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15 November 2010

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Abstract

In this paper, we estimate wage differentials among Italian university Graduates three years after graduation due to sequential geographic mobility. By means of a matching procedure we quantify wage premia associated with the choice of studying far from home, moving after graduation and moving back home after graduation. We find evidence of large gains for those who move after graduation, little benefits for those who choose to go back home after having studied in regions different from that of origin. We also assess a "transitivity" result for the estimated treatment effects.

*The authors aknowledge the PRIN/MIUR and SINTeSIS projects for financial support.

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Keywords: Geographic mobility; wage differentials; kernel matching.

JEL Classification Numbers: J24, J31, J61.

1 Introduction

It is a matter of fact that higher education is on average associated with higher wages to the extent that it increases the level of skills and, thus, of productivity. However it remains an open question whether, among university graduates, there are other factors able to make students more successful in their early labour market outcomes. In this paper, we address this issue by analysing the impact of sequential geographic mobility on wages for a sample of Italian university graduates three years after graduation. In particular, we determine to what extent internal migration from domicile to higher education and, subsequently, to first employment affects the wages of young graduates.

Since the earlier literature, migration has been soon recognized as a human capital investment carried out by income-maximizers individuals (Sjaastad, 1962; Bowles, 1970; Greenwood, 1975). As such, one would expect migration to be accordingly rewarded through higher earnings for those who choose to migrate compared to those who did not. Then, what triggers the migration decision and what consequences do we observe on individuals and the labour market as a whole? Mainstream research has devoted great attention to answer these questions, and a large consensus has been reached on the causes of the migration decision. In particular, Bowles' pioneering contribution identifies the present value of expected income as one of the key variables affecting the choice of moving[1]. In addition, regional differences in the returns to skills may drive the size and skill composition of migration flows (Borjas et al., 1992). Other factors include career progressions (Schlottmann and Herzog, 1984), industry composition, amenity differentials, relative employment opportunities and relative real wages (Treyz et al., 1993). Gottlieb and Joseph (2006) narrow the analysis to the college-to-work migration decision and show that science and technology graduates migrate to better educated places, that PhD graduates value amenity characteristics more than other groups and that foreign students from some immigrant groups migrate to places where those groups are already concentrated.

Conversely to the large body of the literature focused on the determinants of internal mobility, only few studies attempted so far to deal with the effects of inter-regional migration on labour market outomes. Moreover, it is not clear whether the migration decision has a direct impact on wages and, if so, whether it is negative or positive. Indeed, Nakosteen and Westerlund (2004) and Lehmer and Ludsteck (2010) find a positive and significant effect of migration on gross income, Détang-Dessendre et al. (2004) emphasize the absence of any impact of internal migration on wages, and Tunali (2000) shows that a large fraction of migrants experience a negative return to migration.

The patterns of students' internal migration cannot be underestimated in terms of policy implications both by universities and central/regional governments. Italian universities compete on students enrollment to increase the level of attractiveness both to raise the quality level of their pupils and because they are awarded

[1] As a consequence, age has a negative impact on the propensity to migrate, while schooling acts positevely.

greater funds from the government. Policy makers can be interested in retaining human capital to stem the brain drain from poorer areas as well as to increase economic efficiency.

From an economic perspective, geographic mobility is closely related to differences in local labour markets and is able to broaden individuals' opportunities over jobs and locations (Malamud and Wozniak, 2006). This may result in a selectivity problem because individuals with greater incentives are also those who choose to migrate. We use a non-parametrized matching procedure to control for the selection process by exploiting all the information contained in the data. We also perform a subsample analysis to check the reliability and stability of the results.

The rest of the paper proceeds as follows. Section 2 provides the basic economic intuitions and motivations of internal geographic mobility. Section 3 focusses on the data. In section 4 we briefly describe the econometric model, while in section 5 we present the empirical results. Section 6 concludes.

2 Internal migration of graduates and early earnings

Economists have long recognized that individuals are pushed to migrate because they wish to accrue their future income streams by exploiting greater opportunities in the destination area. Indeed, Borjas et al. (1992) provide theoretical intuitions and empirical evidence of the role played by differences in the returns to skills to predict movements across different geographic areas within a country. This reasoning can be accomodated to the migration decisions of university students. In particular, the migration pattern can be thought of as the result of a two-stage process through which students first choose the university they want to attend, and then they move to the place where they wish to find a job. The economic rewards to this process are the core of our analysis. It is reasonable to consider the two migration choices as separate decisions taken in two different points in time.

Similarly to Lansing and Morgan (1967), we believe that comparing the labour market outcomes between those who have shown some mobility pattern and individuals belonging to the destination area might be misleading. Thus, we wish to uncover the economic effect of geographic mobility on wages by comparing the income of those who have been mobile - according to our definitions of mobility - with the income of those otherwise similar students who have not shown the same mobility patterns. Moreover, by following this approach we do not have to predict wages for all the possible destinations that have not been chosen by individuals, but only wages for a well-defined control group.

In order to do so, we first split Italy into four macro-areas, namely North-East, North-West, Center and South, then we define five mobility variables[2] able to track the migration patterns. We define *stayers* those who never leave the area of origin - neither to study nor to work; *early movers* are those who migrate to study and remain in the same area to work; *late movers* study in their area of origin and move to a different area for employment; *back-movers* are those who choose to go back to their area of origin after having studied far from home. According to these definitions, we implement five evaluation studies aimed at detecting possible wage differentials due to different inter-regional mobility patterns. Specifically, the

[2]For a similar approach see Faggian et al. (2006).

evaluation studies are:

1. Early Mover vs. Stayer;
2. Early Mover vs. Late Mover;
3. Late Mover vs. Stayer;
4. Back Mover vs. Stayer;
5. Back Mover vs. Early Mover.

3 Data

To carry out the empirical analysis, we use data from the 2004 and 2007 waves of the Graduates' Employment Survey[3] (GES, hereafter). The survey is conducted by the ISTAT (National Institute of Statistics) every three years since 1995 and covers a sample of individuals who graduated three years earlier[4]. The sample provides valuable information on academic curriculum, labour market experiences, individual characteristics, and family background. Moreover, the data offer detailed information on the region of residence before going to university, on the region where the university is located and on the region of work. The questionnaire also asked whether the student actually moved to the University location or was only a pendular. This allows us to construct individuals' mobility patterns with greater confidence.

[3]Indagine sull'Inserimento Professionale dei Laureati.

[4]Since we observe wages three years after graduation, we cover the hypothesis that it takes time for an individual to receive returns to migration. Yankow (2003) illustrates this point and finds that highly educated workers receive returns to mobility with a lag of nearly two years.

We decide to pool the two waves to increase the sample size. From the original sample, we keep individuals holding only one degree and with a paid job, while we drop the observations whose individuals were already working during their studies. Moreover we exclude from the analysis individuals graduated in medicine, physical education (gym) and defense. We end up with a sample of 15886 individuals with complete information on their mobility paths, wage earned, study history, family background.

The outcome variable we consider is the net-of-taxes hourly wage obtained by those individuals who are full-time employed at the date of the survey.

4 Econometric model

In order to assess the effect of early and late mobility on wages, we adopt a non-parametrized matching protocol. The framework is the standard *potential outcome approach* as defined in Rubin (1974) and Holland (1986), in which, for each individual and for a given intervention (treatment), we can only observe either the outcome conditional on receiving the treatment (Y_1) or the outcome conditional on non-receiving the treatment (Y_0). The evaluation problem simply arises because, for each person, we can only observe one of the two potential outcomes and the effect of the treatment on a single unit ($\Delta Y = Y_1 - Y_0$) can never be assessed. However, we can still focus on different informative measures to quantify average impacts. In the present study we are concerned with the mean impact of the treatment on the treated[5], i.e. the *average treatment effect on the treated* (ATT). Formally, let D the indicator of the treatment status, X a non-empty vector of

[5]For an extensive survey on other parameters of interest, the reader may refer, among others, to Imbens (2004).

observed characteristics and τ the estimand. The ATT can be written as:

$$\tau^{ATT} = E\left(Y_1 - Y_0 | X, D = 1\right) = E\left(Y_1 | X, D = 1\right) - E\left(Y_0 | X, D = 1\right) \quad (1)$$

While the mean outcome in the treatment regime is identified from the data, the missing counterfactual must be appropriately estimated. Several approaches are available to the econometrician[6]. According to Frolich (2004), kernel matching seems to perform better in propensity score matching procedures. Thus we decide to use this methodology to achieve greater reliability. Moreover, matching estimators have proven to be more effective in the presence of a large reservoir of control units (Imbens, 2004). Our control groups satisfy this condition and lead us to the choice of kernel matching.

Technically, kernel matching use weighted averages of all units in the control group to estimate counterfactual outcomes. The weight is proportional to the propensity score distance between a treatment case and all the control cases. Thus, as in Heckman et al. (1998), the estimator can be written as:

$$\tau_K^{ATT} = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_{1i} - \frac{\sum_{j \in C} Y_{0j} G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \right\}$$

Moreover, the closest control cases are given the greatest weight.

[6] For a comprehensive survey of different estimators see Imbens and Wooldridge (2009).

5 The Effect of Geographic Mobility on Wages

In this section, we first give detail about the propensity score estimation and the balancing properties of our matched sample. Then, we focus on the wage returns to mobility choices. We also provide the empirical evidence on the subsample of individuals whose area of origin is the South.

5.1 Kernel Matching on the Propensity Score

We estimate the propensity score by logistic regression for each treatment we consider. In particular, we include pre-treatment variables only to reduce potential selection problems. We also stress the fact that our sample includes graduates only, so the subpopulation we consider is less heterogenous compared to other similar studies at least on two dimensions. First, all the sample includes labour market entrants, so we do not have to be concerned with job-to-job transitions and their incentive effects on the propensity to migrate. Second, we reduce the dimensions along which self-selection might acts and we deal with it by using a rich set of covariates for the estimation of the propensity score.

In particular, we match individuals on area of origin, university locations, personal characteristics, high school grades and typologies, family background and fields of study. Compared to other studies, our set of covariates is richer and makes us confident that that the sample selection problem is minimized[7].

Following Rosenbaum and Rubin (1985) and Lechner (2001), the match quality has been assessed through the analysis of the reduction in the mean absolute

[7] Among many others, Falaris (1988) applies a nested logit model and uses information on education, age, race and distance to control for selectivity. Yankow (2003) specifies a Probit model to predict selectivity corrections and uses information on race, education, experience, job tenure and few personal characteristics.

Table 1: Balancing properties of the matched sample

Treatment	Control	Bias Before	Bias After	% Reduction
Early Mover	Stayer	18.001	2.581	85.66
Early Mover	Late Mover	11.291	0.807	92.85
Late Mover	Stayer	10.434	0.881	91.56
Back Mover	Stayer	10.578	4.795	54.67
Back Mover	Early Mover	14.801	4.248	71.30

Notes: The reduction of bias is computed as $BR = 100 \cdot \left(1 - \frac{B_{after}}{B_{before}}\right)$

standardized bias. Since most of our covariates are dichotomous, the standardazied bias has been computed according to the following formula:

$$B_{before}(X) = 100 \cdot \frac{p_T - p_C}{\sqrt{\frac{p_T(1-p_T)+p_C(1-p_C)}{2}}} \quad B_{after}(X) = 100 \cdot \frac{p_T^M - p_C^M}{\sqrt{\frac{p_T(1-p_T)+p_C(1-p_C)}{2}}}$$

where p_T and p_C are the proportions of the covariates, respectively, in the treatment and the control group, while the M suffix refers to the matched sample.

As table 1 suggests, we are able to reduce the unbalance in the original sample in all the evaluation studies.

5.2 Average Treatment Effects on the Treated

Our main results are shown in table 2. The first two columns describe the treatment and control status. Columns (3) to (6) report the number of observations by treatment status that satisfy the common support criteria. The average

Table 2: Kernel-Matching results

		N. Treated Units		N. Control Units				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	Control	Off support	On support	Off support	On support	**ATT**	S.E.	Coeff.
Early Mover	Stayer	3	598	33	11995	0.028	0.011	1.028
Early Mover	Late Mover	0	601	10	2462	-0.114	0.013	0.893
Late Mover	Stayer	3	2459	2	12026	0.142	0.008	1.153
Back Mover	Stayer	0	542	157	11871	-0.006	0.012	0.994
Back Mover	Early Mover	16	526	17	584	-0.023	0.020	0.977

Notes:

treatment effects and standard errors are, respectively, in columns (7) and (8).

The estimated ATT is the difference of hourly log-wages, thus the log of the ratios between hourly wages for treated and control units. By taking the exponential of the ATT, we recover the coefficients of proportionality between wages for treated individuals and controls. Column (9) shows the coefficients. The results reported in table 2 suggest that the greater gain is associated with the condition of late movers both with respect to early movers and stayers. In particular, early movers earn 2.8% more than stayers, but they lose 10.7% if compared to late movers. Late movers earn 15.3% more than stayers. The choice of moving back home after graduation never pays off. If we consider the relative gain with respect to stayers, the effect has a negative sign, but its magnitude appears to be small.

A corollary result emerges from a closer inspection of the table. Consider the ATT between early mover (EM) and late mover (LM), $EM - LM = -0.114$. Now consider the stayer category (ST); by adding and subtracting ST, it follows that $(EM - ST) - (LM - ST) = -0.114$. Having estimated the two terms in parenteses, we are able to perform this test. It is actually the case that $0.028 - (-0.142) =$

-0.114. This *transitivity* result is somehow reassuring and can be interpreted as a robustness check of our estimates.

5.3 Subsample Analysis

In this section we present the results on the subsample of individuals whose region of origin is the South of Italy. This choice reflects the mobility patterns of Italian young adults and is aimed at reducing the selectivity problem that might undermine the results presented in the previous section. Historically, italian internal migration flows have shown a clearcut direction from South to North. Thus, the estimates based on the original sample might be affected by the presence of heterogenous sub-population with different self-selection incentives. Thus, we decided to isolate in the sample those individuals whose region of origin is the South.

Table 3 reports the number of treated and control units satisfying the common support criteria, the ATT, the standard errors and the coefficients of proportionality.

We first notice that our estimates are close in magnitude to the estimates reported in the previous section. This is in line with the idea that most of internal migration involves individuals from the South.

6 Concluding remarks

In this paper we have measured the average wage gains induced by sequential geographic mobility. The analysis is based on a matched sample of Italian university graduates three years after graduation. According to our estimates, the choice

Table 3: Kernel-Matching results - Subsample

		N. Treated Units		N. Control Units				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	Control	Off support	On support	Off support	On support	**ATT**	S.E.	Coeff.
Early Mover	Stayer	1	457	10	2679	0.031	0.013	1.031
Early Mover	Late Mover	1	457	1	1402	-0.113	0.015	0.893
Late Mover	Stayer	2	1401	2	2687	0.149	0.011	1.160
Back Mover	Stayer	0	242	47	2642	0.011	0.021	1.011
Back Mover	Early Mover	1	241	27	431	-0.011	0.025	0.989

Notes:

of moving after graduation seems to be the best option. The subsample analysis confirms the results.

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