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On Migration and Unemployment: Evidence from Italian graduates

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ABSTRACT

This paper examines the impact of the unemployment rate on the decision to migrate among recent Italian graduates. A fixed-effects approach is used to avoid potential omitted variable problems. This method allows us to account for unobservable location-specific characteristics that are likely to be correlated with the unemployment rate and the probability that an individual migrates. The empirical results highlight the importance of controlling for location-specific effects and show that lower employment opportunities are likely to encourage people to migrate if they do not have a job, but exert no influence on those who are employed.

1. INTRODUCTION

INDIVIDUALS MUST CONSIDER NUMEROUS FACTORS in deciding whether or not to migrate from one location to another. Labour market conditions (usually measured by the unemployment rate) are likely to play a significant role in explaining out-migration, as people in areas with high rates of unemployment are expected to show a higher probability of migrating relative to those in areas with low unemployment.

Although there is a large body of literature on the relationship between the unemployment rate and the decision to migrate, previous studies may suffer from a key defect. These studies do not solve the omitted variable problem, as they lack adequate controls for regional and local characteristics that are themselves likely to be correlated with the unemployment rate and the probability that an individual migrates. Thus, it is quite possible that previous estimates of the effect of the unemployment rate on the likelihood of migrating are biased. For instance, consider a particularly depressed area with persistently high unemployment and several other ills including above average murder, rape and assault rates. This implies that if the crime rate is not included in the migration specification, the unemployment rate would be picking up the effect of this omitted variable on out-migration.

One can think about many other location-specific characteristics (e.g. pollution, quality and availability of public services, climate) that may affect the propensity to migrate. As it is not possible to include all these factors in the migration specification, one way of dealing with this problem is to use the fixed-effects approach.[2] Additionally, empirical studies on human migration have, with few exceptions,[3] have ignored the effect of labour force status on the probability of migrating. It would seem reasonable to suggest that local unemployment rates are likely to be of most concern for the unemployed and perhaps of no or little concern for those individuals who have a job. This argument is often used to explain insignificant or even unexpected signs on the coefficient for local unemployment rate in migration-decision equations (see, for instance, Axelsson and Westerlund, 1998).

In this paper we examine the relation between unemployment and the inter-provincial migration of labour in Italy, taking the two above-mentioned issues simultaneously into account. Using a unique dataset we carry out a cross-sectional analysis in order to assess the effect of individual and area characteristics on the probability of migrating. Our attention is focused on recent graduates for three reasons. First, migration frequently occurs at the end of a period in investment in human capital, such as the completion of university (Greenwood, 1975). Second, using data on recent graduates we are able to follow individuals from their entry into the labour market. This eliminates the problem associated with misclassification across migrant status. If information about individuals is not available since their labour market entry, then the past migratory history of the individual becomes completely uncertain. Thus, it is possible that some individuals who migrated prior to the available information, could incorrectly be classified as non-migrants. As pointed out by Yankow (1999), many previous studies suffer from this misclassification bias. Third, one would expect unemployment to act as a 'push' factor that encourages people to move especially if they are young and well-educated (Lansing and Mueller, 1967).

The remainder of the paper is as follows. A simple model for an individual's decision to migrate is developed in Section 2. Section 3 outlines the data and variables used in the empirical analysis. Empirical results are given in Section 4 and some conclusions are provided in Section 5.

2. The model

In economic theory, migrants are generally motivated by the expectation of reward associated with their move. Two theories that have been advanced in the economic literature to explain the effect of labour market conditions on the decision to migrate, view migration either as an investment decision (the human capital approach) or as a spatial job search process. Following the human capital approach, individuals choose to migrate only if the present value of the expected benefits that accrue to them from migration exceeds the cost of their move (Sjaastad, 1962). In the second theory, labour mobility is considered to be the result of a job search process (Jackman and Savouri, 1992 and Lindley *et al.*, 2002). It is assumed that job searchers from one region look for work across a range of locations and will migrate as they find a match with a vacancy from another region. In this framework, migration is interpreted as being the outcome of a successful job search process rather than being a pre-condition for it.

Following the approach used by several studies (see, for instance, Nakosteen and Zimmer, 1980) an individual's decision to migrate can be specified as:

$$I_i^* = \alpha_o + \alpha_1 X_i + \alpha_2 Z_i + \varepsilon_i \tag{1}$$

where I_i^* is a latent variable indicating the indirect utility of migrating; X_i is a vector of individual characteristics; Z_i is a vector of characteristics of the origin locality (including unemployment rate) and ε_i is a random disturbance term. We observe each individual i only in one state of the world, i.e. we only observe $I_i = 1$ if $I_i^* > 0$ and $I_i = 0$ if $I_i^* \leq 0$. Thus our dependent variable, I_i, takes the value of one if an individual migrates, and zero otherwise.

Our approach consists of setting up an augmented migration decision equation by including location-specific dummies and hence allowing the intercept to vary across areas of origin. The rationale for this is that in deciding whether to migrate, an individual considers a number of amenities in his/her origin locality (e.g. climate, crime rates, pollution) that are likely to be correlated with the unemployment rate and the probability that an individual migrates. The fixed-effects approach allows us adequately to control for geographical characteristics that may affect migration, thereby isolating the effect of the unemployment rate on the probability of migrating. Therefore, the error term of Equation (1) should be composed of a location specific-component and a purely random element.

Following this consideration the model becomes

$$Ii^* = \alpha_o + \alpha_1 X_i + \alpha_2 Z_i + \upsilon_i + \mu_i \tag{2}$$

where υ_i represents area specific heterogeneity and μ_i is a random error term.

3. Data and variables

This study uses data from a survey carried out by the National Statistical Italian Institute (ISTAT) in 2001 on individuals who graduated from all Italian universities in 1998. The original dataset contains information on 20,844 individuals. The survey asks questions on previous educational attainment, degree results, employment status, as well as a variety of personal attributes. These data make it possible to observe each individual's province[4] of residence at two distinct points in time: before enrolling at university and three years after completing university. We classify individuals as migrants if the province of residence reported before they were enrolled at university differs from the province of residence reported three years after their graduation. After deleting from the sample those individuals who were living abroad before enrolling at university and following the removal of observations with missing variables of interest, we are left with a dataset of 20,551 people.

Although the response rate achieved (i.e. 57.3 per cent) is not unusually low for surveys of this type (see Dolton and Vignoles, 2000; Allen and Van der Velden, 2001), in our sample of university graduates there is the potential for some bias. A number of graduates have moved house and not left new contact details. Thus, if graduate mobility is not random this may lead to some bias. Additionally, there is also the possibility that the response rate was higher amongst the more successful graduates and thus the reader should take this into account when generalising the findings of this study.

As outlined in Section 2, our explanatory variables include both individual and area characteristics. Individual attributes comprise subject of study at university, degree classification at university, postgraduate qualification, age, gender, marriage/cohabitation, the presence of a dependent child[5] and self-employment. Furthermore, we also introduce a dichotomous variable recording whether graduates have moved to attend university. The underlying reason for this stems from a common result in migration research, according to which individuals who have moved at least once are found to have a higher propensity to migrate than those who have not moved at all (Da Vanzo, 1983; Newbold, 1997). Individuals with a past migratory history are unlikely to be tied psychologically to a particular local area, and hence are more footloose. In the case of recent university graduates, this finding would imply that students leaving their domicile to attend university are more likely to migrate than their peers who studied at their local university.

As regards area characteristics, our primary interest lies in each province's average unemployment rate between 1998 and 2001, given the aim of this study to examine the impact of labour market conditions on migration. In order to control for the effect of experience on employment prospects, we use each province's unemployment rate among people aged between 15 and 29. The data source for this variable is the Labour Force Survey (carried out by the ISTAT). In the light of the significant difference in unemployment between males and females in Italy, in our empirical analysis we also distinguish by gender in the unemployment rate.[6] Unfortunately, it has not been possible to include in the specification any measure of provinces' wealth such as average hourly earnings or per capita income. While data on the former are not available, data on the latter are highly inaccurate since we are unable to correct for cost of living differences across provinces. Although this factor is likely to be very important in explaining out-migration, this is less of a problem in our analysis, as our specification comprises a set of province dummies.

We use the responses to a question that asks individuals if they were in their current employment before completing university, to test the hypothesis that higher unemployment rates are likely to provide a significant incentive to move for the individuals who are unemployed, but exert no or little influence on those who are employed. More specifically, we construct a dummy variable that takes the value of zero if the individual started his/her current job before graduation, and one otherwise.[7] In our final sample the proportion of people who began their current job before completing university is 32.5 per cent. Following the approach of Da Vanzo (1978) this dummy variable is interacted with provinces' unemployment rates in an attempt to isolate the effect of labour market conditions only on those individuals who were potentially seeking employment after graduation.[8]

Table 1: Descriptive statistics

	Migrants mean	*Non-migrants mean*
INDIVIDUAL CHARACTERISTICS		
Female	0.554	0.540
Age		
Between 24 and 25	0.030	0.019
Between 26 and 28	0.472	0.473
Between 29 and 30	0.255	0.251
31 or more	0.244	0.257
Subject of study		
Engineering	0.144	0.109
Architecture	0.040	0.058
Law	0.093	0.116
Political Science	0.064	0.074
Agricultural studies	0.034	0.039
Languages	0.064	0.059
Education, Italian, Psychology	0.158	0.178
Biological Science, Pharmacy, Chemistry	0.092	0.107
Mathematics and Physics	0.066	0.049
Medicine	0.076	0.057
Economics	0.169	0.154
Degree classification		
Between 70 and 89	0.033	0.039
Between 90 and 99	0.180	0.220
Between 100 and 104	0.213	0.216
Between 105 and 110	0.313	0.302
110 cum laude	0.261	0.223
Married/cohabiting	0.648	0.717
Child	0.089	0.091
Postgraduate qualification	0.174	0.135
Moved to attend university	0.519	0.225
Self-employed	0.081	0.139
AREA CHARACTERISTICS		
Unemployment rate (percentage)	30.313	24.661
Unemployment rate*not being in the current job before graduation	20.515	14.968
Number of observations	3,322	17,229

Table 1 reports some characteristics of migrants and non-migrants. In line with the findings obtained by similar studies (Pissarides and Wadsworth, 1989), migrants are more likely to have a postgraduate qualification, less likely to be married or cohabiting, less likely to have a dependent child and less likely to be self-employed relative to non-migrants. Given our primary interest in labour market conditions, we should also note that migrants are more likely to come from provinces with higher unemployment relative to non-migrants.

4. Empirical results

Table 2 presents the results from modeling the probability that a university graduate has migrated — three years after graduation. A binomial logit model is used. The first half of this table presents the estimated marginal effects (with *p*-values) from our basic specification (specification 1) that includes the unemployment rate together with all the control variables discussed in section 3.

Table 2: Binomial Logistic Regression: marginal effects on the probability of 'Having Migrated'

	ME	*p-value*	*ME*	*p-value*
	specification 1		*specification 2*	
Constant	0.192*	0.000	0.204*	0.000
INDIVIDUAL CHARACTERISTICS				
Female	0.833*	0.000	1.065	0.449
Age - Reference group is 30 or more				
Between 24 and 25	1.329**	0.031	1.376**	0.018
Between 26 and 28	1.013	0.807	1.051	0.378
Between 29 and 30	1.059	0.321	1.103	0.097
Married/Cohabiting	0.575*	0.000	0.568*	0.000
Child	0.768*	0.001	0.761*	0.001
Postgraduate qualification	1.265*	0.000	1.240*	0.000
Moved to attend university	3.890*	0.000	3.156*	0.000
Self-employed	0.489*	0.000	0.482*	0.000
Subject of study - Reference group is Economics				
Engineering	1.212*	0.010	1.227*	0.007
Architecture	0.642*	0.000	0.642*	0.000
Law	0.737*	0.000	0.708*	0.000
Political Science	0.817**	0.028	0.841***	0.064
Agricultural studies	0.777**	0.033	0.785**	0.045
Languages	0.835***	0.057	0.838***	0.067
Education, Italian, Psychology	0.661*	0.000	0.669*	0.000
Biological Science, Pharmacy, Chemistry	0.718*	0.000	0.711*	0.000
Mathematics and Physics	1.079	0.420	1.066	0.506
Medicine	1.051	0.588	1.061	0.525
Degree Classification- Reference group is 110 cum laude				
Between 70 and 89	0.633*	0.000	0.607*	0.000
Between 90 and 99	0.645*	0.000	0.622*	0.000
Between 100 and 104	0.780*	0.000	0.755*	0.000
Between 105 and 110	0.844*	0.002	0.821*	0.000
AREA-CHARACTERISTICS				
Unemployment rate	1.014*	0.000	0.991	0.159

Table 2 ...cont

PROVINCE DUMMIES *Reference group is Milano*	*ME* *specification 1*	*p-value* *specification 1*	*ME* *specification 2*	*p-value* *specification 2*
Torino			0.987	0.933
Vercelli			2.757*	0.001
Novara			1.515	0.107
Cuneo			0.900	0.669
Asti			2.640*	0.004
Alessandria			1.246	0.376
Aosta			0.653	0.440
Imperia			2.804*	0.000
Savona			1.881**	0.022
Genova			1.593**	0.014
La Spezia			1.867**	0.049
Varese			1.671*	0.006
Como			1.759*	0.007
Sondrio			1.093	0.797
Bergamo			0.780	0.277
Brescia			0.719	0.155
Pavia			1.182	0.519
Cremona			1.064	0.832
Mantova			1.039	0.884
Bolzano			2.102*	0.008
Trento			0.973	0.909
Verona			0.760	0.201
Vicenza			0.595**	0.041
Belluno			1.026	0.937
Treviso			0.989	0.958
Venezia			1.855*	0.000
Padova			0.937	0.751
Rovigo			2.515*	0.002
Udine			1.266	0.243
Gorizia			2.182**	0.029
Trieste			2.348*	0.003
Piacenza			1.071	0.829
Parma			0.717	0.277
Reggio Emilia			1.005	0.986
Modena			0.995	0.983
Bologna			0.967	0.872

Table 2 ...cont

Province dummies *Reference group is Milano*	*ME*	*p-value*	*ME*	*p-value*
	specification 1		*specification 2*	
Ferrara			1.401	0.272
Ravenna			0.644	0.175
Forli-Cesena			1.041	0.883
Pesaro e Urbino			1.232	0.410
Ancona			0.918	0.706
Macerata			1.455	0.172
Ascoli-Piceno			1.398	0.179
Massa-Carrara			1.593	0.213
Lucca			0.725	0.430
Pistoia			1.262	0.562
Firenze			1.503**	0.023
Livorno			2.681*	0.000
Pisa			1.244	0.434
Arezzo			0.658	0.202
Siena			0.683	0.330
Grosseto			1.421	0.276
Perugia			1.059	0.813
Terni			1.332	0.279
Viterbo			1.416	0.306
Rieti			4.294*	0.000
Roma			1.010	0.956
Latina			1.910*	0.009
Frosinone			2.097*	0.006
Caserta			3.051*	0.001
Benevento			2.787*	0.001
Napoli			2.468*	0.006
Avellino			3.296*	0.000
Salerno			2.694*	0.000
L'Aquila			1.782**	0.039
Teramo			1.551	0.147
Pescara			3.052*	0.000
Chieti			1.965*	0.003
Campobasso			4.183*	0.000
Foggia			4.023*	0.000

Table 2 ...cont

PROVINCE DUMMIES *Reference group is Milano*	*ME* *specification 1*	*p-value*	*ME* *specification 2*	*p-value*
Bari			2.020*	0.001
Taranto			5.581*	0.000
Brindisi			4.275*	0.000
Lecce			3.854*	0.000
Potenza			3.423*	0.000
Matera			7.482*	0.000
Cosenza			3.214*	0.000
Catanzaro			5.736*	0.000
Reggio Calabria			4.381*	0.000
Trapani			2.022**	0.024
Palermo			3.300*	0.001
Messina			2.962*	0.001
Agrigento			2.738*	0.004
Caltanissetta			4.083*	0.000
Enna			4.636*	0.001
Catania			1.892**	0.038
Ragusa			1.877**	0.046
Siracusa			3.392*	0.000
Sassari			1.915**	0.025
Nuoro			4.999*	0.000
Cagliari			1.443	0.255
Pordenone			1.038	0.888
Isernia			2.779**	0.016
Oristano			5.583*	0.000
Biella			2.123***	0.071
Lecco			1.014	0.969
Lodi			1.832	0.136
Rimini			0.652	0.228
Prato			1.906	0.133
Crotone			2.996*	0.005
Vibo-Valentia			2.383**	0.035
Verbano-Cusio-Ossola			1.533	0.317
Number of observations	20,551		20,551	
(-)2 Log Likelihood	16454.980		16094.261	
Nagelkerke - R^2	0.137		0.165	

*denotes significance at 1%
**denotes significance at 5%
***denotes significance at 10%

Having a postgraduate qualification is found to increase the probability of migrating. One possible explanation is that the markets for more educated individuals are more national in scope relative to less-educated individuals (Schwartz, 1973). Furthermore, it is also quite possible that more and better information about vacancies is available for more educated people (Greenwood, 1975). On the other hand, being married or cohabiting and having a dependent child lower the probability of migrating. This result is consistent with the argument put forward by Mincer (1978), according to which family ties tend to discourage migration. This may be particular important in Italy where family bonds are strong.

In line with our expectations, students who have moved to attend university are found to be significantly more likely to migrate relative to their peers who have attended the local university. This finding is in line with the result obtained by McCann and Sheppard (2001) for UK graduates. Degree classification also seems to exert an important influence on an individual's decision to migrate. It appears that graduates with higher classifications are more likely to migrate than those with lower qualifications. For instance, graduates with a classification of 110 *cum laude* are 36.7 per cent more likely to move than their peers with a degree score of 70-89. Finally, subject of study is found to be an important determinant of migration. For instance, individuals who studied Engineering are 21.2 per cent more likely to migrate than their counterparts in Economics. Conversely, for students of Law and Political Science the probability of migrating is lower than for Economics students. Moving to our main variable of interest, the sign of the coefficient on the unemployment rate is as expected. This result suggests that the probability that a given graduate migrates is higher if the graduate lives in a high-unemployment province.

In order to account for the possibility that the unemployment rate is picking up the effect of omitted location-specific variables, we add province dummies to specification 1. Since in Italy there are 103 provinces, we introduce 102 dummies in the specification (we use Milano as the benchmarking province). This allows us to avoid perfect multicollinearity and thereby not to fall into the dummy variable trap. The result of this new specification (specification 2) is depicted in the second half of table 2. The inclusion of the province dummies has improved the fit of the model. With the exception of gender, the sign and the statistical significance of the coefficients on the individual characteristics are largely unchanged relative to those obtained in specification 1. On the other hand, the estimate on the unemployment rate differs significantly from that reported in the first half of table 2. The parameter on the unemployment rate is now not statistically significant and suggests a negative impact on the probability of migrating.

We test formally whether the set of province dummies makes a significant contribution to explaining the decision to migrate. A standard F-test rejects easily the null hypothesis that the coefficients on the additional 102 dummies are all zero at any conventional significance level, with F=5.2. Thus, this result supports the appropriateness of the unrestricted model.

Our finding underscores the importance of using the fixed-effects approach when estimating the impact of the unemployment rate on the decision to migrate. This is crucial as it is quite possible that the unemployment rate is picking up the effect of omitted location-specific characteristics on the probability of migrating. Thus, an important implication from this finding is that one should be very cautious in interpreting the results of studies on migration that do not control for unobservable location-specific characteristics. Estimates on the unemployment rate from these studies could in fact be biased.

Given the unexpected outcome obtained in specification 2, one may test whether this can be attributed to the different responsiveness to labour market conditions of the unemployed relative to the employed. Therefore, in specification 3 we substitute the unemployment rate with the interaction term between the dummy variable indicating whether an individual did not begin his/her current job before graduation and the unemployment rate. Since, in non-linear models such as logit and probit, the interpretation of the coefficient of the interaction term is not straightforward as in linear models (Chunrong and Norton, 2003), specification 3 is estimated using a linear probability model. From the first columns of table 3, which reports the result of this new specification, it emerges that the coefficient on this interaction term is statistically significant[9] and has the expected positive sign. Thus, the empirical result shows that slack labour markets may act as an incentive to migrate only for those people who are potentially looking for a job. Although this finding is in line with previous research, it assumes here a great relevance as we control for unobservable location-specific factors.

However, due to the binary nature of the dependent variable, the linear probability model suffers by definition from heteroskedasticity. Two methods have been widely used to deal with this problem. The first is to employ a weighted least squares (WLS) estimator. This is done by first retaining the predicted values, $\hat{I}_i$, from the previous linear probability regression. Following the approach suggested by Wooldridge (2000, p.272), we adjust those predicted values that are less than zero or greater than unity by setting $\hat{I}_i = 0.01$ if $I_i < 0$ and $\hat{I}_i = 0.99$ if $\hat{I}_i > 1$. Next with these predictions the weights, w_i, are calculated using the formula $w_i = \frac{1}{\sqrt{\hat{I}_i(1-\hat{I}_i)}}$ and thus the WLS estimates can be computed. The second method to deal with heteroskedasticity is to use White's Heteroskedastic consistent covariance matrix estimator. The second and third columns of table 3 present the estimates of the linear probability models where the problem of heteroskedasticity has been addressed employing the White's Heteroskedastic consistent covariance matrix estimator (specification 4) and the WLS estimator (specification 5) respectively. As regards the interaction term, these findings are in line with the output of the first columns of table 3, thereby suggesting that employed graduates may respond less to unemployment than unemployed graduates.

Table 3: Linear Probability Regression - estimates of the probability of 'Having Migrated'

	Parameter Specification 3	*S.E.*	*Parameter* Specification 4^a	*S.E.*	*Parameter* Specification 5^b	*S.E.*
Constant	0.181*	0.015	0.181*	0.014	0.204*	0.012
INDIVIDUAL CHARACTERISTICS						
Female	-0.013**	0.005	-0.013**	0.005	-0.007***	0.004
Age - Reference group is 30 or more						
Between 24 and 25	0.039**	0.018	0.039***	0.020	0.013	0.020
Between 26 and 28	0.002	0.007	0.002	0.007	-0.017*	0.005
Between 29 and 30	0.007	0.007	0.007	0.007	-0.005	0.005
Married/Cohabiting	-0.072*	0.006	-0.072*	0.007	-0.061*	0.005
Child	-0.030*	0.010	-0.030*	0.010	-0.022*	0.008
Postgraduate qualification	0.024*	0.007	0.024*	0.008	0.020*	0.006
Moved to attend university	0.166*	0.006	0.166*	0.008	0.158*	0.008
Self-employed	-0.090*	0.008	-0.090*	0.007	-0.050*	0.004
Subject of study - Reference group is Economics						
Engineering	0.024**	0.010	0.024**	0.010	0.010	0.009
Architecture	-0.048*	0.013	-0.048*	0.012	-0.036*	0.008
Law	-0.031*	0.010	-0.031*	0.009	-0.013***	0.007
Political Science	-0.018	0.011	-0.018	0.011	-0.031*	0.009
Agricultural studies	-0.026***	0.014	-0.026***	0.014	0.009	0.010
Languages	-0.022***	0.012	-0.022***	0.012	-0.031*	0.010
Education, Italian, Psychology	-0.047*	0.009	-0.047*	0.009	-0.035*	0.007
Biological Science, Pharmacy, Chemistry	-0.040*	0.010	-0.040*	0.010	-0.029*	0.008
Mathematics and Physics	0.009	0.012	0.009	0.013	0.001	0.012
Medicine	0.028**	0.012	0.028**	0.013	0.004	0.012
Degree Classification- Reference group is 110 cum laude						
Between 70 and 89	-0.063*	0.014	-0.063*	0.014	-0.031*	0.010
Between 90 and 99	-0.058*	0.008	-0.058*	0.008	-0.040*	0.006
Between 100 and 104	-0.036*	0.008	-0.036*	0.008	-0.029*	0.006
Between 105 and 110	-0.026*	0.007	-0.026*	0.007	-0.027*	0.006
AREA-CHARACTERISTICS						
Unemployment rate* not being in current job before migration	0.001*	0.0002	0.001*	0.0002	0.001*	0.0002

Table 3 *...cont*

	Parameter	*S.E.*	*Parameter*	*S.E.*	*Parameter*	*S.E.*
	Specification 3		*Specification 4*[a]		*Specification 5*[b]	
PROVINCE DUMMIES						
Referenca group is Milano						
Torino	-0.013	0.015	-0.013	0.012	-0.044*	0.009
Vercelli	0.137*	0.043	0.137*	0.052	0.090	0.060
Novara	0.036	0.031	0.036	0.031	-0.020	0.017
Cuneo	-0.021	0.028	-0.021	0.028	-0.048*	0.015
Asti	0.126*	0.046	0.126**	0.054	0.096***	0.057
Alessandria	0.004	0.029	0.004	0.028	-0.039***	0.020
Aosta	-0.075	0.061	-0.075	0.055	-0.108*	0.035
Imperia	0.142	0.045	0.142**	0.057	0.100	0.066
Savona	0.053	0.036	0.053	0.042	0.021	0.041
Genova	0.021	0.019	0.021	0.018	-0.024	0.015
La Spezia	0.057	0.044	0.057	0.055	0.025	0.059
Varese	0.046**	0.021	0.046**	0.019	-0.012	0.018
Como	0.062**	0.025	0.062**	0.024	0.006	0.023
Sondrio	-0.007	0.047	-0.007	0.053	-0.055	0.054
Bergamo	-0.017	0.022	-0.017	0.018	-0.039*	0.012
Brescia	-0.026	0.021	-0.026	0.016	-0.046*	0.012
Pavia	0.011	0.027	0.011	0.024	-0.031	0.020
Cremona	0.002	0.033	0.002	0.030	0.036	0.025
Mantova	-0.005	0.032	-0.005	0.032	-0.059**	0.029
Bolzano	0.111*	0.040	0.111**	0.050	0.073	0.055
Trento	-0.009	0.027	-0.009	0.025	-0.033***	0.019
Verona	-0.030	0.021	-0.030***	0.018	-0.046*	0.011
Vicenza	-0.043***	0.024	-0.043**	0.019	-0.027**	0.013
Belluno	-0.010	0.043	-0.010	0.047	-0.056	0.042
Treviso	0.002	0.023	0.002	0.021	-0.028**	0.014
Venezia	0.064*	0.020	0.064*	0.021	0.037***	0.019
Padova	0.003	0.019	0.003	0.016	0.020***	0.012
Rovigo	0.094**	0.039	0.094	0.045	0.049	0.047
Udine	0.019	0.024	0.019	0.025	0.018	0.024
Gorizia	0.093***	0.050	0.093	0.060	0.066	0.065
Trieste	0.090**	0.038	0.090**	0.043	0.063	0.045
Piacenza	0.003	0.033	0.003	0.029	-0.047***	0.025
Parma	-0.024	0.027	-0.024	0.020	-0.046*	0.013
Reggio Emilia	0.003	0.029	0.003	0.025	-0.046**	0.019
Modena	0.004	0.025	0.004	0.021	-0.027	0.017
Bologna	0.0003	0.021	0.0003	0.017	-0.027***	0.014

Table 3 *...cont*

	Parameter	*S.E.*	*Parameter*	*S.E.*	*Parameter*	*S.E.*
	Specification 3		*Specification 4*[a]		*Specification 5*[b]	
PROVINCE DUMMIES						
Referenca group is Milano						
Ferrara	0.018	0.034	0.018	0.031	0.008	0.026
Ravenna	-0.057***	0.032	-0.057**	0.026	-0.080*	0.015
Forli-Cesena	-0.005	0.031	-0.005	0.029	-0.036	0.023
Pesaro e Urbino	0.014	0.030	0.014	0.031	0.007	0.025
Ancona	-0.031	0.026	-0.031	0.026	-0.076*	0.011
Macerata	0.032	0.035	0.032	0.038	-0.002	0.035
Ascoli-Piceno	0.023	0.034	0.023	0.038	-0.024	0.038
Massa-Carrara	0.013	0.047	0.013	0.051	-0.037	0.046
Lucca	-0.036	0.036	-0.036	0.025	-0.037**	0.016
Pistoia	0.014	0.044	0.014	0.042	0.054	0.033
Firenze	0.033***	0.020	0.033***	0.019	0.022	0.016
Livorno	0.088**	0.036	0.088**	0.042	0.075***	0.044
Pisa	0.009	0.030	0.009	0.026	-0.047*	0.018
Arezzo	-0.055	0.034	-0.055***	0.028	-0.076*	0.016
Siena	-0.040	0.038	-0.040	0.032	-0.048**	0.020
Grosseto	0.006	0.044	0.006	0.053	-0.065**	0.032
Perugia	-0.015	0.026	-0.015	0.023	-0.048*	0.019
Terni	0.005	0.033	0.005	0.037	-0.036	0.030
Viterbo	0.00002	0.039	0.00002	0.036	-0.067**	0.032
Rieti	0.187*	0.051	0.187*	0.069	0.160**	0.077
Roma	-0.032*	0.012	-0.032*	0.010	-0.054*	0.008
Latina	0.047	0.030	0.047	0.033	0.010	0.032
Frosinone	0.033	0.030	0.033	0.033	-0.002	0.032
Caserta	0.046***	0.024	0.046***	0.026	0.010	0.025
Benevento	0.072**	0.036	0.072***	0.042	0.017	0.046
Napoli	0.007	0.015	0.007	0.013	-0.028**	0.011
Avellino	0.096*	0.033	0.096**	0.039	0.050	0.043
Salerno	0.065*	0.021	0.065*	0.023	0.024	0.024
L'Aquila	0.026	0.034	0.026	0.036	-0.026	0.035
Teramo	0.028	0.039	0.028	0.043	-0.023	0.039
Pescara	0.134*	0.035	0.134*	0.042	0.089***	0.047
Chieti	0.065**	0.030	0.065**	0.035	0.040	0.033
Campobasso	0.161*	0.035	0.161*	0.044	0.123**	0.051
Foggia	0.144*	0.026	0.144*	0.032	0.101*	0.037
Bari	0.029	0.019	0.029	0.018	-0.020	0.015
Taranto	0.205*	0.028	0.205*	0.037	0.184*	0.041

Table 3 *...cont*

	Parameter Specification 3	S.E.	Parameter Specification 4[a]	S.E.	Parameter Specification 5[b]	S.E.
PROVINCE DUMMIES						
Referenca group is Milano						
Brindisi	0.192*	0.035	0.192*	0.046	0.163*	0.052
Lecce	0.132*	0.023	0.132*	0.027	0.093*	0.031
Potenza	0.120*	0.029	0.120*	0.036	0.078**	0.040
Matera	0.312*	0.037	0.312*	0.050	0.293*	0.057
Cosenza	0.060*	0.021	0.060*	0.023	0.017	0.023
Catanzaro	0.180*	0.028	0.180*	0.036	0.149*	0.042
Reggio Calabria	0.113*	0.027	0.113*	0.032	0.079**	0.036
Trapani	0.041	0.038	0.041	0.045	-0.004	0.045
Palermo	0.042***	0.022	0.042***	0.022	-0.006	0.023
Messina	0.052**	0.026	0.052	0.027	0.005	0.029
Agrigento	0.041	0.034	0.041	0.041	0.008	0.044
Caltanissetta	0.125*	0.042	0.125**	0.058	0.123**	0.062
Enna	0.112**	0.047	0.112***	0.064	0.103	0.069
Catania	-0.008	0.021	-0.008	0.020	-0.050*	0.013
Ragusa	0.024	0.040	0.024	0.049	0.062	0.049
Siracusa	0.092*	0.033	0.092	0.042	0.057	0.045
Sassari	0.019	0.029	0.019	0.030	-0.031	0.028
Nuoro	0.210*	0.036	0.210*	0.051	0.200*	0.055
Cagliari	-0.036	0.023	-0.036***	0.021	-0.078*	0.010
Pordenone	-0.009	0.033	-0.009	0.036	-0.022	0.032
Isernia	0.101***	0.060	0.101	0.079	0.107	0.081
Oristano	0.215*	0.053	0.215*	0.070	0.176**	0.082
Biella	0.101***	0.059	0.101	0.070	0.069	0.076
Lecco	0.013	0.038	0.013	0.032	-0.035	0.027
Lodi	0.055	0.050	0.055	0.051	0.014	0.056
Rimini	-0.068***	0.037	-0.068**	0.033	-0.057**	0.022
Prato	0.063	0.053	0.063	0.053	0.003	0.054
Crotone	0.089***	0.051	0.089	0.068	0.083	0.075
Vibo-Valentia	0.050	0.053	0.050	0.066	0.015	0.070
Verbano-Cusio-Ossola	0.038	0.061	0.038	0.078	0.032	0.067
Number of observations	20,551		20,551		20,551	
R^2	0.111		0.111		0.104	

*denotes significance at 1%
**denotes significance at 5%
***denotes significance at 10%

a The White's Heteroskedastic consistent covariance matrix estimator has been used to work with the heteroskedastic disturbance term.
b The WLS estimator has been used to work with the heteroskedastic disturbance term.

This result is consistent with that obtained by Antolin and Bover (1997) who find that in Spain higher local unemployment rates exert a significantly stronger influence on the decision to migrate among the unregistered unemployed relative to the employed. The rationale for distinguishing between unregistered and registered unemployed lies in the authors' belief that benefit-receipt by the latter group may deter migration. This paper adopts a similar approach. The large majority of people who were searching for a job just after graduation were also in a situation where they were unable to claim unemployment benefits given their lack of labour market experience.

5. Conclusions

In this paper we have analysed the effect of the unemployment rate on the decision to migrate among recent Italian graduates. Three main conclusions emerge from our study. First, as location-specific characteristics are likely to be correlated with labour market conditions and the probability that an individual migrates, one should use the fixed-effects approach when estimating the impact of the unemployment rate on the decision to migrate. Second, studies that do not control for omitted location-specific characteristics are likely to produce quite misleading results. Third, we find some evidence supporting the hypothesis that lower employment opportunities are likely to encourage individuals to migrate if they are looking for a job, but have no influence on those who are employed. This result is robust as we account for unobservable area-specific characteristics. An important implication of this finding is that migration of recent graduates seems to be working as an equilibrating force in the labour market.

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Endnotes

1. University of Westminster, Department of Economics and Quantitative Methods. Email: G.D.I.Pietro@westminster.ac.uk The author would like to thank two anonymous referees for their helpful comments and suggestions. However, any errors ot omissions remain the author's responsibility.

2. This method has been also adopted by Rees and Mocan (1997).

3. See Herzog et al. (1993) and references therein.

4. In Italy there are 103 provinces (administrative units comparable to US counties).

5. Unfortunately the survey does not provide information on the age of the child/children and on the employment status of wives/husbands or partners.

6. One may also observe that using gender differences in the unemployment rate helps us to avoid perfect collinearity. It is impossible to estimate a model with province dummies and location characteristics that are the same for all individuals in the same province.

7. One may note that this dummy variable may not entirely be suitable to test whether the employed and the unemployed have different sensitivities to labour market conditions. Individuals who were working before graduation but were in a different job than the current one are misclassified as non-working. However, the magnitude of this bias is particularly small given the low labour mobility in Italy.

8. One would expect labour market participation to be very high among recent graduates as it is expected to increase with increased education.

9. Moulton (1990) observes that within datasets where aggregate data have been merged with micro-observations, errors are unlikely to be independent. This implies that the conventional OLS technique may yield standard errors that are seriously biased downwards. More precisely, Moulton (1990) concludes that because of this problem, the *t*-statistics associated with aggregate variables are likely to be biased upwards by a factor of between 3 and 5. As regards our empirical analysis, it is important to note that even in the worst case (i.e. when the t-statistic is reduced by a factor of 5) the interaction term is still statistically significant at all conventional levels in the regression outputs depicted in table 3.

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