.082**	-0.062
	p-value	0.185	0.020	0.025	0.269

Table 57: The tables present the difference between the transition probabilities from group 95-97 (high unemployment) minus group 91-93 (low unemployment) for the analysis with a different definition of first spell. The p-values for high education columns are from the conditional test considering age the ones for low education are from the unconditional test. Differences marked * or ** are significant around 10% and at 5% respectively.

		North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	cl1	0.505	0.379	0.000	0.470	0.527	0.188	0.002	0.060	0.000	0.050	0.045	0.000
Occupation	cl2	0.000	0.254	0.000	0.001	1.000	0.003	0.002	1.000	0.003	0.000	0.388	0.000
	cl3	0.721	0.634	0.384	0.768	1.000	0.762	0.507		0.706	0.621	0.300	0.248
Occupation	cl1	0.286	0.572	0.167	1.000	1.000	1.000	0.050	1.000	0.031	0.029	0.655	0.020
no	cl2	0.032	1.000	0.019	0.001		0.001	0.001	1.000	0.003	0.000	1.000	0.000
Apprentices	cl3	0.568		0.539	0.866		1.000	0.408		0.332	0.472	0.241	0.349
Occupation	cl1	0.519	0.566	1.000	1.000	0.524	0.334	0.007	0.408	0.011	0.310	0.556	0.080
replaced	cl2	0.014	0.763	0.017	0.001	0.508	0.004	0.004	0.563	0.003	0.000	0.298	0.000
Apprentices	cl3	0.491	0.561	0.521	1.000	1.000	1.000	0.434		0.245	0.305	1.000	0.247
	cl1	0.000	0.007	0.004	0.002	0.397	0.999	0.982	0.457	0.651	0.000	0.090	0.001
Age	cl2	0.008	1.000	0.012	0.686	0.292	0.600	0.754	0.426	0.992	0.040	1.000	0.035
	cl3	0.702	0.954	0.551	0.963	0.964	0.996	1.000		1.000	0.637	0.887	0.465
	cl1	0.000			0.000			0.610			0.000		
Education	cl2	0.462			0.904			0.315			0.756		
	cl3	0.687			0.761			0.318			0.574		
	cl1										0.199	0.552	0.006
Region	cl2										0.774	0.293	0.875
	cl3										0.034	0.323	0.035

Table 54: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.

		North low & high	North low	North high	Center low & high	Center low	Center high	South low & high	South low	South high	Italy low & high	Italy low	Italy high
	cl1	0.000	0.898	0.005	0.014	0.495	0.008	0.001	0.077	0.000	0.090	0.139	0.000
Occupation	cl2	0.652	0.610	0.004	0.078	1.000	0.174	0.606	1.000	0.546	0.727	0.837	0.000
	cl3	0.092	0.358	0.053	0.377	0.208	0.455	0.639		0.572	0.147	0.172	0.069
Occupation	cl1	0.370	1.000	0.257	0.043	1.000	0.044	0.721	0.662	0.867	0.081	0.778	0.115
no	cl2	0.349	0.560	0.556	0.070	1.000	0.066	0.504	1.000	0.488	0.599	1.000	0.541
Apprentices	cl3	0.056		0.028	0.893	0.245	1.000	0.472		0.449	0.074	0.250	0.028
Occupation	cl1	0.108	0.174	0.819	0.140	0.672	0.023	0.266	0.216	0.713	0.031	0.056	0.173
replaced	cl2	0.191	1.000	0.481	0.074	1.000	0.034	0.516	1.000	0.465	0.630	0.780	0.521
Apprentices	cl3	0.101	1.000	0.034	0.896	0.328	0.794	0.465		0.420	0.082	1.000	0.030
	cl1	0.000	0.000	0.069	0.000	0.548	0.182	0.334	0.990	0.206	0.000	0.001	0.000
Age	cl2	0.107	0.677	0.270	0.733	0.223	1.000	0.346	0.317	0.512	0.160	0.226	0.099
	cl3	0.890	1.000	0.963	0.976	0.893	0.943	1.000		0.997	0.993	1.000	1.000
	cl1	0.000			0.000			0.855			0.000		
Education	cl2	0.002			0.072			0.159			0.002		
	cl3	0.262			1.000			0.550			0.293		
	cl1										0.000	0.317	0.000
Region	cl2										0.000	0.013	0.000
	cl3										0.001	0.590	0.000

Table 56: P-values of test between the two groups, for each sub-group and starting class. For type of occupation, education and area of work we run the Pearson's χ^2 test while for age we run the Kolmogorov-Smirnov test. The null hypothesis is the equality of probability distributions. Empty cells are those for which was not possible to obtain a test because of lack of observations.