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TESIS DOCTORAL

Econometric Analysis of Income Mobility and Wage Growth

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Abstract

My dissertation consists in three empirical studies on income mobility and wage growth.

In the first chapter I compare short run income mobility between the North and South of Italy. Using the panel of the Survey on Household Income and Wealth for the period 2004-2008, I show that individuals from the South face a worse income dynamic than those from the North even when accounting for age and education. I use a nonparametric one-sided test for comparing conditional transition probabilities with a continuous covariate. The test is based on covariate matching techniques, does not assume any functional form for the dependence of the transition probability on the covariate, allows for different sample design and has a pivotal distribution.

In the second chapter I use Italian administrative data to study the effect of adverse labor market entry conditions on wage mobility of young males. I 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. I use a nonparametric testing procedure. I 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. I 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.

In the third chapter I investigate the returns to internal migration for Italian young males. Using Italian administrative data I find a significant positive effect on wage growth in the first eleven years of career when individuals migrate towards North in the first five years of career. On the other hand I find a significant negative effect on the wage of the first year following migration when the destination is South. I show that it is essential to consider the destination and the timing when studying returns to migration.

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Chapter 1

Comparing conditional transition probabilities: Is Italian Income Mobility Region Specific?

1.1 Introduction

It is well known that Italy is characterized by an important economic difference between the North and the South, with the first richer, more industrially developed and fast growing. Our application tests whether this difference have also an impact on the individuals' short run income mobility. More specifically, the empirical question is if an individual from the South of Italy has the same chances to improve/worsen her social condition than an individual from the North in the short run, where the social condition is given by her position on the national income distribution.

In order to answer the question, we compare the conditional transition matrices of the two regions for the period 2004-2008 using the panel of the Survey on Household Income and Wealth (SHIW) database by Bank of Italy. In the analysis, we take into account age and education. Not considering the regional age structure when studying short run income mobility could lead to misleading results: it is in fact well known that income mobility varies during individuals' life time, being highest at the beginning of the working career. A similar reasoning can be done for education: it is expected that individuals with higher education face a more positive income dynamic. Besides, education can be seen as the channel through which individuals can increase their possibilities of improving their income dynamic and make it more independent of the economic environment they live in[1]. A partial answer to our question can be indirectly found in Cappellari [2004] whom analyzes Italian workers' transition probabilities of leaving or entering the low wage class through a parametric model. However, in his analysis, he does not take into account individuals' age as a continuous covariate (he includes a dummy for more that 30 years potential labor market) and the analysis concerns only one class of income. We do not know any other work that compares North and South Italian short run income mobility.

The results of our analysis show a situation in which individuals of similar age and education face a more positive income dynamics in the North than in the South of Italy. In particular these differences are found in the poorest part of the population and the richest. Inside a unique country such as differences have consequences in terms of welfare (e.g. Boeri and Brandolini [2005]), affect individuals' economic decisions such as migration (e.g. see Mocetti and Porello [2010] for an analysis on the recent dynamics of Italian labor mobility) and should be considered by government's policies (e.g. Cappellari [2004]).

In the literature, conditional transition probabilities with continuous covariates are generally studied through parametric models such as linear probability models or probit. The first type of models cannot be used to compare the conditional probability overall the covariate support. For the probit, Bhattacharya and Mazumder [2011] point out that such as type of models are not adequate from a theoretical point of view "...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 analysis gives them misleading results in their empirical application. For these reasons a nonparametric test would be more adequate.

While comparing conditional transition probabilities with discrete covariates (e.g. education) can be done splitting the sample in classes reducing the analysis to an unconditional comparison and apply the results by Formby et al. [2004], the problem becomes more involved when the covariates are continuous (e.g. age). We introduce a methodology that was never applied in this context. We extend some of the tools available in literature for the comparison of two samples regression functions to the case of conditional transition probabilities. In fact, the comparison of conditional transition probabilities can be seen as the comparison of regression curves where the transition probability is the dependent variable. If the regression curves of the two groups coincide overall the common support of the covariate, we say they are the same. The same applies if the conditional transition probabilities coincide overall the support of the covariate.

In the statistical literature, several papers addressed the problem of testing the equality of two regression functions against two-sided alternatives: see e.g. Härdle and Marron [1990], Hall and

[1]Individuals with higher education have more working opportunities and can choose among them. The fact of having a choice makes individuals more independent from the economic environment compared to others that do not have any.

Hart [1990], King et al. [1991], Delgado [1993], Neumeyer and Dette [2003] and Ferreira and Stute [2004] among others. Some of them use covariates matching techniques for the purpose: see e.g. Hall and Turlach [1997], Cabus [1998], Pardo-Fernández et al. [2007] or Srihera and Stute [2010]. One-sided alternatives where considered by Hall et al. [1997], Koul and Schick [1997, 2003], Neumeyer and Pardo-Fernández [2009]. Among these, the last paper proposes a test based on the regressions residuals, while the others present tests based on covariate matching techniques.

We introduce an intuitive tests to study the hypothesis of equal conditional transition probabilities between two samples against a one-sided alternative. The test is based on the work of Cabus [1998], Koul and Schick [1997, 2003] and Neumeyer and Dette [2003] and allow for a continuous covariate with a possibly different distribution and support in the two samples. The test do not assume any functional form for the dependence of the transition probability on the covariate and it has a pivotal asymptotic distribution. The test is simple, intuitive and give reasonable good performances even with limited sample sizes. The test relies on the assumption that the two conditional probability curves do not cross over the common support.

A nonparametric two-sided test for comparing conditional transition probabilities could be derived using the work of Cabus [1998] and Neumeyer [2004]. Such as two-sided test would be more general and would not rely on the non crossing assumption of the conditional probability curves. On the other side it would require empirical processes techniques and a bootstrap procedure in order to be implemented, and a larger number of observations than the one-sided test for obtaining a similar power.

The rest of the paper is structured as follows: we first introduce the testing methodology in Section 2; we derive its asymptotic properties and run a Monte Carlo simulation in Section 3. We apply it to our empirical question in Section 4. We conclude in Section 5.

1.2 Test statistic and asymptotics

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.

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 $Y^{(s)}$ 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 period zero and the covariate $X^{(s)} = x$. We write it:

$$p^{(s)}(C_0, C_1, x) = \frac{\Pi^{(s)}(C_0, C_1, x)}{\Pi^{(s)}(C_0, x)}, \tag{1.1}$$

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.

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

$$H_0 : p^{(1)}(C_0, C_1, x) = p^{(2)}(C_0, C_1, x) \quad \forall\, x \in I; \tag{1.2}$$

against the alternative:

$$H_1 : p^{(1)}(C_0, C_1, x) \geq p^{(2)}(C_0, C_1, x) \text{ for all } x \in I \text{ with strict inequality for at least a subset of positive measure of } x \in I \tag{1.3}$$

We can characterize the null and the alternative hypothesis through the integral:

$$\gamma = \int \left[\Pi^{(1)}(C_0, C_1, \bar{x})\Pi^{(2)}(C_0, \bar{x}) - \Pi^{(2)}(C_0, C_1, \bar{x})\Pi^{(1)}(C_0, \bar{x})\right] f_{X^{(1)}}(\bar{x}) f_{X^{(2)}}(\bar{x}) d\bar{x} \tag{1.4}$$

Under the null hypothesis γ is zero, while it is positive under the alternative.

It should be noticed that the consistency of the test is based on the assumption that the two conditional transition probability curves do not cross overall the common support of the covariate. Such as assumption can be sustained in our application with the following reasoning: if the regional economic environment does affect the income mobility of the individuals living in it, this effect should have the same direction for all the individuals, no matter their age. Another natural context in which this assumption can be sustained is in the treatment effect literature, where it is assumed the treatment has a specific directional effect overall the covariate support: e.g. the effect of a training program on the probability of being employed should be positive no matter the age of the individuals that participate to the program.

We estimate γ by:

$$\begin{aligned}\gamma_{n_1 n_2} =& \frac{1}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \Big[1\{Y_{i0}^{(1)} \in C_0\} 1\{Y_{i1}^{(1)} \in C_1\} 1\{Y_{j0}^{(2)} \in C_0\} \\ & -1\{Y_{j0}^{(2)} \in C_0\} 1\{Y_{j1}^{(2)} \in C_1\} 1\{Y_{i0}^{(1)} \in C_0\} \Big] \times \frac{1}{h} k\left(\frac{X_i^{(1)} - X_j^{(2)}}{h}\right).\end{aligned} \tag{1.5}$$

Under standard assumptions in literature and using the results of Neumeyer [2004] it can be shown that both under the null and the alternative hypothesis, $\gamma_{n_1 n_2}$ is an unbiased estimator of γ and

$$\sqrt{\frac{n_1 n_2}{n_1+n_2}}\,(\gamma_{n_1n_2}-\gamma) \xrightarrow{d} N(0,\sigma^2).$$

Since the test statistics converges to a normal distribution both under the null and under the alternative, the test is consistent (e.g. see Theorem 3.3.1 in Lehmann [1999]) and we can use the t-statistic:

$$t_{n_1n_2} = \frac{\gamma_{n_1n_2}}{\hat{\sigma}_0/\sqrt{\frac{n_1n_2}{n_1+n_2}}}, \tag{1.6}$$

to conduct the one-sided test of H_0 against H_1, where

$$\begin{aligned}
\hat{\sigma}_0^2 &= (1-\rho)\frac{1}{n_1}\sum_i^{n_1}\Big[\hat{\Pi}^{(1)}(C_0,C_1,X_i^{(1)})\hat{\Pi}^{(2)}(C_0,X_i^{(1)})^2 + \hat{\Pi}^{(1)}(C_0,X_i^{(1)})\hat{\Pi}^{(2)}(C_0,C_1,X_i^{(1)})^2 \\
&\quad -2\hat{\Pi}^{(1)}(C_0,C_1,X_i^{(1)})\hat{\Pi}^{(2)}(C_0,X_i^{(1)})\hat{\Pi}^{(2)}(C_0,C_1,X_i^{(1)})\Big]\,\hat{f}^{(2)}(X_i^{(1)})^2 \\
&\quad +\rho\frac{1}{n_2}\sum_j^{n_2}\Big[\hat{\Pi}^{(1)}(C_0,C_1,X_j^{(2)})^2\hat{\Pi}^{(2)}(C_0,X_j^{(2)}) + \hat{\Pi}^{(1)}(C_0,X_j^{(2)})^2\hat{\Pi}^{(2)}(C_0,C_1,X_j^{(2)}) \\
&\quad -2\hat{\Pi}^{(1)}(C_0,C_1,X_j^{(2)})\hat{\Pi}^{(1)}(C_0,X_j^{(2)})\hat{\Pi}^{(2)}(C_0,C_1,X_j^{(2)})\Big]\,\hat{f}^{(1)}(X_j^{(2)})^2
\end{aligned} \tag{1.7}$$

and $f^{(s)}(x)$, $\Pi^{(s)}(C_0,x)$, $\Pi^{(s)}(C_0,C_1,x)$ are estimated as follows for $s=1,2$ respectively:

$$\hat{f}^{(s)}(z) = \frac{1}{n_s h^{(s)}}\sum_{j=1}^{n_s} k\left(\frac{z-X_j^{(s)}}{h^{(s)}}\right) \tag{1.8}$$

$$\hat{\Pi}^{(s)}(C_0,z) = \frac{1}{n_s h^{(s)}\hat{f}^{(s)}(z)}\sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)}\in C_0\}k\left(\frac{z-X_j^{(s)}}{h^{(s)}}\right) \tag{1.9}$$

$$\hat{\Pi}^{(s)}(C_0,C_1,z) = \frac{1}{n_s h^{(s)}\hat{f}^{(s)}(z)}\sum_{j=1}^{n_s} 1\{Y_{j0}^{(s)}\in C_0\}1\{Y_{j1}^{(s)}\in C_1\}k\left(\frac{z-X_j^{(s)}}{h^{(s)}}\right), \tag{1.10}$$

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

Assuming a specific local alternative, it would be possible to derive a most powerful one-sided test modifying the weighting function $w(\bar{x})$, e.g. Koul and Schick [2003], Neumeyer and Pardo-Fernández [2009]. However, to assume a local alternative is beyond the scope of the paper.

1.2.1 The unconditional test

If the transition probability does not depend on any covariate, the null hypothesis becomes

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

against the alternative

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

where $p^{(s)}(C_0, C_1)$ is the unconditional transition probability from class C_0 to C_1.
Define:

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

where $\hat{\Pi}^{(s)}(C_0, C_1)$ is the estimated joint probability of variable $Y^{(s)}$ to be in state C_0 in period zero and in state C_1 in period one, $\hat{\Pi}^{(s)}(C_0)$ is the estimated probability of $Y^{(s)}$ being in state C_0 and $\hat{p}^{(s)}(C_0, C_1)$ is the estimated unconditional transition probability.

Assuming sample independence and $n_1/N \to \rho \in (0,1)$ as $N \to \infty$, it can be shown that under H_0:

$$\sqrt{\frac{n_1 n_2}{n1 + n2}}\left(\hat{p}^{(1)}(C_0, C_1) - \hat{p}^{(2)}(C_0, C_1)\right) \xrightarrow{d} N(0, \sigma_u^2),$$

with

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

The unconditional t-statistic is:

$$t_u = \frac{\hat{p}^{(1)}(C_0, C_1) - \hat{p}^{(2)}(C_0, C_1)}{\hat{\sigma_u}/\sqrt{\frac{n_1 n_2}{n_1+n_2}}}. \tag{1.11}$$

which can be compared to the critical values given by the standard normal distribution in order to reject or not the null hypothesis.

When considering conditional transition probabilities, if the covariate $X^{(s)}$, $s = 1, 2$, is categorical with L common categories $x \in \{x_1, x_2, ..., x_L\}$, a way of testing the equality between the two conditional transition probabilities is by splitting the sample in the covariate categories and run an unconditional test inside each subsample separately. If the sample is split, the covariate is a constant in each subsample and it does not need to be considered when comparing the transition probability between the two samples. In this framework the unconditional test is adequate. However splitting the sample in the covariate categories and run the unconditional test is not optimal to test the equality between the transition probability uniformly on the covariate categories. It is not optimal for testing the null hypothesis $H_0 : p^{(1)}(C_0, C_1, x = x_l) = p^{(2)}(C_0, C_1, x = x_l)$ *for all* $x_1, x_2, ..., x_L$, against the alternative $H_1 : p^{(1)}(C_0, C_1, x = x_l) \geq p^{(2)}(C_0, C_1, x = x_l)$ *for all* $x_1, ..., x_L$ *with strict inequality for at least one common category* x_l. In this case a joint test over the covariate categories is needed. This because testing each subsample separately and pooling the results to test the equality of the transition probability uniformly on the covariate categories would result in a sequential testing procedure where the asymptotic size is out of control. A possible way of testing the joint null hypothesis would be by means of a χ^2 test, which is a two-sided test and straightforward when the transition probability depends on one categorical covariate only.

In our analysis on income mobility we compare conditional transition probabilities before considering individuals' age and then considering age and education. In the first analysis we consider age as continuous and use our nonparametric one-sided test, while in the second analysis we split the sample into the categories high education and low education and run our nonparametric test in the two separate subsamples without pooling the results to obtain a join test for the two education categories. As we describe in details next Section, the choice is motivated by the fact that it is economically interesting to consider the two education categories as different populations. In order to obtain a joint test for both education categories, we could discretize age in classes and run a χ^2 test using the two discrete variables age and education. Discretizing age would also allow to use the χ^2 test in the analysis in which we consider only education. However, in our empirical analysis we have too few observation available for discretizing age and split the sample in both age and education classes and we leave this approach for more appropriate empirical applications.

1.3 Monte Carlo simulation

We run a Monte Carlo with a 1000 simulation. We tailor the simulation to the case of conditional transition probabilities, which is a novelty in the literature on the testing of the equality of regressions functions. Following Neumeyer and Dette [2003] and Srihera and Stute [2010] we take the bandwidths:

$$h = \left(\frac{n_1 \hat{\sigma}_1^2 + n_2 \hat{\sigma}_2^2}{(n_1 + n_2)^2} \right)^{\frac{7}{24}} \quad \textit{and} \quad h^{(s)} = \left(\frac{\hat{\sigma}_s^2}{n_s} \right)^{\frac{1}{5}},$$

for the estimation of $\gamma_{n_1 n_2}(C_0, C_1; x)$ and of $f^{(s)}(x)$, $\Pi^{(s)}(C_0, x)$, $\Pi^{(s)}(C_0, C_1, x)$, for $s = 1, 2$, respectively. We take as $\hat{\sigma}_s$ sample s covariate X standard deviation.

Since the transition probability is the probability of passing to class C_1 being in class C_0 and the value of X, we can consider modelling it with a binary response model where the index variable characterizes the transition from one class to the other and depends on the covariate. In all the scenarios presented, we studied the conditional transition probability of $Y^{(s)}$ being below the median of the set $[Y_{0i}^{(1)} \bigcup Y_{0j}^{(2)}]$ in the first period and above the median of the set $[Y_{1i}^{(1)} \bigcup Y_{1j}^{(2)}]$ in the second period, with $i = 1, ..., n_1$ and $j = 1, ..., n_2$.

We generate $Y_0^{(s)}$ to be log-normal and $X^{(s)}$ to be in the interval [0,1]. Then, for those observations with the value of $Y_0^{(s)}$ below the median in the first period, we generate the index variable that represents the transition to be above the median next period as:

$$d_i^{(s)} = \begin{cases} 1 & b_0 + b_x^{(s)} X_i^{(s)} \geq -e_i \\ 0 & otherwise \end{cases}$$

where $e \sim N(0,1)$ and b_0, $b_x^{(s)}$ change when imposing the null hypothesis or the alternative. b_0 is obtained in order to have around half of $d_i^{(s)} = 1$, $i = 1, ..., n_s$. Given this setup, sample 1 and sample 2 share the same conditional transition probability if the coefficient $b_x^{(s)}$ is the same for $s = 1, 2$.

In simulation (i) and (ii) we impose the null.
Simulation (i) is the simplest case we consider: $b_x^{(1)} = b_x^{(2)} = 1$ and the marginals are the same in the two samples: $Y_0^{(1)} \sim Y_0^{(2)} \sim exp(u)$ where $u \sim N(0,1)$ and $X^{(1)} \sim X^{(2)} \sim U(0,1)$.
In (ii) $b_x^{(1)} = b_x^{(2)} = 0.7$. $Y_0^{(2)}$ has higher average and variance than $Y_0^{(1)}$ and $X^{(1)}$ has a lower average than $X^{(2)}$: $Y_0^{(1)} \sim exp(u)$, $Y_0^{(2)} \sim exp(u^*)$ where $u \sim N(0,1)$ and $u^* \sim N(1,(1.5)^2)$; $X^{(1)} \sim N(0.3,(0.4)^2) \times 1_{[0 \leq X^{(1)} \leq 1]}$ and $X^{(2)} \sim N(0.8,(0.4)^2) \times 1_{[0 \leq X^{(2)} \leq 1]}$
In simulation (iii) and (iv) we impose the alternative.
In (iii) the marginals are the same in the two samples and distributed as in (i), but $b_x^{(s)}$ are different: $b_x^{(1)} = 1, b_x^{(2)} = 0.2$.
In (iv) $Y_0^{(s)}$ is equal for $s = 1, 2$ and distributed as in (i), while $X^{(1)} \sim N(0.2,(0.4)^2) \times 1_{[0 \leq X^{(1)} \leq 1]}$ and $X^{(2)} \sim N(0.8,(0.4)^2) \times 1_{[0 \leq X^{(2)} \leq 1]}$. Besides, $b_x^{(1)} = 1$ and $b_x^{(2)} = 0.5$.

The results of the simulation are presented in Table 1.1(a) while in Table 1.1(b) there are those of the unconditional test for simulations (ii) and (iv) respectively. The test performs properly both under the null and the alternative, even with sample sizes smaller than 200 observations. The unconditional test is over-sized under the null hypothesis in (ii) and has a quite low power under the alternative in (iv) in Table 1.1(b). Simulations (ii) and (iv) are examples of situations in which it would be misleading to use the unconditional test. In these simulations the marginal distributions of the variables compensate the coefficients of X in order to obtain different unconditional transition probabilities under the null in (ii) and similar unconditional transition probabilities under the alternative in (iv).

1.4 Italian regional income mobility

Income mobility is often studied by means of transition matrices containing the transition probabilities of passing from a class of the income distribution to another during the analyzed period.

Table 1.1: Simulation results for the one-sided test.

(a) Imposing the Null and the Alternative Through a Probit

	n1		50			100			200			1000	
	n2	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
	50	0.109	0.052	0.003	0.105	0.058	0.013	0.091	0.051	0.007	0.113	0.064	0.015
i	100	0.099	0.042	0.003	0.122	0.058	0.009	0.113	0.061	0.011	0.112	0.054	0.012
	200	0.094	0.050	0.015	0.106	0.047	0.011	0.112	0.060	0.013	0.100	0.054	0.015
	1000	0.122	0.065	0.015	0.120	0.059	0.005	0.105	0.048	0.014	0.108	0.053	0.011
	50	0.113	0.053	0.003	0.113	0.061	0.003	0.088	0.035	0.007	0.106	0.052	0.008
ii	100	0.103	0.050	0.010	0.101	0.044	0.009	0.105	0.056	0.011	0.101	0.048	0.011
	200	0.107	0.049	0.007	0.097	0.041	0.004	0.099	0.044	0.006	0.118	0.052	0.009
	1000	0.089	0.047	0.014	0.104	0.053	0.010	0.095	0.052	0.013	0.124	0.063	0.015
	50	0.434	0.279	0.073	0.506	0.351	0.111	0.510	0.366	0.125	0.591	0.448	0.185
iii	100	0.499	0.348	0.105	0.606	0.475	0.201	0.699	0.554	0.282	0.789	0.660	0.395
	200	0.530	0.391	0.161	0.698	0.557	0.268	0.811	0.704	0.420	0.943	0.899	0.711
	1000	0.582	0.433	0.197	0.792	0.690	0.404	0.948	0.901	0.706	0.999	0.999	0.997
	50	0.211	0.102	0.015	0.238	0.137	0.024	0.263	0.170	0.035	0.286	0.165	0.038
iv	100	0.238	0.130	0.030	0.286	0.164	0.037	0.336	0.211	0.059	0.376	0.248	0.079
	200	0.264	0.148	0.038	0.316	0.205	0.069	0.377	0.242	0.093	0.509	0.376	0.145
	1000	0.297	0.181	0.050	0.338	0.234	0.084	0.532	0.378	0.153	0.820	0.718	0.469

(b) Unconditional Test's Results

	n1		50			100			200			1000	
	n2	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
	50	0.219	0.110	0.029	0.221	0.112	0.023	0.240	0.135	0.033	0.243	0.125	0.032
ii	100	0.241	0.126	0.038	0.212	0.126	0.021	0.228	0.107	0.025	0.225	0.133	0.040
	200	0.208	0.101	0.029	0.206	0.121	0.033	0.244	0.131	0.035	0.250	0.140	0.037
	1000	0.231	0.118	0.041	0.258	0.153	0.031	0.269	0.137	0.036	0.340	0.213	0.064
	50	0.215	0.100	0.027	0.217	0.113	0.029	0.236	0.126	0.027	0.226	0.120	0.027
iv	100	0.227	0.127	0.045	0.198	0.113	0.020	0.200	0.095	0.017	0.220	0.122	0.025
	200	0.206	0.104	0.027	0.198	0.118	0.023	0.221	0.105	0.021	0.217	0.114	0.026
	1000	0.196	0.107	0.033	0.222	0.124	0.027	0.200	0.105	0.028	0.208	0.105	0.027

Rejection probabilities obtained with a 1000 simulations; the null and the alternative are imposed as described in section 2 and the results are given for various sample size.

We compare these transition probabilities between North and South of Italy, taking into account first just age and then also education, using our test.

Given the differences in the economic environment they live in, we would expect individuals from the North to face a more positive income mobility than those from the South. In terms of transition matrices, we would expect the transition probabilities above the diagonal of the matrix to be higher in the North than in the South, while those below the diagonal to be lower. Although this outcome is predictable, it could be just the result of a different age or education structure inside the two regions. Differences in transition probabilities become relevant if present between individuals with similar age and education.

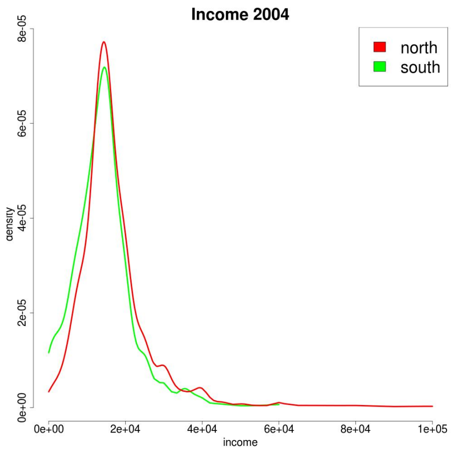
We use the Survey of Households Income and Wealth (SHIW) database by Bank of Italy[2]. The units of analysis are those individuals belonging to the active population: employed, self-employed, unemployed. The yearly income is obtained as the sum of employed income, transfers and self employed income. We consider period 2004-2008, the most recent data available in the SHIW. Similar length periods were considered by Cappellari [2004] and Boeri and Brandolini [2005] in the study of short run income mobility. The transition matrices of the two regions have common exogenous boundaries: the classes of income are obtained from the total national distribution of the active population (also region Center is considered for obtaining the total national distribution). The Regions are determined following the definition in variable "area3" of the SHIW. There is not immigration in the panel. After polishing the data [3], the final panel for the whole Italy consists of 2347 individuals; 1156 are individuals from the North, 701 are from the South.

Figure 1.1 presents the national distribution of income for the active part of the Italian population and compare North and South's distribution in years 2004 and 2008. From the graphs it can be seen that the disposable individual income increased in the period and that the North's distributions slightly dominates the South's both years. Figure 1.1(d) shows the 2004 age distribution for the first class of income in the two regions: the two distributions look quite different indicating that age must be taken into account when comparing transition probabilities. The above observations are confirmed by Tables A.1 and A.2 in the Appendix, where we report the descriptive statistics of the variables and the national quantiles used to form the classes in the following analysis.

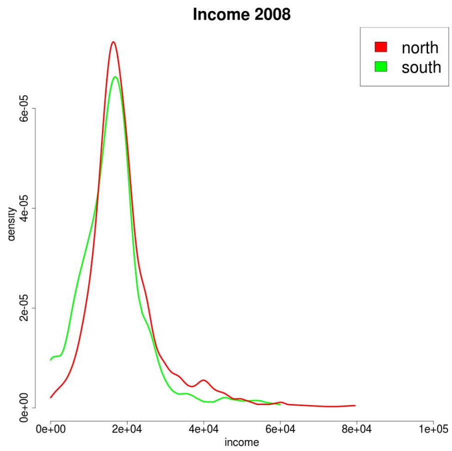
We report the estimated 3x3 income transition matrices for North and South in Tables 1.2(a) and (b) respectively. Table 1.2(c) presents the differences between the two regions (North-South). The number of classes guarantees a reasonable number of observations in each cell and power

[2]See Faiella and Gambacorta [2007] for a description of the database

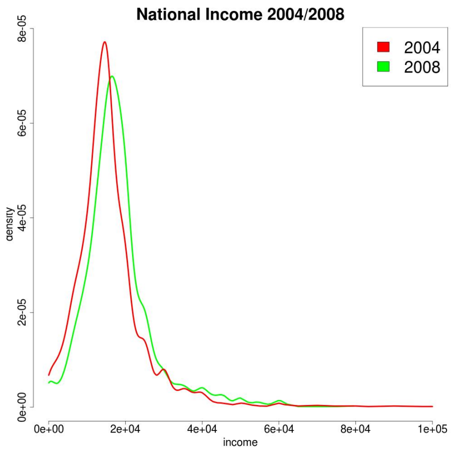
[3]We excluded from the panel individuals with negative income or inconsistent age. Further we trimmed the top 0.5% of the national income distribution in the two years before merging the panel in order to avoid outliers.



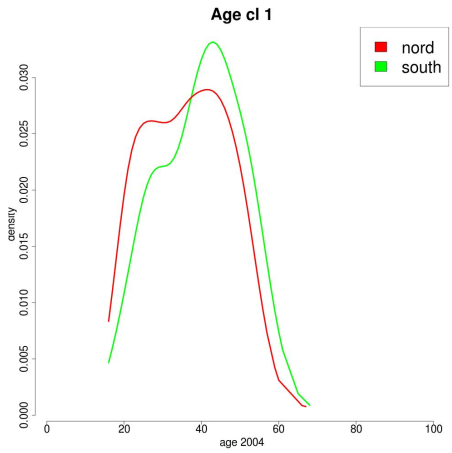
(a) North and South 2004 Income Distribution.



(b) North and South 2008 Income Distribution.



(c) National Income Distribution.



(d) North and South 2004 Age Distribution.

Figure 1.1: Comparison of income and age distributions

Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel sample. Distributions are obtained through kernel estimation using the Gaussian kernel and rule of thumb bandwidth.

to the test[4]. The number of observations for each starting class is presented in the last column of Tables 1.2(a) and (b). The sign of the differences in Table 1.2(c) are, in general, as expected: negative below the diagonal and positive above. This means the probabilities of worsening the income class are higher in the South, while those of improving are higher in the North. The diagonal contains the probabilities of not changing class. For class 1, the poorest, the probability is higher in the South while for class 3 it is higher in the North. In conclusion, it seems that individuals from the North faced a more positive income mobility, with higher probabilities to improve the income class and to stay at the top class, and lower probabilities to worsen the class or to stay in the poorest. Next, we are going to test if these differences are statistically significant taking into account the age structure of the two regions.

Table 1.2: Unconditional Transition Probabilities.

(a) Prob. North

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.66	0.22	0.13	326
1/3-2/3	0.28	0.48	0.24	416
>2/3	0.11	0.20	0.69	414

(b) Prob. South

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.75	0.15	0.10	279
1/3-2/3	0.28	0.47	0.25	232
>2/3	0.20	0.24	0.56	190

(c) North-South

	<1/3	1/3-2/3	>2/3
<1/3	-0.09	0.07	0.02
1/3-2/3	0.00	0.02	-0.02
>2/3	-0.09	-0.04	0.13

Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.
In the matrices, the classes in 2004 are in rows, those of 2008 in column. e.g. row <1/3 contains the transition probabilities of those individuals who were in the lowest class of income in 2004.

1.4.1 Analysis considering age

Table 1.3(a) reports the results of our test. The test is run on the common support of age using the Epanechnikov kernel and the same bandwidths as in the Monte Carlo simulations. We multiplied the bandwidths by a constant in order to check the robustness of the results. We considered the following values for the constant $wh = \{0.5, 1, 2, 5, 8\}$. The results are stable. We present the results for $wh = 5$. Since the test is one-sided we run it in the direction given by the economic intuition of income mobility being more positive for the individuals from the North. For the transition probabilities below the diagonal of the transition matrix and the probability of remaining in class 1 of the income distribution, we consider the null hypothesis of equality against the one-sided alternative of North's conditional probability being lower than the South at least for some age. For the transition probabilities above the diagonal of the transition matrix

[4] A similar choice was done in Cappellari [2004] where one of the chosen thresholds for the low wage class was the third decile of the wage distribution.

and the probabilities of staying in class 2 and 3, we consider the one-sided alternative of North's conditional probability being higher than the South at least for some age. Notice that this economic intuition is supported by the sign of the differences in 1.2(c).

The test rejects the null of equality at 5% significant level for the probabilities in the first and third rows of the matrix, while it does not for the second. This means that individuals from the South that were in the poorest class of the income distribution in 2004 faced significantly lower probabilities to pass to the second or third class in 2008 compared to individuals from the North with a similar age. On the other hand, individuals from the South that were in the third class in 2004 faced a higher probability of being in class 2 or 1 than individuals from the North with a similar age. The test does not reject the null of equality for individuals that where in the middle class in 2004. We conclude that, as expected, individuals from the North faced a significantly more positive income mobility than individuals from the South. Table 1.3(b) presents the results

Table 1.3: Conditional test of the differences between North and South transition probabilities.

(a) One-sided p-values

	<1/3	1/3-2/3	>2/3
<1/3	0.000	0.000	0.023
1/3-2/3	0.502	0.221	0.809
>2/3	0.000	0.046	0.000

(b) Probit p-values

	<1/3	1/3-2/3	>2/3
<1/3	0.003	0.025	0.071
1/3-2/3	0.485	0.417	0.397
>2/3	0.004	0.040	0.000

The null is equality between North and South transition probabilities. The direction of the alternative for the one-sided test is given by the economic intuition of individuals from the North having a more positive income mobility than those from the South. Intuition supported by the sign of the difference North-South in Table 1.2(c). The numbers contained in the cells are the p-values.
Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.

obtained when the above hypotheses were tested by means of a standard probit methodology. When a parametric model such as the probit is used, the above test reduces in testing linear restrictions on the estimated parameters. We estimated the following probit for the transition probabilities:

$$p(C_0, C_1, x) = \Phi\left(\beta_0 + \beta_{1N} \times Age + \beta_{1S} \times Age \times d^{(S)} + \beta_2 \times Age^2\right)$$

which is the one that overall best fits the data.[5] The null hypothesis of equality of transition matrices between North and South in the probit model becomes $H_0 : \beta_{1S} = 0$. The results in Table 1.3(b) confirm those obtained with our nonparametric test.

We highlighted above that the one-sided test is consistent only under the assumption the two transition probability curves do not cross on the covariate support. To check if the non-crossing assumption is satisfied, we estimated the conditional transition curves for each cell of the transition matrix and report them in Figure A.1 in Appendix. The non-crossing assumption seems to be satisfied for the transition from class 1 to 3. The non-crossing assumption seems to not

[5]The estimated models can be seen in Table A.3 in Appendix. We tried several model specification, and the one we propose is the one that fits the data the best. In particular we excluded a specification with the interaction term between age squared and the dummy for the South because never significant in any transition probability.

hold for the transition from class 3 to 2. However, the fact that the null hypothesis is rejected indicates that the weighted average of the probability of passing from class 3 to 2 is higher in the South, where the weights are determined by the density functions of age in the two samples. The one-sided test is not adequate to test the transition probabilities in the second row of the matrix because the non-crossing assumption is not satisfied and the null hypothesis is not rejected.

Next we apply our methodology to compare upward and downward transition probabilities between the two regions. We define upward probability as the individual's probability of improving her social position: to be in an higher class next period. We define downwards probability as the probability of worsening the social position. We estimate and test up/downwards transition probabilities for the 3 classes analyzed above. The results of the test are presented in

Table 1.4: Testing Upwards and Downwards Conditional Transition Probabilities.

	UP				DOWN			
	North	South	North-South	Test	North	South	North-South	Test
<1/3	0.34	0.25	0.09	0.000	-	-	-	-
1/3-2/3	0.24	0.25	-0.02	0.809	0.28	0.28	0.00	0.502
>2/3	-	-	-	-	0.31	0.44	-0.13	0.000

The tables report the probabilities for the two regions, their difference and the p-value of the tests. The null is equality between North and South transition probabilities. The direction of the alternative for the one-sided test is given by the economic intuition of individuals from the North having a more positive income mobility than those from the South.
Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.

Table 1.4 and confirm what we found in the previews analysis: individuals from the North faced a significantly higher upward probability in the first of the three classes and a lower downward probability in the top class.

1.4.2 Analysis considering age and education

In what follows, we extend the analysis including education as second covariate: we are going to test if income mobility among individuals with similar age and education is the same in the North and South of Italy. In the SHIW, education is a categorical covariate. We divide the sample in two: individuals that just attended compulsory education studying 8 years [6], and those that achieved high school diploma, bachelor degree and post graduate studies. After cleaning the data to avoid inconsistent education between the two years, we find that in the North around 60% of the individual have higher education, while in the South around 52%.

The fact of splitting the sample in education classes forces us to bring the analysis from 3 classes of income to 2 in order to have some power in testing. We run the above analysis on a 2×2 transition matrix, where the classes are defined by the median of the national active population.

[6] In 2007 compulsory education in Italy became 10 years; but this does not affect the sample

In order to have comparable results, we run also the test considering just age as in the previews analysis. The results of the test are presented in Table 1.5, while the transition probabilities, their differences and the number of observations in each class are given in Table 1.6. Table 1.5 shows that the extra covariate does not mitigate the differences between the income mobility of North and South of Italy, which significantly persist also among individuals with similar education. In fact, we reject the null hypothesis of equality of the transition probabilities in both education subsamples.[7] In the period, individuals from the North faced a statistically significant more positive income mobility. The estimated conditional transition probability curves are given in Figure A.2 in Appendix. The figure shows that the assumption of non-crossing curves is satisfied, with the exception of the transition probability of individuals in the lower half of the income distribution with just compulsory education.

These results are in line with those in Cappellari [2004]: in the parametric model he uses for studying the transition probabilities to enter and exit the low wage class, the coefficients of the dummy variables for education and for the different regions are all significant.

In conclusion, our analysis showed that individuals that lived and worked in the North of Italy between 2004 and 2008 faced a more positive income dynamic than individuals living in the South with similar age and education.

Table 1.5: Testing Transition Probabilities around the median accounting for age and education.

		conditional on age		
cl. 2004	cl. 2008	unconditional on ed.	low ed.	high ed.
1	1	0.338	0.970	0.003
1	2	0.338	0.970	0.003
2	1	0.003	0.005	0.087
2	2	0.003	0.005	0.087

The p-values of the tests are reported. The null is equality between North and South transition probabilities. The direction of the alternative for the one-sided test is given by the economic intuition of individuals from the North having a more positive income mobility than those from the South.
Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.

1.5 Concluding remarks

We investigated if individuals from the South of Italy face a different short run income mobility than individuals from the North. Using the data from the SHIW for the period 2004-2008 and a new nonparametric testing procedure, we have shown that individuals from the South face a worse income dynamic than those from the North with similar age and education.

[7] As mentioned in Section 1.2, we do not obtain a joint result for both education categories with our testing procedure, we consider the results for each education subsample separately.

Table 1.6: Conditional transition probabilities and classes size in the education analysis.

Unconditional on education						
cl. 2004	cl. 2008	North	South	N-S	Tot.cl1 N	Tot.cl1 S
1	1	0.71	0.72	-0.01	510	421
1	2	0.29	0.28	0.01	510	421
2	1	0.24	0.31	-0.07	499	255
2	2	0.76	0.69	0.07	499	255
Compulsory education						
cl. 2004	cl. 2008	North	South	N-S	Tot.cl1 N	Tot.cl1 S
1	1	0.81	0.77	0.04	254	240
1	2	0.19	0.23	-0.04	254	240
2	1	0.40	0.51	-0.11	152	80
2	2	0.60	0.49	0.11	152	80
High education						
cl. 2004	cl. 2008	North	South	N-S	Tot.cl1 N	Tot.cl1 S
1	1	0.61	0.65	-0.04	255	181
1	2	0.39	0.35	0.04	255	181
2	1	0.17	0.21	-0.04	346	175
2	2	0.83	0.79	0.04	346	175

Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.

The nonparametric one-sided test we introduced was never used in the comparison of conditional transition probabilities. The test is based on covariate matching techniques, do not assume any functional form for the dependence of the transition probability on the covariate and allow for different sample design. We analysed its small sample properties showing the test behaves properly also with relatively small sample sizes.

Chapter 2

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

2.1 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 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 a nonparametric 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. 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

[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.

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 talk about the data we use, in section 4 and 5 we present the results of our analysis and in section 6 we conclude.

2.2 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.[3] 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%.[4] Figure 2.1 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

[3]Unemployment rate data are from the Italian national statistics institute (Istat) and available at www.istat.it.
[4]We run the analysis on periods 87-89 and 91-93 as robustness check.

Figure 2.1: Unemployment and first wage

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

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 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.[5]

[5]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 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 B.34 in the Complementary Material.

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. If the transition probability depends on a covariate, we call it conditional and test it with a conditional nonparametric test in the spirit of Cabus [1998], Neumeyer and Dette [2003] and Neumeyer [2004]. If the probability does not depend on any covariate, we perform a standard unconditional t-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:

$$H_0 : p^{(1)}(C_0, C_1, x) = p^{(2)}(C_0, C_1, x) \quad for \;\; all \;\; x \in I; \tag{2.1}$$

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:

$$H_0 : p^{(1)}(C_0, C_1) - p^{(2)}(C_0, C_1) = 0, \tag{2.2}$$

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 subgroups. For example instead of comparing group 86-88 and group 90-92 we compare wage mobility between individuals from group 86-88 who started to work in the North of Italy and with high education with similar individuals from group 90-92. Which test is used and the subgroups 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.

2.3 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[6] 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).[7]

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).[8] 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

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

[7]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 B.2 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%.

[8]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[9]. 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.

2.4 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 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

[9]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.

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 the covariate categories creating subgroups 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.

Table 2.1: Comparison of the proportion of the different types of first occupation, education, first area of work in the two groups, and sample sizes.

	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

In Table 2.1 we present the probability distribution of the demographic characteristics in the whole groups and in the four subgroups 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.[10] 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 these individuals the second occupation they held.[11] We investigate independence in all three cases. In Table 2.2 we report the p-values of the tests; the null hypothesis is the equality of the covariate' s probability distribution in the two subgroups. More details on the covariates' frequency distribution for each subgroup we use in the analysis and test statistics can be found in the Complementary Material of the paper.

In Table 2.2, 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 B.1 and B.2 in the Appendix that once we account for age, we overall do not reject the null hypothesis.[12] 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 subgroup North, high education, although the rejection of the null hypothesis at 5% is not clear in this case. Tables B.3 and B.4 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.

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.

[10] 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.

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

[12] 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.

Table 2.2: Demographic 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	0.332	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

P-values of test between the two groups, for each subgroup 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.

2.5 Comparison of wage mobility and other labor market outcomes

Figure 2.2 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.[13] 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.

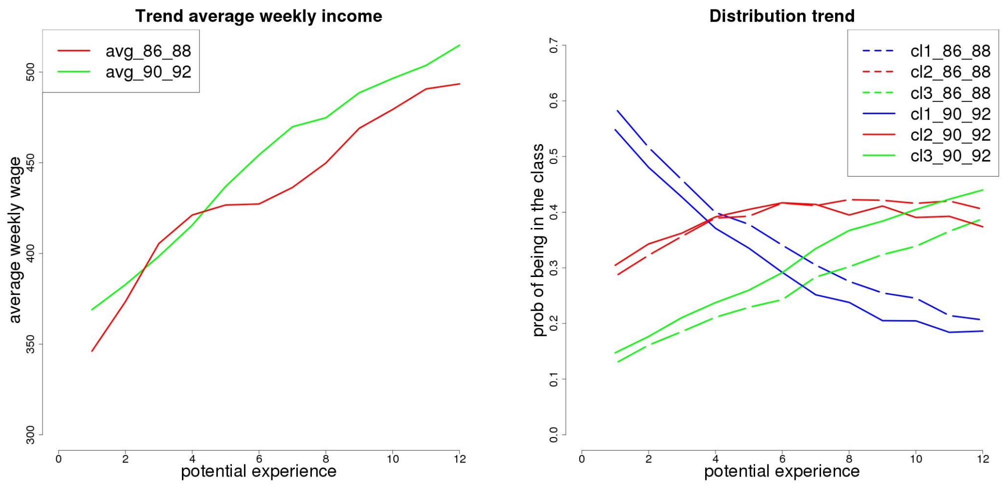


Figure 2.2: Evolution of the real mean weekly wages and of the probabilities of being in the three income classes over the potential experience.
Sources: Authors' calculation.

We summarize the results of our comparison of wage mobility in Table 2.3. We focus on the upward probabilities from class 1 and on the up and downward probabilities from class 2.[14] The subgroups considered are North, Center, South with high education and the whole Italy with low education.

[13]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.

[14]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.

Table 2.3 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.[15]

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. 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 2.3, 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

[15] 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.

mainly arise after the first four years of potential experience.[16] 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.[17] 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 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 B.2 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.

[16]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.

[17]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.

Table 2.3: Comparison of wage mobility.

(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

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.

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 B.5 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 B.6 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 2.1, 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.

2.5.1 Robustness Checks

We summarize in here the main robustness checks outcomes, while we report all the details in Section B.5 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 2.2 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.[18] 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

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

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 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.[19] 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.

2.5.2 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 2.4 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 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

[19] The evolution of the young male unemployment rate in the three areas is presented in Figure B.1 in the Appendix.

Table 2.4: Comparison of other labor market outcomes.

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

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.

with good wage prospective during the high unemployment period will have a persistent effect on new workers.

2.6 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.[20] 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.

[20]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”.

Chapter 3

Internal migration and wage growth in Italy.

3.1 Introduction

Italy is a country characterized by a strong internal migration, where for internal migration we mean moving among the three macro areas North, South and Centre. According to ISTAT[1] more than three millions individuals moved among Italian regions between 1995 and 2004. From an economic point of view, an individual migrates if he has an expected utility gain. This gain can be given by an increase in the wage or by an increase in the likelihood of finding a job. In this paper we focus on the effect of migrating on the salary of young males using Italian administrative data from the Italian Social Security Institute (INPS).

In the literature the effect of internal migration on wages has been recently studied, among others, by Böheim and Taylor [2007] for Britain, Ham et al. [2011], Yankow [2003] for US, Détang-Dessendre et al. [2004] for France. The findings differ: Ham et al. [2011] find a positive contemporaneous effect on wages for college graduates and a negative effect for high school dropouts, Böheim and Taylor [2007] find a positive premium, Yankow [2003] finds a positive immediate return for individuals without college education and a delayed positive effect for college graduated, Détang-Dessendre et al. [2004] do not find any significant effect of migration.

In our analysis on the effect of migration on individuals' wage we focus on young males who have high school as the highest level of education. We run two types of analysis. First we study the effect of migrating on wage growth of the first eleven years of career, then we study the returns to migration on the wages of the following five years. Our analysis follows the steps of Böheim and Taylor [2007], however it differentiates in two aspects: in their analysis they use a first

[1] http://demo.istat.it/altridati/trasferimenti/index_e.html

difference approach to estimate the immediate effect of migration while we use the differenced approach to study the effect on the wage growth in the first eleven years of career; we use a dynamic fixed effect model to study the returns to migration on the wages of the years following migration while they use a static fixed effect model. To our knowledge this is the first work that studies the effect of internal migration on Italian wages.

We find a positive effect on wage growth in the first eleven years of career if the migration spell takes place in the first five years of experience and has the North as destination. On the other hand, we find a negative immediate effect of migration when it has South as destination.

The rest of the paper is structured as follows: in section 2 we describe the data used, in section 3 we present the analysis and the results, in section 4 we conclude.

3.2 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 per year, where every record corresponds to an employment spell. Since individuals could have more than one record per year, we summarize the information in order to obtain one observation per person per year.

In the data the following information on job spells is available: the number of months, weeks, days worked in the year, a string of zeros and ones showing in which months the individual worked, if the spell is part-time, the sum of gross monthly wages and the geographic area where the spell takes place. We have also demographic information on individuals such as sex, province and year of birth. Information on firms such as sector and number of employees is limited to period 1997-2002. We are able to assign firm sectors to job spells preceding 1997 and following 2002 assuming firms do not change sector and at the cost of losing several observations.

There is not information about the education of individuals in the data. Since we assume education does not change for the individuals in the sample and use individual fixed effect techniques in the analysis, this is not a concern.

Only young males who entered the labour market after 1985 at age 14-22 and for whom we observe the 11th year of experience are included in the sample. We consider as new workers those who do not appear in year 1985 and have their first job spell successively. The first spell is the first non-seasonal occupation that lasts more than 12 weeks (we consider a spell to be seasonal if it lasts less than 17 weeks and ends in September or October).

Yearly weekly wages are obtained dividing the total yearly income by the total number of weeks worked (for part time workers we use the number of weeks used for determining the contribution period for old age benefits). For each year and for each individual, we select the most representative spell in terms of weeks worked, spell type (full-time preferred over part-time) and timing (later spells preferred). We call it main spell of the year. Spells that last less than 13 weeks are not considered when determining the number of spells held by the individuals and job changing.

When studying the effect of migration on wages of the five following years, we assume migration and job change to happen at the end of the year and attribute to the year in which they take place the same weekly wage of the previous.[2] This attribution is not unrealistic and allows to fully capture the returns on wages of changing job and migrating.

We estimate inter-year spell duration, tenure and actual experience, exclude from the sample those individuals for whom it was not possible to determine a unique main spell per year, trim top and bottom 1% of the weekly wage distribution, exclude negative wages or wages equal to zero and remove individuals with special wages.

The final sample is an unbalanced panel composed by 8965 males who enter the labor market at age 14-22 and with 11 to 18 years of maximum experience at 2004.

3.3 The Analysis

We investigate the effect of internal migration on the wages of Italian young males at the beginning of their career. In particular we study the effect of moving across the areas North, South and Center of Italy. We consider individuals who entered the labor market between age 14 and 22. This selection should exclude individuals with college education from the sample: the usual minimum age at which individuals obtained a degree in Italy in the analyzed period was 23.

Table 3.1 presents the distributions of first migration and job changing on potential experience in our panel. Out of 8965 individuals, 881 migrates. There is not a clear trend of migration in experience and around half of the migrations have the North as destination. On the other hand, a large number of individuals change job at least once in the first 11 years of career. Also for what concerns job changing there is not a clear trend in experience.

[2]The weekly wage is an average of the wages obtained overall the year. If migration and/or job change happen during the year, then the weekly wage is the average of the two jobs held by the individual and the effect of migration and/or job change on salaries would result smoothed out. This problem could be solved by considering the single spells as unit of time and not the years. We leave this as possible extension of the analysis.

Table 3.1: Job changes and migration.

	exp1-11	exp1	exp2	exp3	exp4	exp5	exp6	exp7	exp8	exp9	exp10	exp11
Change job	8590	2011	2505	2774	2700	2604	2285	2059	1911	2014	2112	2386
First migration	881	98	78	76	81	91	78	85	71	66	67	90
First migr. to N.	469	38	36	48	48	54	39	46	38	36	38	48
First migr. to C.	222	35	17	9	15	22	24	19	21	18	16	26
First migr. to S.	186	25	24	19	18	15	15	19	10	12	13	16

The table indicates how many individuals of the sample changed job and/or migrated for each year of experience. The total number of individuals is 8965.

We run two type of analyses: first we study the effect of migrating on individuals' wage growth in the first 11 years of career, then we analyse the returns to migration on the wages of the years following migration. We implement the first analysis by means of a model in difference while we use a dynamic fixed effect model for the second analysis.

3.3.1 The effect on wage growth in the first 11 years of career

To study the effect of migration on wage growth in the first 11 years of career the following log-linear wage equation is considered:

$$w_{ilt} = X_{ilt}\beta + A_{lt}\alpha + \phi_l + \upsilon_i + \gamma_t + \epsilon_{ilt} \tag{3.1}$$

where w_{ilt} is the logarithm of the real weekly wage of person i, at time t, in location l, X_{ilt} are individual/job characteristics that change over time and among areas, A_{lt} are area specific characteristics that change over time, ϕ_l and υ_i are time invariant location and individuals' characteristics respectively, γ_t are time varying factors common to all individuals.

In X_{ilt} we include the number of job spells held at time t, the number of times the worker changed working area, the square of the age, actual experience held and its square, tenure in the current job and its square, a dummy indicating if the main occupation held by the individual at time t is part-time, dummies for the main occupation at t and its sector. A_{lt} is a set of interactions between year dummy variables and areas dummy variables.

We take the difference between the wage at the eleventh year of career and the wage at the first. As first year of experience we consider the first whole year in the labor market.

The model in differences is:

$$\Delta_{10}w_{il11} = \theta_1 JobChange + \theta_2 JobChange \times Migration + \Delta_{10}X_{il11}\beta + \Delta_{10}A_{l11}\alpha + \Delta_{10}\gamma_{11} + \Delta_{10}\epsilon_{il11} \tag{3.2}$$

Where $JobChange$ and $Migration$ are discrete variables or sets of variables that capture the information on individuals' job changing and migrating. In the analysis, different specifications for $JobChange$ and $Migration$ are considered, taking into account when they occurred and, in the case of migration, towards what area.

To keep the analysis simple, we focus on the first migration spell without considering if an individual migrated more than once. In our data around 50% of the movers migrates once, 30% twice and the rest more times.[3] $Migration$ is included in the equation only through the interaction term with $JobChange$. In order to obtain the effect of migration on wages we need to compare migrants with the best possible control group. Since migration usually coincides with changing occupation, the most appropriate control group is those individuals who change job but do not migrate. This choice is common in literature.

Taking first differences removes the fixed effects ϕ_l, υ_i and, under the assumption of exogeneity, OLS gives an unbiased estimation of the effect of migration on wages.

We assume that, once controlled for fixed effects, migration is exogenous. The presence of time varying self-selection is not proven in the literature. Nakosteen and Zimmer [1980, 1982], Robinson and Tomes [1982] and Gabriel and Schmitz [1995] find evidence of positive self-selection into migration; while Hunt and Kau [1985] and Borjas et al. [1992] find no evidence. In more recent papers, Détang-Dessendre et al. [2004] find some evidence of self-selection for individuals with college degree while they cannot find any for lower educated; Yankow [2003] finds that, for low educated workers, instrumenting migration reduces the magnitude of the positive immediate effect of migrating on wage growth by less than 1% and reduces the significance of the coefficient from 5% to 10%, which cannot be considered a strong evidence in favor of self-selection. Besides, in both Yankow [2003] and Böheim and Taylor [2007] time invariant self-selection is assumed when studying the effect of migration on successive years wage.

We present the results of the estimation of model (3.2) in Table 3.2. The coefficients of the other regressors included in the model are presented in Table C.1 of the Appendix. We present four specifications for migration in Table 3.2. In column (1) we just consider if the individual migrates, in column (2) we add the area of destination of the first migration, in columns (3) and (4) we also include if first migration took place in the first five years of career or afterwards. The results show that first migration has a positive significant effect on individuals' wage growth only if it has North as destination. Moreover it is only important if it takes place in the first five years of career. These results show that it is essential to consider when migration took place and towards what area. Considering just migration as in column (1) would suggest there is not a significant affect of migration on wages. Considering just the time in which migration takes place as in column (3) would suggest a significant average positive effect of migrating in the first five years, while this is true only for individuals who migrate to the North.

[3] It could be interesting to study if individuals who migrate twice have a different wage outcome than those who migrate only once. We leave this analysis as future work.

Table 3.2: Difference analysis

	Dependent variable:			
	log(weekly_wage)			
	(1)	(2)	(3)	(4)
change job	−0.063	−0.062		
	(0.048)	(0.048)		
change job×area	0.074			
	(0.046)			
change job×area to N.		0.148***		
		(0.053)		
change job×area to C.		0.032		
		(0.064)		
change job×area to S.		−0.029		
		(0.061)		
change job yr.1-5			−0.040*	−0.041**
			(0.021)	(0.021)
change job yr.6-10			0.028	0.029
			(0.024)	(0.024)
change job×area yr.1-5			0.103*	
			(0.054)	
change job×area yr.6-10			0.046	
			(0.050)	
change job×area yr.1-5 to N.				0.207***
				(0.061)
change job×area yr. 1-5 to C.				0.020
				(0.086)
change job×area yr.1-5 to S.				−0.104
				(0.079)
change job×area yr.6-10 to N.				0.068
				(0.061)
change job×area yr.6-10 to C.				0.036
				(0.078)
change job×area yr.6-10 to S.				0.027
				(0.079)
R^2	0.226	0.228	0.228	0.232
Adj. R^2	0.223	0.225	0.224	0.228
Num. obs.	2818	2818	2818	2818
Note:				*p<0.1; **p<0.05; ***p<0.01

The dependent variable is the difference between the log weekly wage at experience 11 minus log weekly wage at experience 1. The other regressors included in the model and not in the table are the differences of: job spells held, the number of times the worker changed working area, the square of the age, the actual experience held and its square, the tenure in the current job and its square, a dummy indicating if the main occupation held by the individual is part-time, the main occupation, the sector of the main occupation, year dummy variables (from 1988 to 1993 the possible staring years), a set of interactions between the year dummy variables and areas dummy variables. For dummies, the reference area is North, year is 1987, occupation is Apprentices, sector is Industry.

Columns (3) and (4) of the table also suggest that individuals who do not change job in the first five years of career have a significantly higher wage growth at the end of the period. This indicates that individuals who find a stable occupation at the beginning of their career enjoy a larger income growth in the long run. This finding is in line with theories on work specific human capital accumulation: to have a stable occupation allows to build a specific human capital that individuals with erratic works cannot develop. This human capital accumulation will result in a higher wage growth. This finding is also in line with the results by Light and McGarry [1998] who find lower wage paths for individuals who undergo persistent job mobility.

3.3.2 The effect on the wage of the years following migration

We use dynamic panel fixed effect techniques to study the consequences of the first migration on successive years wage. The model we estimate is:

$$w_{ilt} = \sum_{z=1}^{A} \rho_z w_{ilt-z} + \sum_{j=1}^{P} \theta_{1j} JobChange_{it-j} + \sum_{j=1}^{P} \theta_{2j} JobChange_{it-j} \times Migration_{it-j} + X_{ilt}\beta + \phi_l + \upsilon_i + \gamma_t + \epsilon_{ilt}; \quad (3.3)$$

where X_{ilt} includes the number of job spells held at time t, the number of times the worker changed working area, the age and its square, experience square, the actual experience held, the tenure in the current job, a dummy indicating if the main occupation held by the individual at time t is part-time, dummies for the main occupation and the sector at time t.
In this framework, θ_{2j} is the effect of the first migration on the wage of j years later. Since we assume job changing and migration take place at the end of the year, the effect of changing area on the wage of the same year is not included.

We again assume that, once controlled for fixed effects, migration is exogenous and estimate the model by means of Arellano-Bond estimator using lags three to seven as instruments. We tried different specifications of the model including up to three legs of the autoregressive component. The estimated parameters are robust to the different specifications. Using an AR(1) specification for wages the null of iid residuals in levels is rejected, while with an AR(2) and an AR(3) it is not. We report the results of the AR(2) specification.

We use all the available observations for each individual considered in the previous analysis. This results in an unbalanced panel in which individuals have from 11 to 18 years of maximum experience.

Including an AR(2) process for wages and Arellano-Bond methodology lead to exclude the first three observations for each individual causing to not consider those migrations that happen in the first three years of experience. The different experience window considered makes the results of this analysis not comparable with the one of the previous section. In this analysis we consider those migrations that take place between the fourth and the seventeenth year of experience, while before we considered from year one to ten. The individuals in the sample we are using in this analysis have larger experience, we include years of experience not considered before (from the twelfth to the eighteenth) and we lose the first three years of career.

We consider up to five lags for migration and the destination area. We present the estimation of equation (3.3) in Table 3.3. The rest of the estimated parameters are presented in Table C.2 in the Appendix. Overall, migration does not have a significant effect on the salaries up to five years later. The only exception is a negative significant effect of migrating towards the South on the wage of the first year following migration. As in the previous analysis, not considering the destination of the migration, e.g. columns (1) and (3), would result in a non significant estimated effect of migration on future wages. In the previous analysis we find a positive effect of migrating towards North before the sixth year of career on the ten years wage growth. In here we do not include in the analysis the first three years of career, this may cause the loss of the positive effect of migrating to the North on wages. The immediate effect of changing job on the successive year wage is positive and significant. The difference in the sign of the effect of changing job on wages in comparison with the previous analysis can be explained in terms of the different experience window we are considering: here more experienced individuals with a larger set of skills and a more stable occupation are considered.

Negative contemporaneous returns to migration on wages between the first and second job for high school dropouts were found by Ham et al. [2011], while they do not find any significant effect for individuals with high school degree and other education levels.

3.4 Concluding remarks

In this work we study the effect of internal migration on the wages of Italian young males. First we focus on the effect of the first migration on wage growth in the first eleven years of career, finding a positive significant effect of the first migration when it takes place in the first five years of career and towards the North. Successively we study the effect of migration on the five successive year wages through a dynamic model and find an immediate significant negative effect of migrating to the South.

The two analyses show the importance of considering the destination of the migration spell and its timing. In both analysis, not accounting for the destination and the timing would lead to non significant effects of migration.

The results suggest that migrating to the North has a positive impact on wage growth while migrating to the South has a negative immediate impact on wages. These results may be

Table 3.3: Dynamic fixed effects model.

	Dependent variable: log(weekly_wage)			
	(1)	(2)	(3)	(4)
change job_{t-1}	0.048***	0.029***	0.049***	0.029***
	(0.008)	(0.006)	(0.008)	(0.006)
change job_{t-2}		0.008		0.007
		(0.006)		(0.006)
change job_{t-3}		0.010**		0.010**
		(0.004)		(0.004)
change job_{t-4}		0.003		0.003
		(0.003)		(0.003)
change job_{t-5}		0.002		0.002
		(0.003)		(0.003)
change job×$area_{t-1}$	−0.030	−0.040		
	(0.025)	(0.035)		
change job×$area_{t-2}$		−0.003		
		(0.027)		
change job×$area_{t-3}$		−0.012		
		(0.023)		
change job×$area_{t-4}$		−0.014		
		(0.019)		
change job×$area_{t-5}$		−0.015		
		(0.015)		
change job×area to $N._{t-1}$			0.041	0.042
			(0.037)	(0.046)
change job×area to $C._{t-1}$			−0.065	−0.088
			(0.058)	(0.081)
change job×area to $S._{t-1}$			−0.110**	−0.122*
			(0.035)	(0.055)
change job×area to $N._{t-2}$				0.030
				(0.040)
change job×area to $C._{t-2}$				−0.048
				(0.057)
change job×area to $S._{t-2}$				−0.007
				(0.044)
change job×area to $N._{t-3}$				0.000
				(0.035)
change job×area to $C._{t-3}$				0.007
				(0.029)
change job×area to $S._{t-3}$				−0.039
				(0.050)
change job×area to $N._{t-4}$				0.000
				(0.025)
change job×area to $C._{t-4}$				−0.004
				(0.027)
change job×area to $S._{t-4}$				−0.034
				(0.053)
change job×area to $N._{t-5}$				−0.011
				(0.017)
change job×area to $C._{t-5}$				−0.037
				(0.025)
change job×area to $S._{t-5}$				0.011
				(0.047)
Num. obs. used	26888	17600	26888	17600
Sargan Test: p-value	0.170	0.824	0.176	0.792
Wald Test Coefficients: p-value	0.000	0.000	0.000	0.000
Autocorrelation test (1): p-value	0.001	0.034	0.001	0.027
Autocorrelation test (2): p-value	0.256	0.608	0.270	0.688

Note: *p<0.1; **p<0.05; ***p<0.01

Arellano-Bond estimator with lags 3 to 7 as instruments. The other regressors included in the model are the number of job spells held at time t, the number of times the worker changed working area, the age and its square, experience square, the actual experience held, the tenure in the current job, a dummy indicating if the main occupation held by the individual at time t is part-time, the main occupation at t, the sector of the main occupation. For dummies, the reference area is North, occupation is Apprentices, sector is Industry.

expected. It is known that the North of Italy is richer and with a better wage mobility than the South. Further, in the analysis we consider individuals with maximum high school education and these individuals are the most affected by the economic environment they live in.[4] If an individual's wage growth depends on the economic environment he lives in, then moving to a richer and more dynamic area will have a positive effect on the evolution of his salaries.

The analysis could be extended in several ways. In this paper it was assumed that, once accounted for individual fixed effect, migration self selection is constant. Although the empirical evidence in the literature is not clear, time varying self-selection is a plausible assumption and it can be argued it should been considered. The most straightforward way to solve the problem would be to find a time varying instrument. The time varying instrument is needed because of the use of difference and fixed effect approaches. We have as only instrument a binary variable that takes value one if the individual starts to work in the same province where he was born. This variable is a measure of the cost of migrating and it is negatively correlated with migration. However it cannot be used in the analysis as it is since it is time invariant. A possible way to address the problem is by substituting the migration binary variable by a propensity score estimated by a probit model. With this approach the model remains identified when using a first difference or fixed effect estimator also if the instrument is time invariant because of the non linear transformation given by the probit. However the application of this approach to our model specifications is not straightforward and needs further investigation.

We considered areas North, South, Centre. With this choice, an individual who lives on the boundary of an area could result as migrant just going to work for a company at the other side of the boundary, without migrating. This problem could be solved removing the area Centre from the analysis or using another definition of migration. An interesting definition of migration could be obtained by using distances: for example an individual migrates if he moves to a province more than 100 km away from the one he used to work in. In order to implement such as definition of migration it would be necessary to construct the database with the distances among Italian provinces. We leave this as future work.

The analysis could also be extended considering the effect of migration on other covariates such as number of weeks worked per year or yearly income. The analysis of these outcome would complement the analysis, although it would present the same self-selection issues reported above.

[4] Individuals with higher education have more working opportunities and can choose among them. The fact of having a choice makes individuals more independent from the economic environment compared to others that do not have any.

Appendix A

Appendix to Chapter 1

A.1 Tables

Table A.1: Regional income and age moments of the active population.

	min	1st q	med	mean	3rd q	max
Inc. North 2004	0	12000	15000	17210	20000	100000
Inc. North 2008	0	14000	17360	19300	22000	79500
Inc. South 2004	0	10000	14000	14300	18000	60000
Inc. South 2008	0	11130	16000	16440	20000	60000
Age North 2004	16	35	42	41	48	67
Age South 2004	16	37	45	43	50	68

Source: authors' calculation from the historical archive of SHIW by Bank of Italy.

Table A.2: National Income Quantiles of the active population.

Quantiles:	0	1/3	2/3	1
Inc. 2004	0	12500	17000	100000
Inc. 2008	0	15000	19542	79500

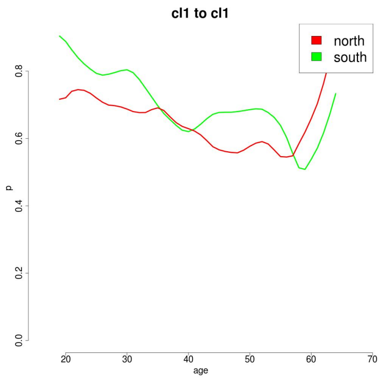
Source: authors' calculation from the historical archive of SHIW by Bank of Italy.

Table A.3: Probit estimates.

cl. 2004	cl. 2008	c	age	age*$d^{(s)}$	age^2
1	1	1.885	-0.065	0.004	0.001
		(0.002)	(0.045)	(0.116)	(0.139)
1	2	-1.382	0.030	-0.005	0.000
		(0.034)	(0.403)	(0.111)	(0.454)
1	3	-3.820	0.117	-0.004	-0.001
		(0.000)	(0.012)	(0.231)	(0.048)
2	1	1.748	-0.113	0.000	0.001
		(0.058)	(0.014)	(0.890)	(0.020)
2	2	-1.568	0.082	0.000	-0.001
		(0.085)	(0.071)	(0.835)	(0.059)
2	3	-1.692	0.035	0.001	0.000
		(0.101)	(0.494)	(0.794)	(0.664)
3	1	-0.343	-0.034	0.007	0.000
		(0.825)	(0.634)	(0.018)	(0.696)
3	2	-0.543	0.004	0.005	0.000
		(0.703)	(0.948)	(0.080)	(0.737)
3	3	-0.493	0.027	-0.008	0.000
		(0.704)	(0.652)	(0.001)	(0.883)

P-values are reported below coefficients.
Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel.

Figure A.1: Conditional transition probabilities



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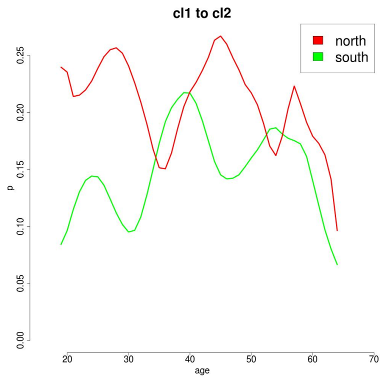

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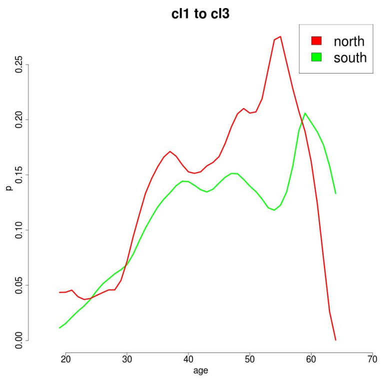

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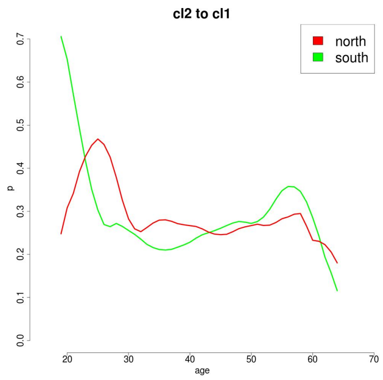

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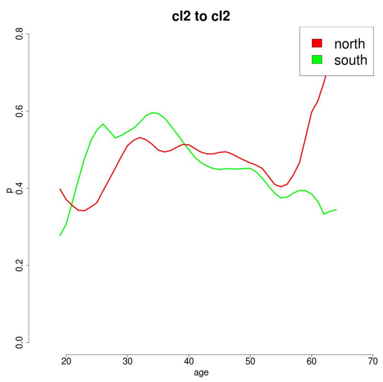

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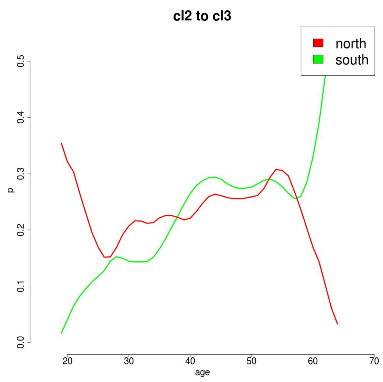

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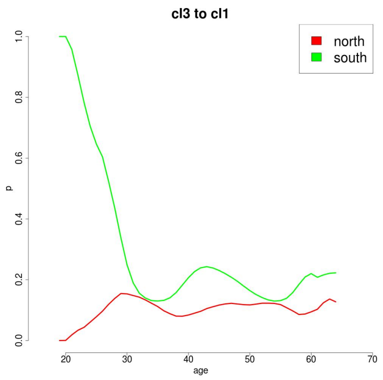

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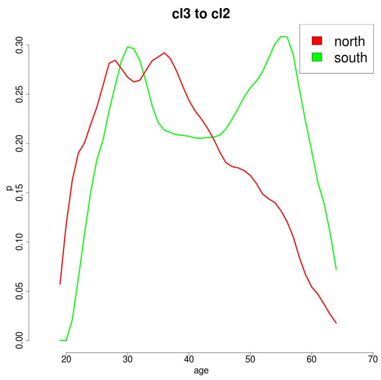
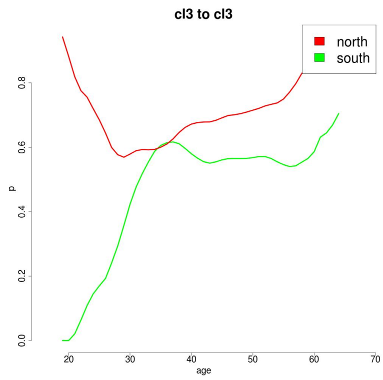


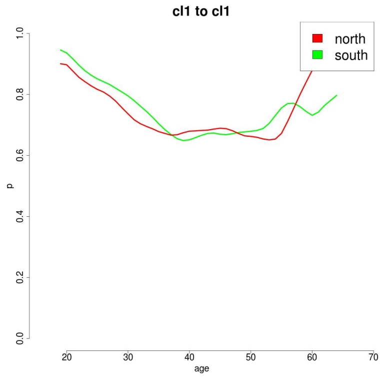
(h) Cl 3 to 2.



(i) Cl 3 to 3.

Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel sample. The conditional transition probabilities were estimated with the methodology described in section 2; with the Epanechnikov kernel,the bandwidths as in the Monte Carlo simulation and weight 5. The reported values are obtained through a moving average of 9 elements of the estimated probabilities.

Figure A.2: Conditional transition probabilities for education classes.



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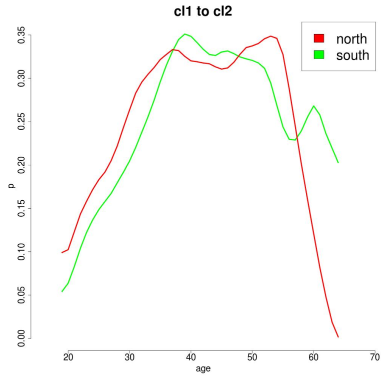
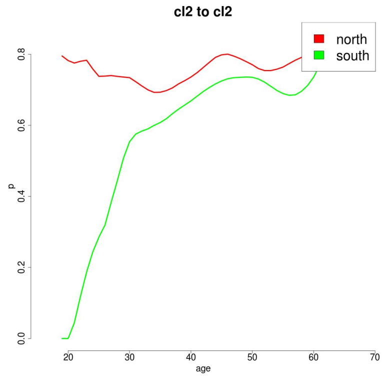


(b) Cl 1 to 2.

(c) Cl 2 to 1.



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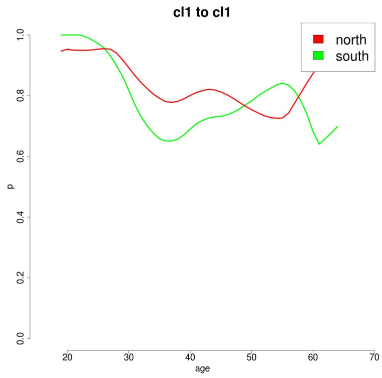

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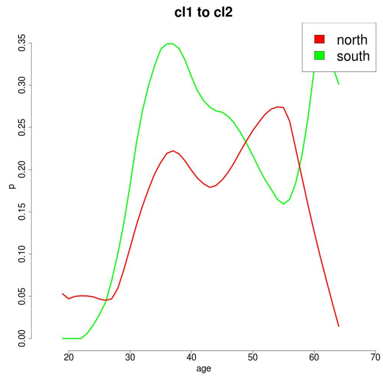

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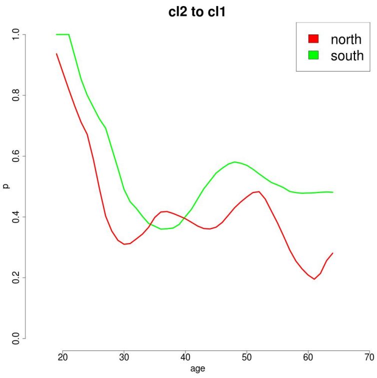

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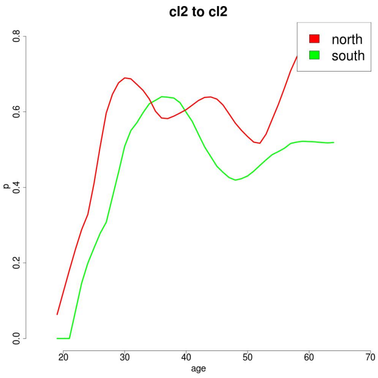

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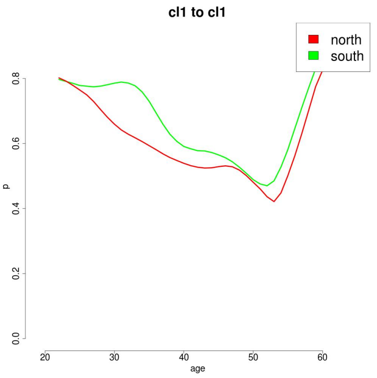
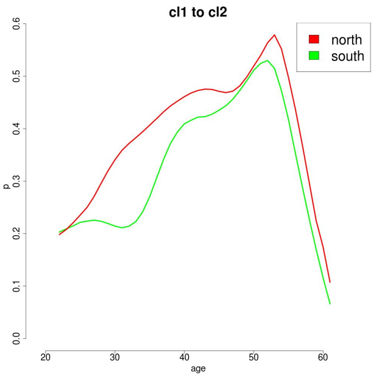


(i) Cl 1 to 1 high ed.



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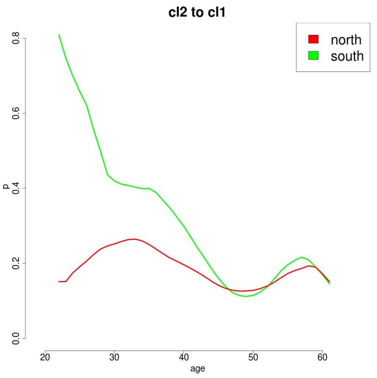
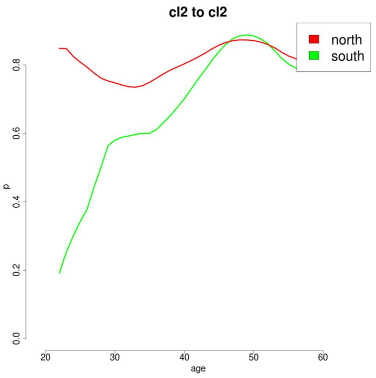


(k) Cl 2 to 1 high ed.



(l) Cl 2 to 2 high ed.

Source: authors' calculation from the historical archive of SHIW by Bank of Italy using the panel sample. The conditional transition probabilities were estimated with the methodology described in section 2; with the Epanechnikov kernel,the bandwidths as in the Monte Carlo simulation and weight 5. The reported values are obtained through a moving average of 9 elements of the estimated probabilities.

Appendix B

Appendix to Chapter 2

B.1 Demographic analysis

Table B.1: Chi-squared test on occupation for age classes, South, high education

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age and starting class. The null hypothesis is the equality of the probability distribution.

Table B.2: Chi-squared test on occupation for age classes, South, high education

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age class and starting class. The null hypothesis is the equality of the probability distribution.

Table B.3: Chi-squared test on occupation for age classes, North, high education

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age and starting class. The null hypothesis is the equality of the probability distribution.

Table B.4: Chi-squared test on occupation for age classes, North, high education

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age class and starting class. The null hypothesis is the equality of the probability distribution.

B.2 Potential experience

Table B.5: Starting experience distribution in the subgroups of analysis

	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 B.6: Test for potential experience at start.

	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

P-values of the Pearson's χ^2 test for experience at start, for the subgroups of analysis and starting class. The null hypothesis is the equality of the probability distribution of experience at start between subgroups.

B.3 Regional Unemployment Rates

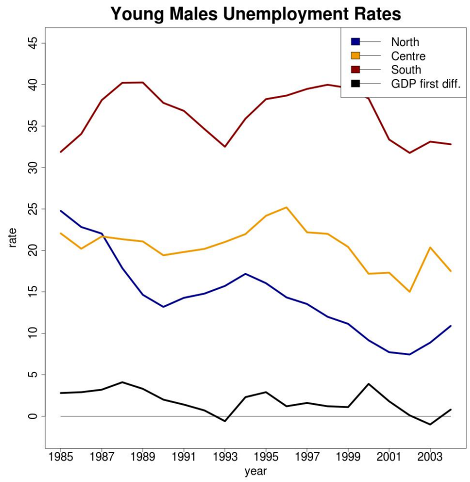


Figure B.1: Regional Unemployment Rates.

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

B.4 Schools Enrollment Rates

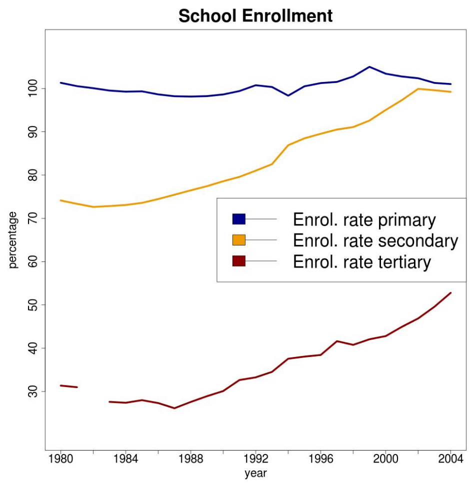


Figure B.2: Primary, secondary and tertiary education gross enrollment rates for males in Italy.

Source: World Development Indicators database by the World Bank (http://data.worldbank.org/).

B.5 Robustness checks

B.5.1 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[1]. Our results are robust to the different definition of first spell.

From Table B.7 and from Tables B.8 and B.9 we see that the demographic analysis results are close to those obtained in the original and we can investigate wage mobility on the same subgroups 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 B.10. The signs of the differences and their significance level are similar to those in the main analysis.

Table B.8: Chi-squared test on occupation for age classes, South, high education - Changing the first spell definition.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age and starting class. The null hypothesis is the equality of the probability distribution.

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

Table B.7: Demographic analysis - Changing the first spell definition.

	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

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.

Table B.9: Chi-squared test on occupation for age classes, South, high education - Changing the first spell definition.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age class and starting class. The null hypothesis is the equality of the probability distribution.

Table B.10: Comparison of wage mobility - Changing the first spell definition.

(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

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.

B.5.2 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 B.11 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 B.12 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 B.13. 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 B.14, 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.

Table B.11: Demographic analysis - Five classes of income

		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
Occupation	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
	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
Occupation no Apprentices	cl1	0.431		0.313	0.495	1.000	0.338	0.734	0.401	0.919	0.179	0.253	0.734
	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
	cl3	0.199	0.663	0.140	0.159	1.000	0.161	0.026		0.057	0.011	0.692	0.010
	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
Occupation replaced Apprentices	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
	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
	cl3	0.059	0.513	0.088	0.218	0.485	0.154	0.053		0.087	0.001	0.382	0.006
	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
Age	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
	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
Education	cl1	0.000			0.048			0.293			0.297		
	cl2	0.000			0.136			0.086			0.042		
	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		
Region	cl1										0.000	0.032	0.000
	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

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.

Table B.12: Comparison of wage mobility - Five classes of income - Short run: periods 89-93 and 93-97 respectively.

		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

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.

Table B.13: Comparison of wage mobility - Five classes of income - Long run: periods 89-99 and 93-03 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

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.

Table B.14: Comparison of wage mobility - Five classes of income - Successive years: periods 93-99 and 97-03 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

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.

B.5.3 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 2.2 shows they have higher wages).

Table B.15 and Tables B.16-B.19 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 B.20. 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.

Table B.16: Chi-squared test on occupation for age classes, North, high education - Select adjacent periods.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age and starting class. The null hypothesis is the equality of the probability distribution.

Table B.15: Demographic analysis - Select adjacent periods

	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

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.

Table B.17: Chi-squared test on occupation for age classes, North, high education - Select adjacent periods.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age class and starting class. The null hypothesis is the equality of the probability distribution.

Table B.18: Chi-squared test on occupation for age classes, South, high education - Select adjacent periods.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age and starting class. The null hypothesis is the equality of the probability distribution.

Table B.19: Chi-squared test on occupation for age classes, South, high education - Select adjacent periods.

(a) With apprentices

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

(b) Without apprentices

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

(c) Replacing apprentices

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

P-values of the Pearson's χ^2 test for type of occupation between the two subgroups, for each age class and starting class. The null hypothesis is the equality of the probability distribution.

Table B.20: Comparison of wage mobility - Select adjacent periods.

(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

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 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.

B.5.4 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 B.21 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 B.22. 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.

Table B.21: Demographic Analysis - Age up to 22.

	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

P-values of test between the two groups, for each subgroup 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.

Table B.22: Comparison of wage mobility - Age up to 22.

(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

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.

B.5.5 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 B.24 and of the potential starting experience in Table B.25 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 B.26. The periods of analysis are the same than in the original. Following the results of the demographic analysis in Table B.24, 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.

Table B.23: Comparison of the proportion of the different types of first occupation, education, first area of work for groups 87-88 91-92, and sample sizes.

	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
Man. & 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 B.24: Demographic analysis - Groups 87-88 and 91-92

	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
Occupation	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
	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 no Apprentices	1	0.103		0.140	0.272	0.631	0.161	0.105	1.000	0.073	0.051	1.000	0.136
	2	0.317	0.686	0.376	0.809		1.000	0.101	1.000	0.095	0.083	0.693	0.118
	3	0.191	1.000	0.166	0.623		0.569	1.000		0.822	0.714	1.000	0.464
Occupation replaced Apprentices	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
	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
	3	0.174	1.000	0.146	0.739		0.622	1.000		0.834	0.706	1.000	0.436
Age	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
	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
Education	1	0.000			0.148			0.228			0.001		
	2	0.005			0.899			0.189			0.003		
	3	0.681			0.388			0.111			0.034		
Region	1										0.000	0.460	0.000
	2										0.000	0.078	0.000
	3										0.000	0.097	0.001

P-values of test between the two groups, for each subgroup 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.

Table B.25: Test for potential experience at start - Groups 87-88 and 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

P-values of the Pearson's χ^2 test for experience at start, for the subgroups of analysis and starting class. The null hypothesis is the equality of the probability distribution of experience at start between subgroups.

Table B.26: Comparison of wage mobility - Groups 88-87 and 91-92

(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

The tables present the difference between the transition probabilities from group 87-88 (high unemployment) minus group 91-92 (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.

B.5.6 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 B.27. 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.

Table B.27: Comparison of wage mobility on the same period 00-04.

		High educ.			Low Education
Prob		North	Centre	South	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

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.

B.5.7 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 B.28 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.

Table B.28: Comparison of wage mobility - 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

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.

B.5.8 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%).[2]

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 B.29 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 B.30 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 B.31 and B.32 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 B.33. 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

[2] The evolution of the young male unemployment rate in the three areas is presented in Figure B.1 in the Appendix.

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.

Table B.29: Comparison of the proportion of the different types of first occupation, education, first area of work for groups 95-97 91-93, and sample sizes.

	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
Man. & 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 B.31: Comparison of the proportion of the different types of first occupation, education, first area of work for groups 87-89 95-97, and sample sizes.

	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
Man. & 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	3174	1381	1434	503	388	819	356	1779	996

Table B.30: Demographic analysis - Groups 95-97 91-93

		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
Occupation	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
	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 no Apprentices	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
	cl2	0.032	1.000	0.019	0.001		0.001	0.001	1.000	0.003	0.000	1.000	0.000
	cl3	0.568		0.539	0.866		1.000	0.408		0.332	0.472	0.241	0.349
Occupation replaced Apprentices	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
	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
	cl3	0.491	0.561	0.521	1.000	1.000	1.000	0.434		0.245	0.305	1.000	0.247
Age	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
	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
Education	cl1	0.000			0.000			0.610			0.000		
	cl2	0.462			0.904			0.315			0.756		
	cl3	0.687			0.761			0.318			0.574		
Region	cl1										0.199	0.552	0.006
	cl2										0.774	0.293	0.875
	cl3										0.034	0.323	0.035

P-values of test between the two groups, for each subgroup 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.

Table B.32: Demographic analysis - Groups 87-89 95-97

		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
Occupation	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
	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 no Apprentices	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
	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
	cl3	0.056		0.028	0.893	0.245	1.000	0.472		0.449	0.074	0.250	0.028
Occupation replaced Apprentices	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
	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
	cl3	0.101	1.000	0.034	0.896	0.328	0.794	0.465		0.420	0.082	1.000	0.030
Age	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
	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
Education	cl1	0.000			0.000			0.855			0.000		
	cl2	0.002			0.072			0.159			0.002		
	cl3	0.262			1.000			0.550			0.293		
Region	cl1										0.000	0.317	0.000
	cl2										0.000	0.013	0.000
	cl3										0.001	0.590	0.000

P-values of test between the two groups, for each subgroup 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.

Table B.33: Comparison of wage mobility - 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

The tables present the difference between the transition probabilities from group 95-97 (high unemployment) minus group 91-93 (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.

B.6 Complementary Material - Extra tables

B.6.1 Data

Table B.34: Final sample size for each year.

year	n. individuals	n. new workers	n. male new workers
1986	121110	6700	3971
1987	117475	5896	3461
1988	116371	5976	3384
1989	116290	5841	3261
1990	116513	5817	3308
1991	118676	5836	3320
1992	119488	5321	3002
1993	115171	3965	2241
1994	111830	3912	2172
1995	112034	4035	2248
1996	113120	3917	2211
1997	109910	3717	2086
1998	107133	4291	2392
1999	108492	4391	2431
2000	114419	4888	2788
2001	117151	4271	2408
2002	121325	4295	2469
2003	126383	4553	2807
2004	128787	3289	2026

B.6.2 Demographic analysis

Table B.35: Occupation distribution, North, high education

Cl	Group	Apprentices	Blue collars	Managers & white collars	Others
1	1	0.18	0.73	0.09	0.00
1	2	0.16	0.75	0.10	0.00
2	1	0.04	0.71	0.25	0.00
2	2	0.03	0.67	0.30	0.00
3	1	0.01	0.44	0.55	0.00
3	2	0.01	0.43	0.55	0.01
all cl.	1	0.07	0.64	0.29	0.00
all cl.	2	0.06	0.62	0.32	0.00

Table B.36: Chi-square test on occupation distribution, North, high education

	test stat	p-value
cl1	3.482	0.521
cl2	5.884	0.093
cl3	4.296	0.352
all cl.	8.151	0.059

Table B.37: Occupation distribution without Apprentices, North, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.88	0.11	0.00
1	2	0.89	0.11	0.00
2	1	0.74	0.26	0.00
2	2	0.69	0.31	0.00
3	1	0.44	0.55	0.00
3	2	0.44	0.56	0.01
all cl.	1	0.69	0.31	0.00
all cl.	2	0.66	0.34	0.00

Table B.38: Chi-square test on occupation distribution without Apprentices, North, high education

	test stat	p-value
cl1	2.831	0.453
cl2	4.509	0.063
cl3	4.259	0.209
all cl.	6.902	0.048

Table B.39: Occupation distribution replacing Apprentices, North, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.88	0.12	0.00
1	2	0.89	0.11	0.00
2	1	0.75	0.25	0.00
2	2	0.70	0.30	0.00
3	1	0.44	0.55	0.00
3	2	0.44	0.55	0.01
all cl.	1	0.70	0.30	0.00
all cl.	2	0.67	0.32	0.00

Table B.40: Chi-square test on occupation distribution replacing Apprentices, North, high education

	test stat	p-value
cl1	2.859	0.407
cl2	5.588	0.039
cl3	4.242	0.217
all cl.	7.065	0.053

Table B.41: Kolmogorov Smirnov test on age distribution, North, high education

	test stat	p-value
cl1	0.122	0.005
cl2	0.177	0.000
cl3	0.088	0.074
all cl.	0.132	0.000

Table B.42: Occupation distribution, Center, high education

Cl	Group	Apprentices	Blue collars	Managers & white collars	Others
1	1	0.11	0.73	0.16	
1	2	0.15	0.71	0.14	
2	1	0.03	0.69	0.28	
2	2	0.01	0.65	0.33	
3	1	0.03	0.38	0.58	0.01
3	2	0.00	0.41	0.59	0.00
all cl.	1	0.06	0.62	0.32	0.00
all cl.	2	0.05	0.60	0.35	0.00

Table B.43: Chi-square test on occupation distribution, Center, high education

	test stat	p-value
cl1	1.553	0.459
cl2	3.459	0.193
cl3	7.404	0.037
all cl.	3.114	0.393

Table B.44: Occupation distribution without Apprentices, Center, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.82	0.18	
1	2	0.83	0.17	
2	1	0.71	0.29	
2	2	0.66	0.34	
3	1	0.39	0.60	0.01
3	2	0.41	0.59	0.00
all cl.	1	0.66	0.34	0.00
all cl.	2	0.63	0.37	0.00

Table B.45: Chi-square test on occupation distribution without Apprentices, Center, high education

	test stat	p-value
cl1	0.140	0.775
cl2	1.460	0.268
cl3	2.594	0.306
all cl.	2.988	0.217

Table B.46: Occupation distribution replacing Apprentices, Center, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.81	0.18	0.01
1	2	0.84	0.16	0.00
2	1	0.72	0.28	
2	2	0.67	0.33	
3	1	0.39	0.59	0.01
3	2	0.41	0.59	0.00
all cl.	1	0.66	0.33	0.01
all cl.	2	0.65	0.35	0.00

Table B.47: Chi-square test on occupation distribution replacing Apprentices, Center, high education

	test stat	p-value
cl1	1.363	0.515
cl2	1.523	0.221
cl3	2.488	0.340
all cl.	3.768	0.150

Table B.48: Kolmogorov Smirnov test on age distribution, Center, high education

	test stat	p-value
cl1	0.059	0.924
cl2	0.119	0.082
cl3	0.159	0.046
all cl.	0.105	0.005

Table B.49: Occupation distribution, South, high education

Cl	Group	Apprentices	Blue collars	Managers & white collars	Others
1	1	0.07	0.85	0.08	0.00
1	2	0.08	0.80	0.12	0.00
2	1	0.03	0.74	0.23	
2	2	0.04	0.64	0.32	
3	1		0.43	0.55	0.02
3	2		0.45	0.55	0.00
all cl.	1	0.05	0.77	0.18	0.00
all cl.	2	0.06	0.70	0.25	0.00

Table B.50: Chi-square test on occupation distribution, South, high education

	test stat	p-value
cl1	6.430	0.121
cl2	5.738	0.057
cl3	1.484	0.568
all cl.	12.903	0.007

Table B.51: Occupation distribution without Apprentices, South, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.91	0.08	0.00
1	2	0.87	0.13	0.00
2	1	0.76	0.24	
2	2	0.66	0.34	
3	1	0.43	0.55	0.02
3	2	0.45	0.55	0.00
all cl.	1	0.81	0.19	0.00
all cl.	2	0.74	0.26	0.00

Table B.52: Chi-square test on occupation distribution without Apprentices, South, high education

	test stat	p-value
cl1	6.129	0.051
cl2	5.247	0.020
cl3	1.484	0.588
all cl.	12.571	0.001

Table B.53: Occupation distribution replacing Apprentices, South, high education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.92	0.08	0.00
1	2	0.88	0.12	0.00
2	1	0.77	0.23	
2	2	0.67	0.33	
3	1	0.43	0.55	0.02
3	2	0.45	0.55	0.00
all cl.	1	0.81	0.18	0.00
all cl.	2	0.75	0.25	0.00

Table B.54: Chi-square test on occupation distribution replacing Apprentices, South, high education

	test stat	p-value
cl1	5.008	0.115
cl2	5.005	0.038
cl3	1.484	0.595
all cl.	11.465	0.002

Table B.55: Kolmogorov Smirnov test on age distribution, South, high education

	test stat	p-value
cl1	0.036	0.959
cl2	0.044	0.981
cl3	0.068	0.986
all cl.	0.045	0.474

Table B.56: Occupation distribution, Italy, low education

Cl	Group	Apprentices	Blue collars	Managers & white collars	Others
1	1	0.89	0.10	0.00	0.00
1	2	0.89	0.11	0.00	0.00
2	1	0.63	0.34	0.03	
2	2	0.63	0.35	0.01	
3	1	0.50	0.47	0.03	
3	2	0.72	0.22	0.06	
all cl.	1	0.85	0.14	0.01	0.00
all cl.	2	0.86	0.14	0.00	0.00

Table B.57: Chi-square test on occupation distribution, Italy, low education

	test stat	p-value
cl1	2.593	0.710
cl2	2.313	0.320
cl3	2.993	0.215
all cl.	4.321	0.372

Table B.58: Occupation distribution without Apprentices, Italy, low education

Cl	Group	Blue collars	Executives	Managers & white collars	Others
1	1	0.97	0.01	0.01	0.01
1	2	0.99	0.00	0.01	0.00
2	1	0.91		0.09	
2	2	0.97		0.03	
3	1	0.94		0.06	
3	2	0.80		0.20	
all cl.	1	0.95	0.01	0.04	0.00
all cl.	2	0.98	0.00	0.02	0.00

Table B.59: Chi-square test on occupation distribution without Apprentices, Italy, low education

	test stat	p-value
cl1	2.593	0.616
cl2	2.305	0.184
cl3	0.836	0.409
all cl.	4.043	0.256

Table B.60: Occupation distribution replacing Apprentices, Italy, low education

Cl	Group	Blue collars	Managers & white collars	Others
1	1	0.97	0.03	0.00
1	2	0.97	0.03	0.00
2	1	0.93	0.07	
2	2	0.95	0.05	
3	1	0.97	0.03	
3	2	0.89	0.11	
all cl.	1	0.96	0.03	0.00
all cl.	2	0.97	0.03	0.00

Table B.61: Chi-square test on occupation distribution replacing Apprentices, Italy, low education

	test stat	p-value
cl1	4.876	0.189
cl2	0.700	0.505
cl3	1.303	0.542
all cl.	4.623	0.208

Table B.62: Kolmogorov Smirnov test on age distribution, Italy, low education

	test stat	p-value
cl1	0.031	0.512
cl2	0.060	0.867
cl3	0.295	0.268
all cl.	0.026	0.651

Table B.63: Area of work distribution, Italy, low education

Cl	Group	North	Center	South
1	1	0.64	0.16	0.19
1	2	0.67	0.17	0.16
2	1	0.72	0.12	0.15
2	2	0.78	0.14	0.07
3	1	0.66	0.09	0.25
3	2	0.78	0.17	0.06
all cl.	1	0.65	0.16	0.19
all cl.	2	0.68	0.17	0.15

Table B.64: Chi-square test on area of work, Italy, low education

	test stat	p-value
cl1	4.253	0.114
cl2	5.917	0.056
cl3	3.173	0.212
all cl.	8.246	0.017

B.6.3 Analysis Tables

Table B.65: Analysis groups 86-88, 90-92, North, high education, periods 89-93 and 93-97 respectively.

(a) Transition prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.45	0.46	0.10	350
1/3-2/3	0.10	0.56	0.34	723
>2/3	0.03	0.12	0.85	363

(b) Transition prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.46	0.44	0.10	481
1/3-2/3	0.07	0.56	0.37	854
>2/3	0.03	0.12	0.85	517

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	-0.02	0.01	0.00
1/3-2/3	0.03	0.00	-0.03
>2/3	-0.00	-0.00	0.00

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.651	0.682	0.942
1/3-2/3	0.038	0.942	0.200
>2/3	0.767	0.947	0.841

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.475	0.170	0.290
1/3-2/3	0.000	0.145	0.005
>2/3	0.020	0.745	0.210

Table B.66: Analysis groups 86-88, 90-92, Center, high education, periods 89-93 and 93-97 respectively.

(a) Transition prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.55	0.36	0.09	171
1/3-2/3	0.15	0.49	0.35	217
>2/3	0.03	0.12	0.85	138

(b) Transition prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.53	0.39	0.09	176
1/3-2/3	0.16	0.60	0.24	237
>2/3	0.02	0.16	0.82	164

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.02	-0.02	0.00
1/3-2/3	-0.00	-0.11	0.11
>2/3	0.01	-0.04	0.02

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.691	0.647	0.934
1/3-2/3	0.905	0.018	0.007
>2/3	0.546	0.376	0.564

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.280	0.120	0.080
1/3-2/3	0.095	0.000	0.000
>2/3	0.230	0.000	0.050

Table B.67: Analysis groups 86-88, 90-92, South, high education, periods 89-93 and 93-97 respectively.

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.64	0.30	0.05	557
1/3-2/3	0.24	0.55	0.21	295
>2/3	0.06	0.23	0.71	110

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.68	0.27	0.05	297
1/3-2/3	0.20	0.59	0.21	180
>2/3	0.06	0.13	0.81	77

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	-0.03	0.03	-0.00
1/3-2/3	0.04	-0.04	-0.00
>2/3	-0.00	0.10	-0.10

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.315	0.292	0.999
1/3-2/3	0.257	0.356	0.981
>2/3	0.972	0.078	0.124

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.030	0.045	0.185
1/3-2/3	0.005	0.020	0.225
>2/3	0.355	0.045	0.020

Table B.68: Analysis groups 86-88, 90-92, Italy, low education, periods 89-93 and 93-97 respectively.

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.60	0.35	0.05	1558
1/3-2/3	0.21	0.61	0.17	229
>2/3	0.31	0.38	0.31	32

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.57	0.38	0.05	1250
1/3-2/3	0.21	0.62	0.17	175
>2/3	0.11	0.33	0.56	18

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.04	-0.04	0.00
1/3-2/3	0.00	-0.01	0.01
>2/3	0.20	0.04	-0.24

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.056	0.048	0.955
1/3-2/3	0.951	0.814	0.812
>2/3	0.068	0.766	0.089

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.005	0.000	0.950
1/3-2/3	0.665	0.215	0.305
>2/3	0.000	0.355	0.000

Table B.69: Analysis groups 86-88, 90-92, North, high education, periods 89-99 and 93-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.26	0.45	0.29	305
1/3-2/3	0.09	0.35	0.56	600
>2/3	0.02	0.09	0.89	304

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.19	0.48	0.33	417
1/3-2/3	0.06	0.30	0.64	794
>2/3	0.01	0.09	0.90	430

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.07	-0.04	-0.04
1/3-2/3	0.03	0.05	-0.08
>2/3	0.01	-0.00	-0.00

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.022	0.348	0.290
1/3-2/3	0.049	0.041	0.002
>2/3	0.554	0.893	0.898

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.000	0.285	0.005
1/3-2/3	0.000	0.000	0.000
>2/3	0.265	0.070	0.445

Table B.70: Analysis groups 86-88, 90-92, Center, high education, periods 89-99 and 93-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.32	0.50	0.18	153
1/3-2/3	0.15	0.45	0.40	167
>2/3	0.03	0.10	0.87	110

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.29	0.42	0.30	182
1/3-2/3	0.06	0.44	0.50	218
>2/3	0.03	0.09	0.87	149

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.03	0.08	-0.11
1/3-2/3	0.09	0.01	-0.09
>2/3	-0.01	0.01	0.00

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.493	0.146	0.014
1/3-2/3	0.008	0.864	0.064
>2/3	0.769	0.871	0.995

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.225	0.025	0.000
1/3-2/3	0.000	0.415	0.005
>2/3	0.075	0.195	0.020

Table B.71: Analysis groups 86-88, 90-92, South, high education, periods 89-99 and 93-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.44	0.44	0.12	421
1/3-2/3	0.17	0.48	0.34	230
>2/3	0.06	0.17	0.77	87

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.39	0.46	0.15	308
1/3-2/3	0.12	0.55	0.33	174
>2/3	0.06	0.13	0.81	68

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.05	-0.01	-0.03
1/3-2/3	0.05	-0.06	0.01
>2/3	-0.00	0.04	-0.04

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.198	0.715	0.191
1/3-2/3	0.130	0.206	0.831
>2/3	0.972	0.487	0.555

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.000	0.285	0.000
1/3-2/3	0.000	0.005	0.210
>2/3	0.025	0.335	0.030

Table B.72: Analysis groups 86-88, 90-92, Italy, low education, periods 89-99 and 93-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.26	0.53	0.21	1304
1/3-2/3	0.12	0.50	0.38	213
>2/3	0.15	0.44	0.41	27

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.28	0.48	0.24	1174
1/3-2/3	0.09	0.44	0.47	155
>2/3	0.11	0.39	0.50	18

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	-0.01	0.05	-0.04
1/3-2/3	0.03	0.06	-0.09
>2/3	0.04	0.06	-0.09

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.496	0.014	0.026
1/3-2/3	0.396	0.262	0.099
>2/3	0.713	0.710	0.540

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.515	0.000	0.000
1/3-2/3	0.000	0.030	0.000
>2/3	0.005	0.195	0.120

Table B.73: Analysis groups 86-88, 90-92, North, high education, periods 93-99 and 97-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.38	0.45	0.17	212
1/3-2/3	0.08	0.46	0.45	608
>2/3	0.01	0.08	0.91	577

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.29	0.52	0.19	242
1/3-2/3	0.06	0.44	0.50	674
>2/3	0.01	0.07	0.91	719

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.08	-0.07	-0.02
1/3-2/3	0.03	0.02	-0.05
>2/3	-0.00	0.01	-0.01

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.058	0.148	0.653
1/3-2/3	0.070	0.468	0.099
>2/3	0.950	0.605	0.646

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.000	0.000	0.135
1/3-2/3	0.000	0.005	0.000
>2/3	0.805	0.115	0.145

Table B.74: Analysis groups 86-88, 90-92, Center, high education, periods 93-99 and 97-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.41	0.48	0.11	118
1/3-2/3	0.10	0.58	0.32	189
>2/3	0.03	0.12	0.85	185

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.39	0.43	0.19	122
1/3-2/3	0.05	0.55	0.41	222
>2/3	0.02	0.03	0.94	174

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.02	0.06	-0.08
1/3-2/3	0.05	0.04	-0.09
>2/3	0.00	0.09	-0.09

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.733	0.376	0.086
1/3-2/3	0.052	0.451	0.063
>2/3	0.806	0.001	0.003

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.395	0.020	0.010
1/3-2/3	0.000	0.485	0.000
>2/3	0.580	0.000	0.000

Table B.75: Analysis groups 86-88, 90-92, South, high education, periods 93-99 and 97-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.53	0.39	0.08	318
1/3-2/3	0.20	0.57	0.23	297
>2/3	0.03	0.20	0.77	158

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.51	0.40	0.09	211
1/3-2/3	0.12	0.60	0.28	207
>2/3	0.02	0.13	0.85	103

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	0.02	-0.01	-0.02
1/3-2/3	0.08	-0.03	-0.05
>2/3	0.01	0.07	-0.08

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.583	0.851	0.521
1/3-2/3	0.016	0.550	0.196
>2/3	0.530	0.124	0.088

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.020	0.190	0.085
1/3-2/3	0.000	0.065	0.000
>2/3	0.025	0.005	0.005

Table B.76: Analysis groups 86-88, 90-92, Italy, low education, periods 93-99 and 97-03 respectively

(a) Transiton prob. 86-88

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.33	0.55	0.12	739
1/3-2/3	0.10	0.59	0.31	630
>2/3	0.04	0.24	0.72	123

(b) Transiton prob. 90-92

	<1/3	1/3-2/3	>2/3	tot cl.
<1/3	0.37	0.48	0.15	586
1/3-2/3	0.10	0.53	0.37	520
>2/3	0.06	0.25	0.69	84

(c) Diff 86-88 minus 90-92

	<1/3	1/3-2/3	>2/3
<1/3	-0.03	0.07	-0.03
1/3-2/3	0.00	0.05	-0.05
>2/3	-0.02	-0.01	0.03

(d) Unconditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.193	0.017	0.099
1/3-2/3	0.929	0.073	0.053
>2/3	0.547	0.815	0.608

(e) Conditional Test p-val.

	<1/3	1/3-2/3	>2/3
<1/3	0.065	0.000	0.000
1/3-2/3	0.215	0.000	0.000
>2/3	0.045	0.695	0.125

Appendix C

Appendix to Chapter 3

C.1 Other Estimates

Table C.1: Difference analysis. Other parameters.

	Dependent variable:			
	log weekly wage			
	(1)	(2)	(3)	(4)
Centre	−0.055	0.005	−0.055	−0.013
	(0.046)	(0.054)	(0.046)	(0.054)
South	-0.097^{***}	−0.029	-0.097^{***}	−0.052
	(0.036)	(0.044)	(0.037)	(0.043)
n. spells	−0.004	−0.004	−0.002	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)
n. migrations	−0.036	−0.032	−0.035	−0.031
	(0.024)	(0.024)	(0.024)	(0.023)
age sq.	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
actual exp.	0.0003	0.0004	0.0002	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
actual exp sq.	0.00000	0.00000	0.00000	0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
tenure	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
tenure sq	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
part-time	-0.075^{**}	-0.075^{**}	-0.074^{**}	-0.075^{**}
	(0.032)	(0.032)	(0.032)	(0.032)
Blue Collars	0.236^{***}	0.237^{***}	0.238^{***}	0.239^{***}
	(0.019)	(0.019)	(0.019)	(0.019)
Executives	0.557^{**}	0.556^{**}	0.563^{**}	0.563^{**}
	(0.250)	(0.250)	(0.250)	(0.250)
Managers & White C.	0.321^{***}	0.323^{***}	0.323^{***}	0.325^{***}
	(0.028)	(0.028)	(0.028)	(0.028)
Others	0.276^{**}	0.277^{**}	0.279^{**}	0.281^{**}
	(0.113)	(0.113)	(0.113)	(0.113)
Craftsmanship	-0.050^{***}	-0.049^{***}	-0.049^{***}	-0.047^{***}

	(1)	(2)	(3)	(4)
	(0.016)	(0.016)	(0.016)	(0.016)
Credit,Insurance,Fiscal	0.269***	0.265***	0.273***	0.269***
	(0.077)	(0.076)	(0.077)	(0.076)
Commerce,Arts,Professions	−0.0001	−0.0005	−0.001	−0.001
	(0.017)	(0.017)	(0.017)	(0.017)
d88	−0.076*	−0.080**	−0.079*	−0.087**
	(0.040)	(0.040)	(0.040)	(0.040)
d89	−0.087**	−0.092**	−0.089**	−0.100**
	(0.041)	(0.041)	(0.041)	(0.041)
d90	0.019	0.015	0.018	0.009
	(0.041)	(0.041)	(0.041)	(0.041)
d91	0.014	0.009	0.011	0.002
	(0.042)	(0.042)	(0.042)	(0.042)
d92	0.016	0.009	0.013	0.003
	(0.042)	(0.042)	(0.042)	(0.042)
d93	−0.002	−0.006	−0.002	−0.009
	(0.045)	(0.045)	(0.045)	(0.045)
Centre×d88	0.009	0.009	0.012	0.012
	(0.048)	(0.048)	(0.048)	(0.048)
Centre×d89	0.114***	0.115***	0.110**	0.115***
	(0.043)	(0.043)	(0.043)	(0.043)
Centre×d90	0.0002	−0.0001	−0.003	−0.004
	(0.042)	(0.042)	(0.042)	(0.042)
Centre×d91	0.024	0.021	0.021	0.022
	(0.047)	(0.047)	(0.047)	(0.047)
Centre×d92	0.049	0.049	0.047	0.042
	(0.046)	(0.046)	(0.046)	(0.046)
Centre×d93	0.097*	0.095*	0.096*	0.095*
	(0.057)	(0.057)	(0.057)	(0.057)
South×d88	0.030	0.031	0.027	0.028
	(0.037)	(0.037)	(0.037)	(0.037)
South×d89	0.102**	0.106***	0.099**	0.105**
	(0.041)	(0.041)	(0.041)	(0.041)
South×d90	0.028	0.036	0.029	0.036
	(0.040)	(0.040)	(0.040)	(0.040)
South×d91	0.015	0.020	0.017	0.020
	(0.043)	(0.043)	(0.043)	(0.043)
South×d92	0.091*	0.094*	0.093*	0.094*
	(0.048)	(0.048)	(0.048)	(0.048)
South×d93	0.106**	0.115**	0.102**	0.108**
	(0.049)	(0.049)	(0.049)	(0.049)
Constant	0.792***	0.772***	0.743***	0.707***
	(0.121)	(0.121)	(0.117)	(0.117)
R^2	0.226	0.228	0.228	0.232
Adj. R^2	0.223	0.225	0.224	0.228
Num. obs.	2818	2818	2818	2818

Note: *p<0.1; **p<0.05; ***p<0.01

The dependent variable is the difference between the log weekly wage at experience 11 minus log weekly wage at experience 1. For dummies, the reference area is North, year is 1987, occupation is Apprentices, sector is Industry.

Table C.2: Dynamic fixed effects model. Other parameters.

	Dependent variable:			
	log weekly wage			
	(1)	(2)	(3)	(4)
w_{t-1}	0.431***	0.294	0.436***	0.312*
	(0.113)	(0.153)	(0.113)	(0.152)
w_{t-2}	−0.034	−0.041	−0.037	−0.050
	(0.074)	(0.097)	(0.074)	(0.096)
n. spells	−0.021***	−0.015***	−0.021***	−0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
n. migration	−0.005	0.007	−0.001	0.007
	(0.012)	(0.013)	(0.012)	(0.013)
age	0.101***	0.096***	0.101***	0.096***
	(0.010)	(0.013)	(0.010)	(0.013)
age sq.	−0.001***	0.000*	−0.001***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
exp sq.	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
actual exp.	−0.003***	−0.004***	−0.003***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
part-time	0.006	0.005	0.007	0.005
	(0.014)	(0.014)	(0.014)	(0.014)
tenure	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Centre	−0.027	−0.028	−0.023	−0.026
	(0.017)	(0.018)	(0.017)	(0.019)
South	−0.041	−0.051*	−0.035	−0.047*
	(0.021)	(0.022)	(0.021)	(0.022)
Blue collars	0.033***	0.046	0.032***	0.044
	(0.008)	(0.026)	(0.008)	(0.026)
Executives	0.046	−1.243	0.046	−1.327
	(0.068)	(5.054)	(0.068)	(5.016)
Managers & White C.	0.046***	0.060	0.047***	0.059
	(0.013)	(0.043)	(0.013)	(0.043)
Others	0.032	0.061	0.033	0.057
	(0.057)	(0.053)	(0.058)	(0.053)
Craftsmanship	−0.016*	−0.015	−0.016*	−0.016
	(0.008)	(0.009)	(0.008)	(0.009)
Credit,Insurance,Fiscal Service	0.078	0.059	0.077	0.059
	(0.076)	(0.067)	(0.075)	(0.067)
Commerce,Arts,Professions	−0.017	−0.015	−0.016	−0.015
	(0.009)	(0.010)	(0.009)	(0.010)
n	8965	8965	8965	8965
T	18	18	18	18
Num. obs.	128273	128273	128273	128273
Num. obs. used	26888	17600	26888	17600
Sargan Test: chisq	73.572	47.048	73.320	48.143
Sargan Test: df	63	57	63	57
Sargan Test: p-value	0.170	0.824	0.176	0.792
Wald Test Coefficients: chisq	3791.321	1264.983	3791.954	1284.390
Wald Test Coefficients: df	21	29	23	39
Wald Test Coefficients: p-value	0.000	0.000	0.000	0.000
Autocorrelation test (1): normal	-3.245	-2.115	-3.266	-2.211
Autocorrelation test (1): p-value	0.001	0.034	0.001	0.027
Autocorrelation test (2): normal	-1.136	-0.512	-1.104	-0.402

	(1)	(2)	(3)	(4)
Autocorrelation test (2): p-value	0.256	0.608	0.270	0.688
Note:				*p<0.1; **p<0.05; ***p<0.01

Arellano-Bond estimator with lags 3 to 7 as instruments. For dummies, the reference area is North, occupation is Apprentices, sector is Industry.

Bibliography

Paolo Barbieri and Stefani Scherer. Labour market flexibilization and its consequences in italy. *European Sociological Review*, 25(6):677–692, 2009.

D. Bhattacharya and B. Mazumder. A Nonparametric Analysis of Black-White Differences in Intergenerational Income Mobility in the United States. Technical Report March, Working paper series, Oxford University, 2011. URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1792798`.

Alain Bigard, Yves Guillotin, and Claudio Lucifora. Earnings mobility: an international comparison of italy and france. *Review of Income and Wealth*, 44(4):535–554, 1998.

Tito Boeri and Andrea Brandolini. The age of discontent: Italian households at the beginning of the decade. IZA Discussion Papers 1530, Institute for the Study of Labor (IZA), March 2005. URL `http://ideas.repec.org/p/iza/izadps/dp1530.html`.

René Böheim and Mark P Taylor. From the dark end of the street to the bright side of the road? the wage returns to migration in britain. *Labour economics*, 14(1):99–117, 2007.

George J Borjas, Stephen G Bronars, and Stephen J Trejo. Self-selection and internal migration in the united states. *Journal of Urban Economics*, 32(2):159–185, 1992.

P Cabus. Un test de type Kolmogorov-Smirnov dans le cadre de comparaison de fonctions de regression. *C.R. Acad. Sci., Paris, Sr. I, Math. 327*, pages 939–942, 1998. URL `http://www.sciencedirect.com/science/article/pii/S0764444299801396`.

Lorenzo Cappellari. Earnings mobility among italian low paid workers. IZA Discussion Papers 1068, Institute for the Study of Labor (IZA), March 2004. URL `http://ideas.repec.org/p/iza/izadps/dp1068.html`.

Lorenzo Cappellari. Earnings mobility among italian low-paid workers. *Journal of Population Economics*, 20(2): 465–482, 2007.

Bruno Contini and Elisa Grand. Disposable workforce in italy. 2010.

Yves Croissant and Giovanni Millo. Panel data econometrics in R: The plm package. *Journal of Statistical Software*, 27(2), 2008. URL `http://www.jstatsoft.org/v27/i02/`.

David B. Dahl. *Export tables to LaTeX or HTML*, 2013. URL `http://CRAN.R-project.org/package=xtable`. R package version 1.7-1.

Fondazione Rodolfo Debenedetti. *INPS Data Archive*. Fondazione Rodolfo Debenedetti, Milano, Italy, 2009. URL `http://www.frdb.org`.

Emilia Del Bono and Daniela Vuri. Job mobility and the gender wage gap in italy. *Labour Economics*, 18(1): 130–142, 2011.

M.A. Delgado. Testing the equality of nonparametric regression curves. *Statistics & probability letters*, 17(3): 199–204, 1993. URL `http://www.sciencedirect.com/science/article/pii/016771529390167H`.

M.A. Delgado and W.G. Gonazález-Manteiga. Significance testing in nonparametric regression based on the bootstrap. *The Annals of Statistics*, 29(5):1469–1507, 2001. URL `http://projecteuclid.org/euclid.aos/1013203462`.

Cécile Détang-Dessendre, Carine Drapier, and Hubert Jayet. The impact of migration on wages: Empirical evidence from french youth. *Journal of Regional Science*, 44(4):661–691, 2004.

Ivan Faiella and Romina Gambacorta. The weighting process in the shiw. Temi di discussione (Economic working papers) 636, Bank of Italy, Economic Research and International Relations Area, June 2007. URL `http://ideas.repec.org/p/bdi/wptemi/td_636_07.html`.

E Ferreira and W Stute. Testing for Differences Between Conditional Means in a Time Series Context. *Journal of the American Statistical Association*, 99(465):169–174, March 2004. ISSN 0162-1459. doi: 10.1198/016214504000000160. URL `http://pubs.amstat.org/doi/abs/10.1198/016214504000000160`.

J.P. Formby, W.J. Smith, and B. Zheng. Mobility measurement, transition matrices and statistical inference. *Journal of Econometrics*, 120(1):181–205, May 2004. ISSN 03044076. doi: 10.1016/S0304-4076(03)00211-2. URL `http://linkinghub.elsevier.com/retrieve/pii/S0304407603002112`.

Paul E Gabriel and Susanne Schmitz. Favorable self-selection and the internal migration of young white males in the united states. *Journal of Human Resources*, pages 460–471, 1995.

Yuji Genda, Ayako Kondo, and Souichi Ohta. Long-term effects of a recession at labor market entry in japan and the united states. *Journal of Human Resources*, 45(1):157–196, 2010.

Peter Hall and Jeffrey D Hart. Bootstrap Test for Difference Between Means in Nonparametric Regression. *Journal of the American Statistical Association*, 85(412):1039– 1049, 1990.

Peter Hall and Berwin a. Turlach. Enhancing convolution and interpolation methods for nonparametric regression. *Biometrika*, 84(4):779–790, 1997. ISSN 0006-3444. doi: 10.1093/biomet/84.4.779. URL `http://biomet.oxfordjournals.org/cgi/doi/10.1093/biomet/84.4.779`.

Peter Hall, Catherine Huber, and Paul L Speckman. Covariate-Matched One-Sided Tests for the Difference Between Functional Means. *Journal of the American Statistical Association*, 92(439):1074– 1083, 1997.

John C Ham, Xianghong Li, and Patricia B Reagan. Matching and semi-parametric iv estimation, a distance-based measure of migration, and the wages of young men. *Journal of Econometrics*, 161(2):208–227, 2011.

W. Härdle and J.S. Marron. Semiparametric comparison of regression curves. *The Annals of Statistics*, 18(1): 63–89, 1990. URL `http://projecteuclid.org/euclid.aos/1176347493`.

Tristen Hayfield and Jeffrey S. Racine. Nonparametric econometrics: The np package. *Journal of Statistical Software*, 27(5), 2008. URL `http://www.jstatsoft.org/v27/i05/`.

Marek Hlavac. *LaTeX/HTML code and ASCII text for well-formatted regression and summary statistics tables*. Harvard University, Cambridge, USA, 2014. URL `http://CRAN.R-project.org/package=stargazer`. R package version 5.1.

Janet C Hunt and James B Kau. Migration and wage growth: a human capital approach. *Southern Economic Journal*, 51(3), 1985.

David A. James and Saikat DebRoy. *R interface to the MySQL database*, 2012. URL `http://CRAN.R-project.org/package=RMySQL`. R package version 0.9-3.

Lisa B Kahn. The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2):303–316, 2010.

Eileen King, Jeffrey D. Hart, and Thomas E. Wehrly. Testing the equality of two regression curves using linear smoothers. *Statistics & Probability Letters*, 12(3):239–247, 1991. URL `http://ideas.repec.org/a/eee/stapro/v12y1991i3p239-247.html`.

Hira L Koul and Anton Schick. Testing for the equality of two nonparametric regression curves. *Journal of Statistical Planning and Inference*, 65, 1997.

Hira L Koul and Anton Schick. Testing for superiority among two regression curves. *Journal of Statistical Planning and Inference*, 117:15 – 33, 2003.

E.L. Lehmann. *Elements of Large-Sample Theory.* Springer Texts in Statistics. Springer, 1999. ISBN 9780387985954. URL `http://books.google.it/books?id=b7uCh19S9z0C`.

Philip Leifeld. Conversion of statistical model output in R to LaTeX and html tables. *Journal of Statistical Software*, 55(8):1–24, 2013. URL `http://www.jstatsoft.org/v55/i08/`.

Lesnoff, M., Lancelot, and R. *Analysis of Overdispersed Data*, 2012. URL `http://cran.r-project.org/package=aod`. R package version 1.3.

Audrey Light and Kathleen McGarry. Job change patterns and the wages of young men. *Review of Economics and Statistics*, 80(2):276–286, 1998.

Marco Manacorda. Can the scala mobile explain the fall and rise of earnings inequality in italy? a semiparametric analysis, 1977–1993. *Journal of Labor Economics*, 22(3):585–613, 2004.

Sauro Mocetti and Carmine Porello. Labour mobility in italy: new evidence on migration trends. Questioni di Economia e Finanza (Occasional Papers) 61, Bank of Italy, Economic Research and International Relations Area, January 2010. URL `http://ideas.repec.org/p/bdi/opques/qef_61_10.html`.

RA Nakosteen and M Zimmer. Migration and income: the question of self-selection. *Southern Economic Journal*, 46(3):840–851, 1980.

Robert A Nakosteen and Michael A Zimmer. The effects on earnings of interregional and interindustry migration*. *Journal of Regional Science*, 22(3):325–341, 1982.

N Neumeyer. A central limit theorem for two-sample U-processes. *Statistics & Probability Letters*, 67(1):73–85, March 2004. ISSN 01677152. doi: 10.1016/j.spl.2002.12.001. URL `http://linkinghub.elsevier.com/retrieve/pii/S0167715204000112`.

N Neumeyer and Holger Dette. Nonparametric comparison of regression curves: an empirical process approach. *The Annals of Statistics*, 31(3):880–920, 2003. URL `http://math.bnu.edu.cn/statprob/CSPS-IMS2005/Abstracts/WinfriedStute.pdfhttp://projecteuclid.org/euclid.aos/1056562466`.

Natalie Neumeyer and Juan C. Pardo-Fernández. A simple test for comparing regression curves versus one-sided alternatives. *Journal of Statistical Planning and Inferenece*, 139:4006–4016, 2009.

Philip Oreopoulos, Till von Wachter, and Andrew Heisz. The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1):1–29, 2012.

J.C. Pardo-Fernández, I. Van Keilegom, and W. González-Manteiga. Testing for the equality of k regression curves. *Statistica Sinica*, 17(3):1115, 2007. URL `http://www.stat.ucl.ac.be/ISpersonnel/vankeile/paper34.pdf`.

R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2013a. URL `http://www.R-project.org/`.

R Core Team. *Read Data Stored by Minitab, S, SAS, SPSS, Stata, Systat, dBase, ...*, 2013b. URL `http://CRAN.R-project.org/package=foreign`. R package version 0.8-54.

Revolution Analytics. *Iterator construct for R*, 2012. URL `http://CRAN.R-project.org/package=iterators`. R package version 1.0.6.

Revolution Analytics. *Foreach parallel adaptor for the multicore package*, 2013. URL `http://CRAN.R-project.org/package=doMC`. R package version 1.3.0.

Francesco Risi. Comparing conditional transition probabilities: Is italian income mobility region specific? *Unpublished working paper*, 2013.

Chris Robinson and Nigel Tomes. Self-selection and interprovincial migration in canada. *Canadian Journal of Economics*, 15(3):474–502, 1982.

Alfonso Rosolia and Roberto Torrini. The generation gap: relative earnings of young and old workers in italy. *Bank of Italy Temi di Discussione (Working Paper) No*, 639, 2007.

Martin Schindler. *The Italian Labor Market: Recent Trends, Institutions, and Reform Options (EPub)*, volume 9. International Monetary Fund, 2009.

Ramidha Srihera and Winfried Stute. Nonparametric comparison of regression functions. *Journal of Multivariate Analysis*, 101(9):2039–2059, October 2010. ISSN 0047259X. doi: 10.1016/j.jmva.2010.05.001. URL `http://linkinghub.elsevier.com/retrieve/pii/S0047259X10001089`.

Luke Tierney. *Code Analysis Tools for R*, 2011. URL `http://CRAN.R-project.org/package=codetools`. R package version 0.2-8.

Robert H. Topel and Michael P. Ward. Job mobility and the careers of young men. *The Quarterly Journal of Economics*, 107(2):pp. 439–479, 1992.

Simon Urbanek. *Parallel processing of R code on machines with multiple cores or CPUs*, 2011. URL `http://CRAN.R-project.org/package=multicore`. R package version 0.1-7.

Jeffrey J Yankow. Migration, job change, and wage growth: a new perspective on the pecuniary return to geographic mobility. *Journal of Regional Science*, 43(3):483–516, 2003.