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Abstract

We analyze the effect of interregional migration on regional unemployment in Italy. With the help of a simple two-region model adapted to the main features of the Italian North-South dualism, we illustrate the effects of labor mobility with and without human capital externalities. Using longitudinal data over the years 2002-2011 for 103 NUTS-3 Italian regions, we document that net outflows of human capital from the South to the North have increased the unemployment rate in the South, while it did not affect the unemployment rate in the North. Our analysis contributes to the literature on interregional human capital mobility suggesting that reducing human capital flight from Southern regions should be a priority.

Keywords: Unemployment, Migration, Human capital, Externalities, Italian regions.

Jel codes: C23, R23, J61

1 Introduction

Skilled workers mobility has raised concerns since the seminal contribution by Bhagwati and Hamada (1974). Today, worries of a brain drain are mitigated: the 'new brain drain literature' has emphasized that emigration prospects incentivize investments in human capital, and that the skill flow need not harm source economies (Beine et al., 2008). However, mobility is not just restricted to those who migrate internationally, and it is well-known that highly-educated individuals are also internally mobile. Though extending the results of the brain drain literature to a regional context may look straightforward, internal mobility may be very different from international mobility. First of all, barriers to internal mobility are almost inexistent, as well as barriers related to human capital transferability and language acquisition. Then -with respect to international migration- internal mobility is only marginally affected by issues such as return migration and/or family relocation. For these reasons, workers easily tend to cluster into high-income regions. How does this affect the regional unemployment? We contribute to answer this question by assessing the effect of interregional migration on regional unemployment in Italy over the 2002-2011 period using data at the NUTS-3 territorial level (namely 103 provinces).

Actually, there is no consensus about the effects of interregional mobility. Basic competitive models predict that labor mobility equalizes wages across regions and eliminates unemployment. In these models, emigration from low-wage to high-wage areas continues until wages converge and unemployment disappears. Therefore, long-run regional unemployment disparities can only be determined by wage rigidity and by factors that hamper or reduce regional mobility, such as frictional effects of distance, transaction costs, regional amenities that compensate for lower wages or for a higher risk of unemployment (Marston, 1985). On the other hand, when one considers the possibility of externalities, the predictions of competitive models can be reversed, and labor mobility may magnify regional disparities. This theoretical ambiguity can only be settled on empirical grounds. As a consequence, the literature has devoted a great deal of work to these issues, but the available evidence is still unclear. Blanchard and Katz (1992) find that labor mobility has been crucial in achieving regional convergence of the unemployment rates in the US; by contrast, Decressin and Fatàs (1995) argue that this adjustment mechanism is ineffective in the EU, where mobility seems not able to shelter workers from asymmetric regional shocks. More recently, Partridge and Rickman (2006) challenge the conclusions of Blanchard and Katz for the US, while Baddeley et al. (2000) question the findings of Decressin and Fatàs for the EU. Wrage (1981) and Groenewold (1997) document that interregional mobility exerts weak (if any) equalizing effects on regional unemployment rates in Canada and in Australia. Inconclusive evidence also emerges for Germany, where some authors suggest that labor mobility reduces regional unemployment disparities (Bayer and Jüssen, 2007) and others find conflicting results (Möller, 1995; Südekum, 2004; Granato et al., 2015). These heterogeneous findings have fostered theoretical explanations based on Kaldorian-like cumulative causation effects originated by selective migration (Burda and Wyplosz, 1992; Feser and Sweeney, 2003; Südekum, 2004; Kanbur and Rapoport, 2005) or New Economic Geography-style agglomeration effects activated by labor inflows (Epifani and Gancia, 2005; Südekum, 2005; Francis, 2009).

The case of Italy is particularly interesting for assessing the effects of regional mobility. It is well-known that the regions of Southern Italy display a worse economic performance with respect to the rest of the Country (see Panel A of Table 1 for an overview of the main macroeconomic indicators and Section 3 for a description of the variables). This divide dates back at least to the XIX century (Daniele and Malanima, 2007; 2011). This long-term dualism has generated permanent outflows of workers, first towards North and South America, then towards Germany, Switzerland and France. In more recent times, international migration has been replaced by internal migration towards the richer and fast-growing industrial districts in the northern regions (Del Boca and Venturini, 2005).[1] However, the characteristics of these emigrants have also changed over time. While in the 60s and 70s unskilled workers were the majority, the "new emigrants" show a substantially higher education, both at the secondary and at the tertiary level (Mocetti and Porello, 2010; Bonasia and Napolitano,

[1]South-North flows never stopped, though they were reduced from the mid 1970s to the mid 1990s. Faini et al. (1997) show that this happened because of several socio-economic factors, like expectations of North-South wage convergence (in line with the "option value of waiting" approach sketched by Burda, 1995), large-scale job creation in the public sector, transaction costs due to mobility and job-matching failures (see also Alesina et al. 2001; Attanasio and Padoa-Schioppa, 1991). The 1992 crisis also caused the fiscal consolidation required to join the Euro area and the end of the "*intervento straordinario*" (extraordinary intervention), namely a special program of transfers to the Southern economy. These factors have stimulated a renewal of migration flows.

2012).[2] The effects of this recent wave of "internal brain drain" on the regional unemployment have not been analyzed yet. We try to fill this gap and, at the same time, we contribute to the literature by adding to the "extremely limited" number of studies that analyze the consequences of migration on *origin* regions (Faggian et al., 2017).

First of all, we try to shed light on the theoretical ambiguity behind the effect of interregional mobility by means of a simple two-region model adapted to the main features of the Italian dualism. In our framework, the labor market in the South is characterized by lower physical capital endowment and more serious distortions with respect to the North. This divide generates South-North migration. In the absence of human capital externalities, this outflow of workers reduces the South-North unemployment gap. However, when we introduce human capital externalities into the model, this result can be reversed, and migration may well intensify the North-South divide. Thus, the actual effect of emigration has to be assessed empirically. This outcome is in line with authors like Südekum (2004), Kanbur and Rapoport (2005), and Epifani and Gancia (2005).

The empirical evidence, based on the estimation of dynamic and spatial dynamic panel data models over the 2002-2011 period, documents that human capital outflows from the South to the North have increased the unemployment rate in the South, while not exerting any significant effect in the North. We conclude that migration seems to have exacerbated local labor market disparities within Italy over the 2002-2011 decade. Our results support the literature that finds an important role of regional externalities, and suggest that human capital flight is detrimental for Southern Italy. This conclusion is in agreement with Fratesi and Percoco (2014), who find that the South-North flow of human capital over the years 1980-2001 has not caused any convergence in the regional growth.

The rest of the paper is organised as follows. Section 2 reports the theoretical model. Section 3 presents the database and some stylized facts on unemployment dynamics and human-capital augmented migration flows. Section 4 presents the econometric model and Section 5 discusses the empirical results. Conclusions follow in Section 6.

[2]This is true especially for regions like Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna. For instance, according to Mocetti and Porello (2010), the Calabria's net migration rate of people holding a degree was -2.3 in the period 1991-1995 and -11.4 in the period 2001-2005.

2 The effect of interregional mobility of human capital

As we have stressed in the introduction, simple competitive models predict that out-migration flows from the South tend to equalize the North-South unemployment gap (Burridge and Gordon, 1981). On the contrary, models featuring human capital externalities come to opposite conclusions (Burda and Wyplosz, 1992; Feser and Sweeney, 2003; Südekum, 2004; Kanbur and Rapoport, 2005; Epifani and Gancia, 2005). In what follows, we present a simple model that summarizes these results.

2.1 The model

We develop a simple theoretical framework in order to show intuitively the conditions under which interregional migration reduces or intensifies regional unemployment disparities. We start from a basic observation, namely, the very existence of unemployment proves that there is no such a thing as a perfect labor market. However, the heterogeneity of unemployment rates also proves that some economies and some labor markets perform better than others. The case of Italy, with the bleak performance of its *Mezzogiorno*, is paradigmatic in this respect. We model the Italian situation by considering an economy with a Southern region (S) and a Northern region (N). N and S include $p = 1, ...p_N$ and $1, ...p_S$ provinces respectively. In both regions the labor market is imperfect -due to a variety of causes like search frictions, efficiency wages, informational asymmetries, inefficient institutions. We sketch these imperfect labor markets in the simplest possible way by assuming that the actual wage w_{rp} in region r ($r = N, S$) and province p is given by the competitive wage $w^*_{rp}(A, K_{rp}, M_{rp})$ plus a rent R.

The competitive wage depends on the total factor productivity A, on the capital stock K_{rp}, and on net in-migration M_{rp} that adds to the existing labor force.[3] The rent $R(x_r)$ depends on the vector x_r that incorporates different, possibly region-specific, sources of distortion. The actual wage is therefore

$$w_{rp} = w^*_{rp}(A, K_{rp}, M_{rp}) + R(x_r). \quad (1)$$

[3]Net in-migration is given by the difference between inflows and outflows of workers. According to Biagi et al. (2011), we only consider long-distance migration (between South and North) because in Italy these movements are determined by wage differentials. By contrast, intra-regional, short-distance migration does not respond to economic factors, and is determined by the search of natural amenities and better quality of life.

The partial derivatives of the competitive wage follow standard intuitions:

$$\frac{\partial w_{rp}^*}{\partial A} > 0; \tag{2}$$

$$\frac{\partial w_{rp}^*}{\partial K_{rp}} > 0; \tag{3}$$

$$\frac{\partial w_{rp}^*}{\partial M_{rp}} < 0. \tag{4}$$

Derivatives (2) and (3) state that the competitive wage increases as the total factor productivity or the capital stock increase. Derivative (4) depicts the effect of the in-migration, and simply states that as the number of workers increases, the competitive wage decreases. These assumptions are quite standard and fit a wide class of production functions.

In order to reproduce the North-South dualism in Italy, we simply assume $K_{Np} > K_{Sp}$ for any p. This implies that, other things being equal, competitive wages in the North are higher than competitive wages in the South. In order to preserve realism, we also assume that, even though rents in the South can be higher than in the North, wages in the South are still lower.[4]

2.2 Migration and unemployment without externalities

In our model, we use the size of the rent as a measure of labor market distortion. Higher rents imply indeed a larger difference between the actual wage and the competitive wage, thus higher unemployment. As a consequence, we describe the unemployment rate in region S and province p as a function of the share of the rent over the actual wage:

$$u_{rp} = \frac{R(x_r)}{w_{rp}^*(A, K_{rp}, M_{rp}) + R(x_r)} \tag{5}$$

Note that in equation (5) the unemployment rate tends to zero as the rent becomes negligible with respect to the competitive wage. On the contrary, if the wage is mostly made by rent, the unemployment rate tends to unity. For the moment, the total factor productivity is held uniform across the country (this assumption will be relaxed in the next section, where we analyze the effect of human capital externalities). We can now compute the effect of out-migration ($dM_{Sp} < 0$) from

[4] Alesina et al. (2001) convincingly argue that the labor market in the South suffers from more severe distortions with respect to the North.

a Southern province by the simple derivative $\partial u_{Sp}/\partial M_{Sp}$:

$$\frac{\partial u_{Sp}}{\partial M_{Sp}} = -\left[-\frac{\partial w^*_{Sp}}{\partial M_{Sp}}\left(\frac{R(x)}{[w^*_{rp}(A, K_{rp}, M_{rp}) + R(x_r)]^2}\right)\right] < 0. \tag{6}$$

In other words, net out-migration reduces the labor in the province, which causes an increase in the competitive wage and reduces the weight of the rent. As a consequence, the unemployment decreases.

The effect of in-migration ($dM_{Np} > 0$) into a Northern province is given by the derivative $\partial u_{Np}/\partial M_{Np}$:

$$\frac{\partial u_{Np}}{\partial M_{Np}} = -\frac{\partial w^*_{Np}}{\partial M_{Np}}\left(\frac{R(x)}{[w^*_{rp}(A, K_{rp}, M_{rp}) + R(x_r)]^2}\right) > 0. \tag{7}$$

Equations (6) and (7) summarize the equilibrating effect of migration in models without externalities. In the next Section we generalize our model in order to allow for the existence of human capital externalities.

2.3 Migration and unemployment with externalities

Since Fujita and Thisse (2002), the existence of regional externalities is well-documented in the literature. We analyze their consequences on the regional divide in line with Shukla and Stark (1990) and Stark and Fan (2008). We use a standard approach, and let externalities work through the total factor productivity A. We now let A be a differentiable function of the human capital, which is proxied by net in-migration of skilled workers. Net out-migration of skilled workers reduces human capital. In-migration of skilled workers has obviously the opposite effect. We write the total factor productivity as follows:

$$A_{rp} = G(M_{rp}), \qquad \text{with} \qquad \frac{\partial G}{\partial M_{rp}} > 0. \tag{8}$$

Equation (5) becomes now

$$u_{rp} = \frac{R(x_r)}{w^*_{rp}(G(M_{rp}), K_{rp}, M_{rp}) + R(x_r)} \tag{9}$$

The effect of out-migration ($dM_{Sp} < 0$) from a Southern province formerly given by equation (6) modifies to

$$\frac{\partial u_{Sp}}{\partial M_{Sp}} = -\left[\underbrace{\frac{\partial w^*_{Sp}}{\partial M_{Sp}}}_{+} + \underbrace{\frac{\partial w^*_{Sp}}{\partial G}\left(\frac{\partial G}{\partial M_{Sp}}\right)}_{-}\right]\frac{R(x)}{[w^*_{rp}(A, K_{rp}, M_{rp}) + R(x_r)]^2} \gtreqless 0, \tag{10}$$

where the term $\frac{\partial w^*_{Sp}}{\partial M_{Sp}}$ measures the effect of net in-migration on labor supply, and the term $\frac{\partial w^*_{Sp}}{\partial G}\left(\frac{\partial G}{\partial M_{Sp}}\right)$ measures the externality effect of net in-migration. These terms have opposite signs, and the final outcome is undetermined. Analogously, the effect of net in-migration ($dM_{Np} > 0$) into Northern provinces will be

$$\frac{\partial u_{Np}}{\partial M_{Np}} = -\left[\underbrace{\frac{\partial w^*_{Np}}{\partial M_{Np}}}_{-} + \underbrace{\frac{\partial w^*_{Np}}{\partial G}\left(\frac{\partial G}{\partial M_{Np}}\right)}_{+}\right]\frac{R(x)}{[w^*_{rp}(A, K_{rp}, M_{rp}) + R(x_r)]^2} \gtreqless 0 \tag{11}$$

It is evident that the effect of emigration on the two regions can now take any sign: the equilibrating effect we have seen in the former section is no longer assured. The net impact of labor mobility on the unemployment cannot be determined *ex-ante*, and becomes an empirical issue.

3 Unemployment dynamics and human-capital augmented migration: some stylised facts

To empirically assess the effect of (human-capital augmented) labour migration on regional unemployment dynamics in Italy, we use yearly regional data over the period 2002-2011. When not differently indicated, all data are taken from Italian government statistics (National Institute for Statistics, ISTAT, and Ministry of Economy and Finance). In particular, migration data come from the "*Indagine sui trasferimenti di residenza*", which is a survey carried out by ISTAT. In keeping with the methodological standards set by the EU Regulation 862/2007, ISTAT has revised the entire data set from 1995 onward. Regarding to the information on the level of schooling of the migrants, the series have been collected since 2002.

As a background to the analysis, Panel A. of Table 1 highlights the deep-rooted mismatch in terms of output, wealth and productivity between Northern and Southern regions of Italy over the period covered by the analysis.[5] About 76 percent of gross domestic product (GDP) is produced in the North; in per capita terms ($GDPpc$), the gap gets somewhat smaller, while productivity (computed as the ratio between value added and hours worked, $prod$) turns out to be around three-fourth of the level attained in the richest part of the Country. A clear North-South divide is confirmed when looking at the dynamics (expressed as average annual rates of growth): in an overall context of weak growth at the national level, a diverging pattern between the two macro-regions can be detected, with Southern regions under-performing the rest of Italy in terms of both GDP and productivity growth rates.

Striking regional differences in labour market performances and population structure also emerge. The South records considerably fewer labour force participants ($part$) and employed residents (emp) than the North (-14.7 and -19.4 percent, respectively), with an average unemployment rate (u) in the Southern regions about three times higher than that of the North (13.7 vs 5.1 percent).

Tab.1

Looking at the direction of (internal) migration,[6] we find preliminary evidence supporting a net migration outflow from the South, with about a million people from the South migrating to the North (long-distance migration). Such an outflow is only partially compensated by internal movements in the opposite direction (i.e. form the North to the South) implying a negative South-North balance of more than 400 thousand people (corresponding to about 3 percent of the working age population in the South). To better capture the hypothesized brain drain effect induced by outmigration, we report the (average) long-distance migration rates weighted by the educational

[5]In the Italian case it is customary to distinguish between South or Mezzogiorno (including the following NUTS-2 regions: Campania, Abruzzo, Molise, Basilicata, Calabria, Puglia, Sicilia and Sardegna) and Center-North or simpler North (including the following NUTS-2 regions: Valle d'Aosta, Piemonte, Lombardia, Province Autonome di Trento e Bolzano, Friuli Venezia Giulia, Veneto, Liguria, Emilia Romagna, Marche, Toscana, Lazio and Umbria).

[6]The net migration rate is the balance between the number of registrations and cancellations of people aged 15 and over (working-age population) from the municipality registry divided by the total residential population aged between 15 and over. In keeping with our theoretical model, we exclude foreign migrants from our empirical analysis in order to focus on the effect of internal migration on regional unemployment dynamics. Moreover, in order to better isolate migration based on economic grounds, we select South-North migration flows, i.e. those originated from Southern to Northern provinces and *viceversa*.

level of migrants ($LDnetMigr^h$), that has been computed according to the formula:

$$LDnetMigr^h = 100 \times \sum_k M_k D_k / P_k D_k \tag{12}$$

where M_k and P_k are the net migration rate and the number of people with the *k-th* level of schooling, respectively, and D_k is the duration in years of the *k-th* level.[7] As the Table shows, the human-capital augmented migration ratio is negative for the South and positive for the North. Moreover, a look at the disaggregation in term of inflow and outflow migration rates ($LDinMigr^h$ and $LDoutMigr^h$, respectively) reveals that the two macro-regions experience similar inflow ratios, so that the net migration rate is mostly driven by an outflow ratio in the South which exceeds markedly that for the North. This evidence is consistent with the view that migration is a selective phenomenon fuelled by spatial mobility of highly educated individuals, as pointed out by Greenwood (1975), Plane and Rogerson (1994) and Molloy et al. (2011). This conclusion is reinforced when human-capital augmented migration flows are computed by distinguishing migrants with low or medium levels of education, $LDnetLowMigr$, and higher degree-holders, $LDnetHighMigr$, giving support to the existence of selective migration flows from the South to the North.

As stressed by Faggian et al. (2017), selective migration is likely to affect substantially the economic performance of both origin and destination regions. To delve deeper into the relationship between regional migration and labour market performances, we turn to the evolution over time of the two key variables of our theoretical model: unemployment rates and human-capital augmented long-distance migration flows. The progressive process of labour market deregulation started in the mid-90s has contributed to a reduction of the nation-wide unemployment rate coupled with a slight reduction in the North-South divide.[8] Focusing on the sample span covered by the present analysis, the national-wide unemployment rate has dropped from 8.6 percent in 2002 to 6.1 in 2007, while it has increased during the crisis returning to 8.4 in 2011; as for the North-South gap, it has been declining from 2002 to 2009 and remained broadly stable since then (Figure 1). At the same time,

[7] We consider four education levels: 1) up to the primary school (LL), 2) lower secondary school (ML), 3) upper secondary school (MH), and 4) tertiary education level (HH). The duration of each level is 3, 8, 13, and 18 years, respectively.

[8] See, among others, Prasad and Utili (1998), Brunello et al. (2001), Kostoris-Padoa-Schioppa and Basile (2002) for the Italian case, and Jiménez-Rodríguez and Russo (2012), for a review of the mid-90s labour market reforms in Europe.

a resurgence of South-North out-migration flows have occurred (Attanasio and Padoa-Schioppa, 1991; Faini et al., 1997; Basile and Causi, 2007), with a structural depletion of the stock of human capital in the South (Figure 2).

Fig.1 - Fig.2

A more granular inspection, based on the univariate density estimate of provincial unemployment rates (computed as arithmetic differences from the national average), shows the existence of an unimodal right-skewed distribution of provincial unemployment rates in 2002 (dotted line), with a higher density for values lower than the national average (Figure 3). In contrast, the distributions of provincial unemployment in 2007 (dashed line) and 2011 (bold line) appear markedly different. In both cases we observe a strong tendency towards polarization, with the main peak much more pronounced than in 2002 and a second lower peak at around the 4 percent above the national average. The change in the distribution reflects the effect of the Great Recession: unemployment rates have started growing in the Northern provinces and, subsequently, in the rest of Italy.

Fig.3

The map of the decile distribution of annual averages of provincial unemployment rates and human capital-augmented migration flows gives support to previous evidence: all Southern provinces have registered negative values during the period 2002-2011, while better labour market conditions clearly emerges for the Northern part of Italy (Figure 4a and Figure 4b). Taken together, the evidence from the maps seem to suggest a negative relationship between migration and labour market performances in a way consistent with the brain drain effects at work (Carrington and Detragiache, 1998; Kanbur and Rapoport, 2005). As pointed out by Faggian et al. (2017), however, the ultimate effect of internal migration flows on regional macroeconomic performances deserve a more in-depth investigation as migration flows might influence origin and destination regions in an asymmetric way. Accordingly, the following Section is devoted to offer compelling evidence on the effect of interregional labour mobility on local labour performances.

Fig.4a and *Fig.4b*

4 Modeling regional unemployment

In order to simultaneously deal with the highly persistent level of regional unemployment and the presence of spatial interdependence, along with spatial and temporal heterogeneity, the most recent literature on regional unemployment (e.g. Lottmann, 2012; Semerikova, 2015) uses a dynamic spatial panel data model with fixed spatial and time effects. The spatial econometric literature provides several alternative specifications of spatial dynamic models. A very general one includes time lags of both the dependent and independent variables, contemporaneous spatial lags of both, and lagged spatial lags of both. However, as Elhorst (2014) points out, this generalized model suffers from identification problems, and is not useful for empirical research. A more parsimonious model (written in vector form for a cross-section of observations at time t) can be expressed as:

$$\mathbf{y}_t = \tau\mathbf{y}_{t-1} + \rho\mathbf{W}\mathbf{y}_t + \eta\mathbf{W}\mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\alpha} + \lambda_t\boldsymbol{\iota}_N + \pi_t\boldsymbol{\iota}_N \times \mathbf{South} + \boldsymbol{\varepsilon}_t \tag{13}$$

where $\mathbf{y}_t$ denotes a $N \times 1$ column vector consisting of one observation of the dependent variable for every spatial unit i ($i = 1, ..., N$) in the sample at time t ($t = 1, ..., T$), which for this study is the current annual regional unemployment rate. $\mathbf{X}_t$ (or $\mathbf{X}_{t-1}$) is an $N \times K$ matrix of the explanatory variables, which here includes measures of (lagged) values of human capital migration rates, as well as other explanatory variables typically included in a regional unemployment model (employment growth rate, participation rate and industry mix).

The $K \times 1$ vector $\boldsymbol{\beta}$ includes the parameters of the explanatory variables. Coefficients τ, ρ and η are the parameters of the dependent variable lagged in time, $\mathbf{y}_{t-1}$, in space, $\mathbf{W}\mathbf{y}_t$, and in both space and time, $\mathbf{W}\mathbf{y}_{t-1}$. The $N \times N$ matrix $\mathbf{W}$ is a non-negative matrix of known constants describing the spatial arrangement of the spatial units in the sample. The specification of this matrix will be further discussed in Section 5.2.

The $N \times 1$ vector $\boldsymbol{\alpha}$ contains spatial specific effects, α_i, meant to control for all spatial-specific, time-invariant variables, the omission of which could bias the estimates in a typical cross-sectional study. Similarly, λ_t denotes time-period specific effects, where $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones, controlling for all time-specific unit-invariant variables, the omission of which could also bias the estimates. Finally, the elements of the disturbance term $\boldsymbol{\varepsilon}_t$ are assumed to be *i.i.d.* across i and t.

Another important source of bias could be the existence of regional heterogeneous responses to common shocks. In fact, different provinces may react to business cycles or other time-varying (common) shocks in different ways, and this heterogeneity has effects on both migration and unemployment. As well known, a way to control for this source of inconsistency is the application of the Common Correlated Estimator (CCE) proposed for the dynamic framework by Chudik and Pesaran (2015). Nevertheless, the application of this estimator to our analysis would require a very large panel dataset, with at least 50 observations in time for each region. Since it is impossible to reach such a dimension of the dataset, we opted for a second best solution, by including interactions between the yearly time dummies and the dummy South ($\boldsymbol{\iota}_N \times \mathbf{South}$), indicating whether the province belongs to the Mezzogiorno area or not. These interaction terms capture the North-South heterogeneous responses to common business cycle effects. And we believe that this control is enough to properly assess the relationship between North-South (long-distance) migration on regional unemployment.

Lee and Yu (2010) have proposed bias-corrected quasi-maximum likelihood (QML) estimators for a dynamic model with spatial and time fixed effects. Unfortunately, these estimators are based on the assumption of only exogenous covariates except for the time and spatial lag terms. Thus, as a first step of our analysis we will report the results of the consistent System-GMM estimator of dynamic models without any control for spatial dependence, but with a control for the endogeneity of r.h.s. variables such as the migration rate, the employment growth rate and the participation rate.

It is also important to remark that the stationarity conditions on the spatial and temporal parameters in a dynamic spatial panel data model like (13) go beyond the standard condition $|\tau| < 1$ in serial models, and the standard condition $1/\omega_{min} < \rho < 1/\omega_{max}$ in spatial models (with ω_{min} and ω_{max} indicating the minimum and maximum eigenvalues of the $\mathbf{W}$ matrix). Indeed, to achieve stationarity in the dynamic spatial panel data model (13), the characteristic roots of the matrix $(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\tau\mathbf{I}_N + \eta\mathbf{W})$ should lie within the unit circle (Debarsy et al. 2012) which is the case when

$$
\begin{aligned}
\tau + (\rho+\eta)\omega_{max} < 1 & \quad \text{if} \quad \rho+\eta \geq 0 \\
\tau + (\rho+\eta)\omega_{min} < 1 & \quad \text{if} \quad \rho+\eta < 0 \\
\tau - (\rho-\eta)\omega_{max} > -1 & \quad \text{if} \quad \rho-\eta \geq 0 \\
\tau - (\rho-\eta)\omega_{min} > -1 & \quad \text{if} \quad \rho-\eta < 0.
\end{aligned}
$$

For the economic interpretation of the estimation results of model (13) in terms of the impact of a variation of an independent variable on the dependent variable, we need to rely on its reduced form. Assuming that the matrix $(\mathbf{I}_N - \rho\mathbf{W})^{-1}$ (known as the *global interaction multiplier*) is invertible, the reduced form of model (13) can be re-written as follows:

$$
\begin{aligned}
\mathbf{y}_t \quad = \quad & (\mathbf{I}_N - \rho\mathbf{W}\mathbf{y}_t)^{-1}(\tau\boldsymbol{\iota}_N + \eta\mathbf{W})\mathbf{y}_{t-1} + \\
& (\mathbf{I}_N - \rho\mathbf{W}\mathbf{y}_t)^{-1}(\mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\alpha} + \lambda_t\boldsymbol{\iota}_N + \boldsymbol{\varepsilon}_t)
\end{aligned}
$$

Taking the partial derivatives of the expected value of $\mathbf{y}$ with respect to each k-th variable in $\mathbf{X}$ in each unit i at each time t, we then obtain the so-called impacts matrices in the *short run*:

$$
\left[\frac{\partial E(\mathbf{y})}{\partial x_{k1}} \cdots \frac{\partial E(\mathbf{y})}{\partial x_{kN}}\right]_t = (\mathbf{I}_N - \widehat{\rho}\mathbf{W})^{-1}(\widehat{\beta}_k\mathbf{I}_N) \tag{14}
$$

and in the *long run*:

$$
\left[\frac{\partial E(\mathbf{y})}{\partial x_{k1}} \cdots \frac{\partial E(\mathbf{y})}{\partial x_{kN}}\right] = \left[(1-\widehat{\tau})\mathbf{I}_N - (\widehat{\rho} + \widehat{\eta})\mathbf{W}\right]^{-1}(\widehat{\beta}_k\mathbf{I}_N) \tag{15}
$$

These matrices are generally full and not symmetric regardless of the sparsity and structure of the interaction matrix $\mathbf{W}$. We may call the region in column j of these matrices the emitting region and the region in row i the receiving region.

For the explanatory variable x_k, the diagonal elements of both matrices give a measure of the so-called *direct effect*, i.e. how much a change in the explanatory variable k for the emitting region i would affect the dependent variable for the same region i. This effect is heterogeneous across regions in presence of spatial autocorrelation due to higher order feedback effects. They arise as a result of impact passing through neighboring regions and back to the regions themselves. This is what Debarsy and Ertur (2010) call interactive heterogeneity, by contrast to standard individual heterogeneity in panel data models. The magnitude of these direct effects mostly depends on the value of β_k, which is constant across the sample. The off-diagonal elements of the matrices give a measure of the so-called *indirect* or *spillover effect*. By contrast to direct effects, the main part is played here by the information content and the structure of the interaction matrix $\mathbf{W}$, which is the main source of heterogeneity, all the parameters being constant across the whole sample. Again, in the computation of the long-run spillover effect the heterogeneity is amplified by the cumulative impact of transitory shocks over time. Not surprisingly, strongly connected regions are more influenced than less connected regions. However, spillovers diffuse to the entire sample.

The average diagonal elements of matrices (14) and (15) can be used as a summary indicator for the short-run and the long-run direct effect (ADE), and the average row-sum of off-diagonal elements as a summary indicator of the indirect (spillover) effect (AIE). The significance levels of these short and long-run average direct and average spillover effects are bootstrapped (Elhorst, 2014).

5 Econometric results

Based on the theoretical North-South model described in Section 2, we focus on the effect of long-distance human capital migration flows on regional unemployment rates, where long-distance migration is defined as migration from Southern to Northern provinces and from Northern provinces to Southern provinces. Thus, the key explanatory variable in the present analysis is the human-capital augmented long-distance net migration rate ($LDnetMigr^h$). In the empirical setup we also consider possible asymmetric effects of in-migration and out-migration by including separately the (the human-capital augmented) long-distance in-migration rate ($LDinMigr^h$) and out-migration rate ($LDoutMigr^h$). Alternatively, we assess the effect of human capital migration flows by using the long-distance migration rate (net, in and out) of highly-educated workers ($LDnetHighMigr$, $LDinHighMigr$, $LDoutHighMigr$), and the migration rate of (net, in and out) of low-educated workers ($LDnetLowMigr$, $LDinLowMigr$, $LDoutLowMigr$). We include all these migration variables in the model with a time period lag with respect to regional unemployment in order to reduce simultaneous biases. Moreover, we control for simultaneous biases in System-GMM estimates by using internal and external instruments.

Not surprisingly, in Section 3 we have shown that net outflows of long-distance migrants are almost entirely a phenomenon in the South. The opportunity of taking long-distance migration flows separately from short-distance migration flows (here defined as migrations from a province to another province within the same NUTS-2 region) is also suggested by Biagi et al. (2011) according to which long-distance and short-distance migrations in Italy reflect very different behaviors. Specifically, long-distance movements of workers are mainly driven by economic opportunities following the logic of the disequilibrium model, while short-distance migrations are primarily directed from large cities towards smaller cities with better quality of life and natural amenities.

In keeping with the existing literature (e.g. Molho, 1995; Partiridge and Rickman, 1997; Overman and Puga, 2002), the regional unemployment rate is likely to depend on factors that affect labor supply and demand. Accordingly, we include in the set of regressors the following variables: *i*) the employment growth rate (Δemp), *ii*) the participation rate ($part$), and *iii*) the share of services employment (ser), manufacturing employment (man) and construction employment ($const$) on total employment.

In order to account for regional disequilibrium labor market dynamics, the (current value of the) employment growth rate ($\Delta emp_{i,t}$) in percentage terms is included in the set of explanatory variables along with the above described measures of lagged long-distance migration. The employment growth rate is expected to have a negative effect on unemployment, net of the partial absorption of new jobs by new immigrants. This is not surprising because the change in employment directly affects unemployment. Another variable capturing disequilibrium effects are wages or unit labor costs. Unfortunately, information on regional wages and regional labor costs is only available at NUTS-2 level and not at the NUTS-3 (province) level. So, we decided to exclude it from the analysis.

The effect of the (current value of the) labor force participation rate ($part_{i,t} = 100 \times \frac{LF_{i,t}}{Workpop_{i,t}}$), defined as the ratio between total labor force and the working population (population aged between 15 and over), is ambiguous. On the one hand, a positive effect may occur if a faster growth of the labor force (i.e., young people) is not compensated by an as much faster growth of new jobs (or vacancies). On the other hand, its expected effect might be negative when factors determining low participation rates in a region also reflect relatively low investments in human capital and low commitment to working life, thus resulting in higher risks for people with these characteristics to become unemployed.

Finally, differences in the industrial mix may affect regional unemployment dynamics. Provinces specializing in growing sectors, such as services, are expected to exhibit lower unemployment rates than those based around declining industries (such as agriculture). As in previous works (Overman and Puga, 2002, among others), we use the employment shares of the industries with an expected negative effect for $ser_{i,t}$ and for $man_{i,t}$ and a positive sign for $cons_{i,t}$.[9]

5.1 Dynamic panel data model

As mentioned above, we start our econometric analysis from the estimation of dynamic panel data models without any control for spatial autocorrelation:

$$\mathbf{y}_t = \tau \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\alpha} + \lambda_t \boldsymbol{\iota}_N + \pi_t \boldsymbol{\iota}_N \times \mathbf{South} + \boldsymbol{\varepsilon}_t \tag{16}$$

Specifically, we use the System-GMM (Generalised Method of Moments) approach (Blundell and Bond, 1998) to account for the endogeneity of right-hand side variables (namely employment growth rates, participation rates and migration rates),[10] We complement internal GMM instruments with a set of external instruments, namely *i*) the share of provincial population aged between 15 and 24 years on total provincial population, *ii*) the share of provincial population aged between 25 and 39 years on total provincial population, *iii*) the share of provincial population aged between 40 and 64 years on total provincial population, *iv*) the log of provincial average house price (source: Bank of Italy), and *v*) the log of provincial disposable income (source: Prometeia). As the age structure of the population may be affected by past migration flows, while the disposable income and house prices may be influenced by past unemployment conditions, these instrumental variables are lagged two years with respect to the dependent variable (the migration rate is included with one year time lag). We also test the validity of these external instruments through the difference in Hansen test after controlling that they do not enter significantly the model. Ultimately, the application of the

[9] We are aware that a finer classification would be advisable for this kind of analysis. Unfortunately, more detailed sectoral information (Census data) is only recorded over decades rather than on a yearly basis.

[10] A number of studies have suggested a possible reverse causality problem in the relationship between unemployment and migration rates (e.g. Pissarides and McMaster, 1990; Jackman and Savouri, 1992; Basile and Causi, 2007).

System-GMM estimator (with internal and external instruments) and the inclusion of spatial fixed effects, time effects, and the interactions between time dummies and the dummy South allow us to handle three main econometric issues which are relevant when modeling spatio-temporal data: namely simultaneity bias, spatial unobserved heterogeneity bias, and omitted time-related factors bias (common factor bias). In the next section, we focus on the role of spatial dependence bias by estimating some specifications of the dynamic spatial panel data model (13).

An important issue in the application of System-GMM estimators concerns the fact that the number of instruments increases with the sample size T (it is quadratic in T). A large number of instruments can overfit instrumented variables and leads to inaccurate estimations of the optimal weight matrix, leading to downward biased two-step standard errors and, thus, wrong inference in the Hansen test (Roodman, 2009). To avoid these problems, we use a restricted set of instruments for GMM estimates. Specifically, the number of instruments for the estimation of first difference equations is set in the range between one and two in that we use one or two lagged levels in time periods $t-1$, $t-2$ as instruments, while we use one period lagged first-differences for GMM in levels equations.

Results from the two-step dynamic System-GMM estimations of model (16) are shown in Table 2, while the estimated long-run effects of the included regressors are reported in Table 3.[11] For all model specifications the test statistics of serial correlation (AR1 and AR2), the Hansen test and the C-statistics for the level equation (i.e. the difference-in-Hansen statistic between the set of instruments of the System-GMM and that of the Arellano-Bond first difference GMM model) and for the external instruments indicate that the instruments used in System-GMM estimations satisfy the required orthogonality conditions, confirming the adequacy of our econometric setup.

Tab.1 and *Tab.2*

The baseline specification (Model 1) is based on total domestic human-capital augmented net migration rates from South to North and *viceversa* (long-distance). Regional unemployment rates turn out to be highly persistent: the lagged dependent variable enter positively and significantly with a parameter of 0.548, in a way consistent with the existent literature. Net of this autoregressive

[11]Long-run effects of the dynamic model are computed as $\frac{\partial y}{\partial x_k} = \frac{\beta_k}{1-\tau}$.

process, the lagged value of the long distance net migration rate has a negative impact on regional unemployment dynamics: the short-run effect is -1.754, while the long-run effect is equal to -3.886 (-1.754/(1-0.548)). This evidence signals the lack of an equilibrating role of labor mobility. In keeping with our theoretical framework, the negative effect of the human-capital augmented net migration rate points to the existence of externalities and gives empirical support to the idea that workforce outflows may worsen local labor market performances. As expected, higher employment growth lowers provincial unemployment (short-run effect equal to -0.037, long-run effect equal to -0.082), while increasing participation rates exert detrimental effects on local labor market performances (short-run effect equal to 0.123, long-run effect equal to 0.273). The positive effect of the participation rate along with the negative effect of the employment growth rate suggests, in particular, that labor market conditions in the less developed areas have worsened as a result of a faster growth of the labor force (i.e., young people) in contrast to a lower growth of new jobs (or vacancies). Finally, higher shares of employment in manufacturing reduce unemployment. Hence, provinces that are specialized in manufacturing industries exhibit, *ceteris paribus*, lower unemployment than provinces with a different industrial structure.

In Model 2, we replace the lagged value of the human-capital augmented long-distance internal net migration rate with the lagged value of the human-capital augmented short-distance net migration rate (where short-distance indicate flows from a province to another province within the same NUTS-2 region). Not surprisingly, the effect of short-distance migration on regional unemployment is statistically not different from zero. As mentioned above, short-distance migration is mainly motivated by non-economic reasons, such as the search for a better quality of life and better natural amenities. Including both short and long-distance net migration rates (Model 3) confirms that only long-distance migration has a significant negative effect on regional unemployment.

Model 4 aims at testing possible asymmetric effects of in-migration and out-migration rates by including separately long-distance human-capital augmented in-migration and out-migration rates, computed as the number of human-capital weighted registrations in and cancellations from the municipality registry (divided by the human-capital weighted total residential working-age population), respectively. The evidence emerging from Model 4 documents that out-migration of human capital increases regional unemployment rates, while in-migration flows of human capital do not exert any significant effect. The Wald test also rejects the equality of the parameters of $LDinMigr^h_{t-1}$ and $LDoutMigr^h_{t-1}$ (the χ^2 is equal to 4.56 with a p-value of 0.033), confirming that in-migration and out-migration rates produce asymmetric effects on regional unemployment in Italy. Therefore, we may conclude that out-migration of human capital from an Italian province (a phenomenon concentrated in the South) determines an increase of the unemployment rate of the region of origin in line with the predictions of our theoretical framework with human capital externalities. The long-run effect of out-migration is 4.943. The effect of employment growth remains negative and highly significant in terms of both short and long run effects. The same conclusion of Model 1 holds true for the participation rate and share of employment in manufacture.

Finally, with Models 5 and 6 we assess the effect of human capital migration flows by using the long-distance migration rate (net, in and out) of highly-educated workers (that is workers with upper secondary school or a tertiary education level), and the migration rate (net, in and out) of low-educated workers (that is workers with an education level up to the primary school or lower secondary school). From Model 5 it clearly emerges that long-distance net-migration rates of highly-educated workers have a negative effect on regional unemployment (thus fostering local labor market imbalances), while long-distance net-migration rates of low-educated workers have a positive effect on regional unemployment (thus reducing local labor market imbalances).

With Model 6 we distinguish between in-migration and out-migration rates of both highly-educated and low-educated workers. The results of Model 6 suggest that out-migration of highly-skilled workers and out-migration of low-skilled workers from a specific region produce different effects on the unemployment rate of that region (positive and significant the first one and non-significant the second one). The coefficients of these two variables turn out to be statistically different (the Wald test rejects the equality of the coefficients of $LDoutHighMigr_{t-1}$ and $LDoutLowMigr_{t-1}$, with the $\chi^2 = 30.08$ and the p-value=0.000). The net effect is therefore again in favor of the model with human capital externalities (labor market consequences from out-migration of highly-skilled workers ultimately dominate the consequences due to out-migration of low-skilled workers). On the other hand, in-migration of highly-skilled workers and in-migration of low-skilled workers to a specific region produce asymmetric effects on the unemployment rate of that region (negative and significant the first one and positive and significant the second one). However, in this case the Wald test does not reject the equality of the parameters (the $\chi^2 = 1.90$ and the p-value=0.168). The net effect is therefore null. Overall, the results from Model 6 are consistent with the evidence from Model 4 where the human-capital weighted out-migration rate has a positive impact on regional unemployment, while the human-capital weighted in-migration rate has a null effect on regional unemployment. Thus, we may conclude that Model 4 better captures the role of human-capital mobility on regional labor market imbalances, showing that only out-migration of human capital has a detrimental effect on regional labor markets, while in-migration of human capital has a null effect. Therefore, in the next Section we only use Model 4 to show the results of the dynamic spatial panel data model (13).

5.2 Dynamic spatial panel data model

The role for spatial autocorrelation on regional unemployment performances may be due to a number of reasons: i) frictional effects of distance related to commuting (Patacchini and Zenou, 2007); ii) agglomeration effects arising from demand linkages across nearby areas (Overman and Puga, 2002); iii) omitted time-varying variables clustered in space (LeSage and Pace, 2009). In order to estimate the dynamic spatial panel data model (13), we use two alternative spatial weights matrices, $\mathbf{W}_1$ and $\mathbf{W}_2$. Each element of $\mathbf{W}_1$ represents a combination of a binary spatial weight based on the critical cut-off criterion and a decreasing function of pure geographical distance, namely the inverse distance function:

$$w_{1,ij} = \begin{cases} d_{ij}^{-1} / \sum_{j \neq i} d_{ij}^{-1} & if \quad 0 < d_{ij} < d^* \\ 0 & if \quad i = j \quad or \quad if \quad d_{ij} > d^* \end{cases}$$

while each element of $\mathbf{W}_2$ represents a combination of a binary spatial weight based on the critical cut-off criterion and the exponential inverse distance function:

$$w_{2,ij} = \begin{cases} exp(-d_{ij}) / \sum_{j \neq i} exp(-d_{ij}) & if \quad 0 < d_{ij} < d^* \\ 0 & if \quad i = j \quad or \quad if \quad d_{ij} > d^* \end{cases}$$

where d_{ij} is the great-circle distance between the centroids of provinces i and j.[12] The selected cut-off distance (d^*) corresponds to the minimum distance that allows all provinces to have at least one neighbor.

The parameter of Model (13) are firstly estimated using bias-corrected QML estimators (Lee and Yu, 2010). This method allows to control for the endogeneity of time and spatial lags of the dependent variable, but not for the endogeneity of the other regressors (e.g. the net migration rate). Thus, we interpret with caution the results of this robustness check against the spatial autocorrelation bias.

The QML estimation results are reported in Table 4. Using $\mathbf{W}_1$, the parameter ρ associated with the spatial lag term $\mathbf{W}\mathbf{y}_t$ turns out to be 0.074 and weakly significant (only at 10%), while using the exponential inverse distance matrix $\mathbf{W}_2$, the parameter ρ is not statistically significant. Simultaneous spatial autocorrelation in regional unemployment in Italy can therefore be considered as negligible. On the other hand, spatial autocorrelation lagged in time is detected: the parameter η associated to $\mathbf{W}\mathbf{y}_{t-1}$ is positive and strongly significant with both $\mathbf{W}$ matrices. The evidence of negligible current spatial autocorrelation and significant lagged in time spatial autocorrelation allowed us to estimate a reduced form of the spatial panel data model without the spatial lag term $\mathbf{W}\mathbf{y}_t$ but using the System-GMM to control for the endogeneity of $\mathbf{X}_t$ variables (see the last column of Table 4).

Table 4

Based on the estimated coefficients of the spatial panel data model reported in Table 4, we computed short and long-run marginal effects for the variables of interest (see Table 5). We again observe that both the short and long-run marginal effects of the long-distance human-capital augmented in-migration rate are not significant, while the short and long-run marginal effects of the long-distance human-capital augmented out-migration rate are positive and significant, thus corroborating the idea that workforce outflows worsen local labor market performances and exacerbate the divide between backward areas and the rest of the Country.

[12] Geographic distance has frictional effects on labour market activity. Workers prefer to find a job in their closer environment because commuting and moving entail monetary and psychological costs. Therefore, we use great circle distances between centroids of provinces to define the entries of the spatial weights matrix.

Focusing on the more robust System-GMM results, we observe that a 1% increase in the out-migration rate in a province generates on average an increase in the unemployment rate of that province (average direct effect, ADE) of about 0.7% in the short run and of about 1.8% in the long run. Moreover, due to different possible spatial spillover mechanisms (frictional effects of distance related to commuting, agglomeration effects arising from demand linkages across nearby areas, and omitted time-varying variables clustered in space), a 1% increase in the out-migration rate in a province generates an increase in the unemployment rate of the other Italian provinces (average indirect effect, AIE) of about 0.9% in the long run. Thus, the average total effect (ATE) in the long run of the long-distance human-capital augmented out-migration rate is equal to 2.7%.

Table 5

6 Conclusions

This work has contributed to the still limited literature that analyzes the consequences of internal migration on origin regions. Simple competitive models show that, in the absence of externalities, interregional migration eliminates disparities in regional unemployment rates. As a consequence, interregional mobility should be encouraged. However, as the literature and our theoretical model show, things may change drastically in the presence of human capital externalities and selective migration. In these cases, interregional labour mobility is likely to magnify regional disparities in the unemployment rate.

This theoretical ambiguity has generated several studies that have come to conflicting conclusions. Our analysis has focused on the Italian case over the 2002-2011 period, which was characterised by a sustained outflow of skilled workers from the South to the North. Using longitudinal data at the NUTS-3 level, we have documented that net outflows of human capital from the South to the North have actually increased the unemployment rate in the South. In particular, we have shown that selective migration exacerbates spatial unemployment disparities in the South: Southern provinces which have experienced the strongest out-migration of skilled workers are also those with the poorest performance in terms of employment. These findings suggest that human capital externalities are very important in Italy.

Our results support the literature that finds relevant externalities at the regional level, and suggest that curbing the brain drain from the South should be a priority in order to reduce the long-run North-South dualism.

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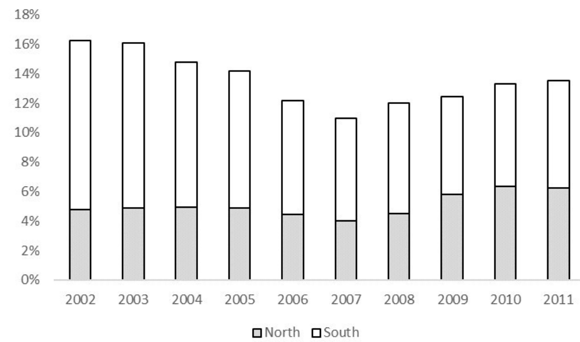


Figure 1: Unemployment rate

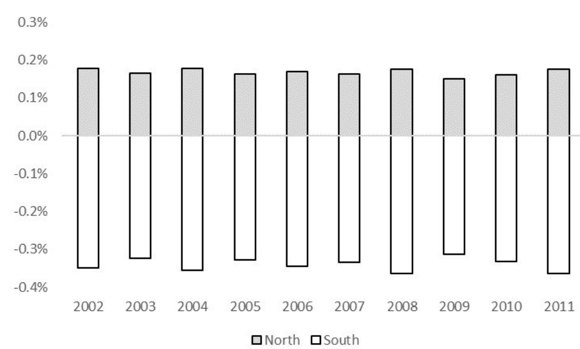


Figure 2: Human capital augmented migration rate

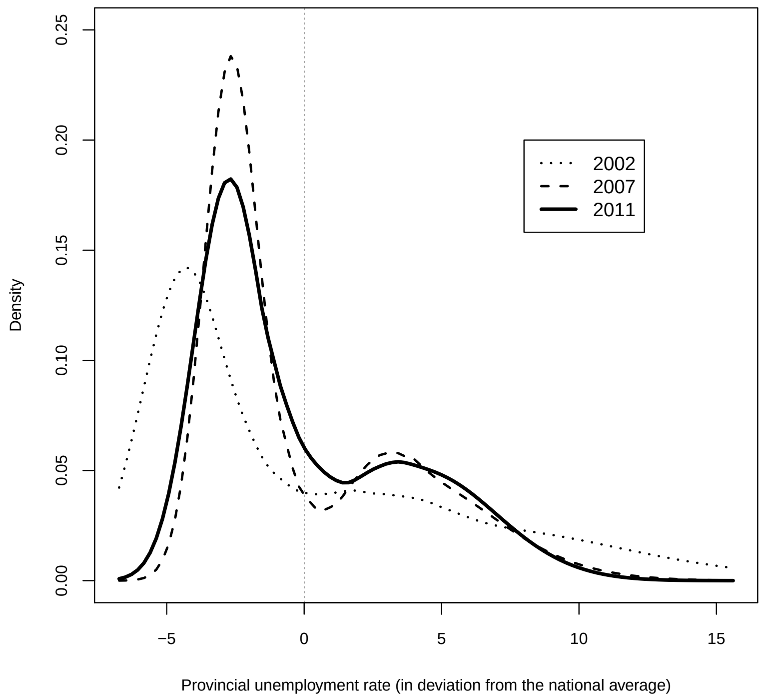
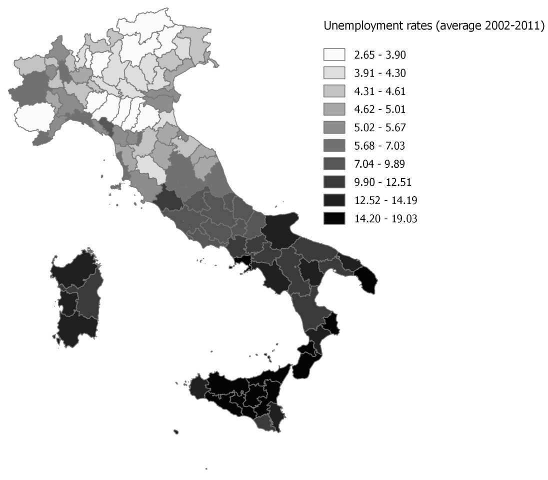


Figure 3: Density estimation of provincial unemployment rates: 2002, 2007 and 2011



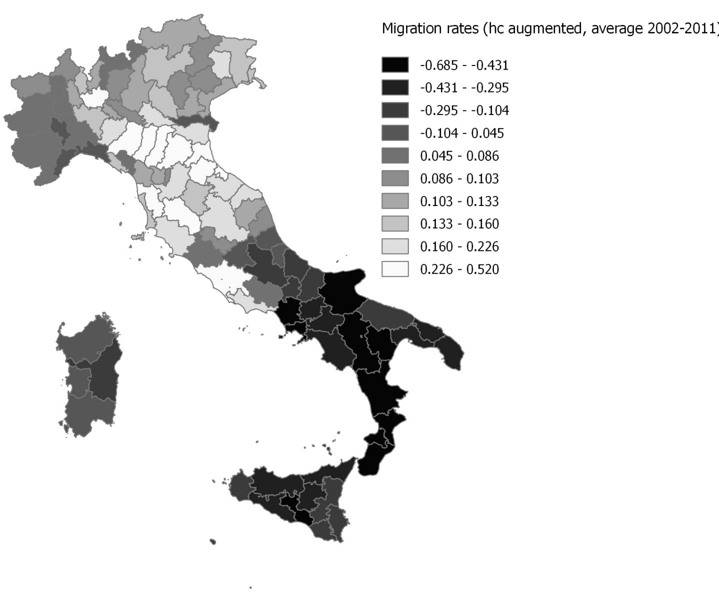


Figure 4: Provincial unemployment and human capital augmented migration rate, 2002-2011 averages

Table 1: Descriptive statistics: 2002-2011 averages

	Italy	North	South	South vs North
A. Main Macroeconomic Indicators				
GDP ('000 euro)	1619607	76.08%	23.84%	.
GDPpc (euro)	27691	32544	18723	57.53%
prod (euro)	32.73	35.16	26.81	76.25%
ΔGDP	0.21%	0.44%	-0.50%	-0.94%
$\Delta GDPpc$	-0.31%	-0.29%	-0.65%	-0.36%
$\Delta prod$	0.00%	0.03%	-0.26%	-0.30%
part	62.32%	67.53%	52.82%	-14.71%
u	7.76%	5.15%	13.71%	8.55%
emp	61.90%	70.81%	51.41%	-19.40%
B. Long-distance migration rates				
$LDnetMigr^h$	.	0.17%	-0.34%	.
$LDinMigr^h$	.	0.33%	0.34%	.
$LDoutMigr^h$	.	0.16%	0.68%	.
$LDnetHighMigr$	.	0.21%	-0.47%	.
$LDinHighMigr$	.	0.37%	0.36%	.
$LDoutHighMigr$	.	0.16%	0.83%	.
$LDnetLowMigr$	.	0.09%	-0.15%	.
$LDinLowMigr$	.	0.26%	0.29%	.
$LDoutLowMigr$	.	0.17%	0.44%	.

Table 2: Dynamic panel data models. Estimation results. Short run effects

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	*Coefficients (standard errors)*					
u_{t-1}	0.548*** (0.026)	0.599*** (0.034)	0.571*** (0.022)	0.593*** (0.014)	0.541*** (0.020)	0.622*** (0.014)
$LDnetMigr^h_{t-1}$	-1.754*** (0.524)		-1.978*** (0.395)			
$SDnetMigr^h_{t-1}$		0.444 (0.573)	0.011 (0.407)			
$LDinMigr^h_{t-1}$				-0.732 (0.612)		
$LDoutMigr^h_{t-1}$				2.009*** (0.490)		
$LDnetHighMigr_{t-1}$					-2.806*** (0.425)	
$LDnetLowMigr_{t-1}$					1.049** (0.539)	
$LDinHighMigr_{t-1}$						-3.422*** (0.528)
$LDoutHighMigr_{t-1}$						2.236*** (0.334)
$LDinLowMigr_{t-1}$						2.714*** (0.546)
$LDoutHighMigr_{t-1}$						-0.097 (0.496)
Δemp_t	-0.037** (0.017)	-0.054*** (0.019)	-0.048*** (0.014)	-0.065*** (0.010)	-0.031** (0.015)	-0.052*** (0.011)
$part_t$	0.123*** (0.028)	0.168*** (0.030)	0.103*** (0.019)	0.074*** (0.019)	0.082*** (0.019)	0.089*** (0.015)
ser_t	-0.024 (0.027)	-0.047 (0.031)	-0.028 (0.021)	0.005 (0.017)	-0.010 (0.018)	0.009 (0.012)
man_t	-0.082*** (0.029)	-0.112*** (0.030)	-0.080*** (0.021)	-0.050*** (0.019)	-0.058*** (0.021)	-0.034*** (0.013)
$cons_t$	0.133 (0.090)	0.156 (0.113)	0.086 (0.056)	0.069 (0.060)	0.150** (0.074)	0.052 (0.057)
$AR(1)$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$AR(2)$	[0.894]	[0.988]	[0.897]	[0.826]	[0.931]	[0.805]
Hansen J	[0.085]	[0.224]	[0.175]	[0.125]	[0.087]	[0.421]
C-Stat. instr. for levels	[0.881]	[0.181]	[0.629]	[0.404]	[0.905]	[0.650]
C-Stat. external instr.	[0.127]	[0.133]	[0.232]	[0.680]	[0.189]	[0.874]

Notes: the dependent variable is u_t. Two-step system GMM method. Standard errors in parenthesis and P-values in brackets. $*$, $**$ and $***$ denote significance at the 1, 5 and 10 per cent levels respectively. Time dummies and interactions between time dummies and the South dummy included in all models. $AR(1)$ and $AR(2)$ are the Arellano and Bond tests for first and second-order serial correlation; Hansen J is the over-identification test; C-statistics are difference-in-Hansen statistics (H_0: exogenous). Number of obs.: 824.

Table 3: Dynamic panel data models. Estimation results. Long run effects

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	*Coefficients (standard errors)*					
$LDnetMigr^h_{t-1}$	-3.886***		-4.618***			
$SDnetMigr^h_{t-1}$		1.107	0.025			
$LDinMigr^h_{t-1}$				-1.800		
$LDoutMigr^h_{t-1}$				4.943***		
$LDnetHighMigr_{t-1}$					-6.126***	
$LDnetLowMigr_{t-1}$					2.289**	
$LDinHighMigr_{t-1}$						-9.066***
$LDoutHighMigr_{t-1}$						5.925***
$LDinLowMigr_{t-1}$						7.189***
$LDoutLowMigr_{t-1}$						-0.257
Δemp_t	-0.082**	-0.134**	-0.112***	-0.159***	-0.069**	-0.138***
$part_t$	0.273***	0.420***	0.241***	0.183***	0.180***	0.234***
ser_t	-0.054	-0.117	-0.065	0.013	-0.023	0.023
man_t	-0.182***	-0.293***	-0.188***	-0.125***	-0.127***	-0.092***
$cons_t$	0.296	0.390	0.202	0.171	0.329**	0.137

Notes: the dependent variable is u_t). $*$, $**$ and $***$ denote significance at the 1, 5 and 10 per cent levels respectively.

Table 4: Model 4S: Dynamic spatial panel data specification. Estimation results

	Inv. dist.	Exponential inverse distance	
	QMLE	QMLE	System-GMM
Variables	*Coefficients (t statistics in parenthesis)*		
u_{t-1}	0.338***	0.345***	0.590***
	(7.890)	(8.377)	(7.630)
Wu	0.074*	0.026	
	(1.926)	(1.036)	
Wu_{t-1}	0.086***	0.100***	0.159***
	(3.014)	(3.980)	(7.620)
$LDinMigr^h_{t-1}$	-0.400	-0.364	-0.397
	(-0.731)	(-0.671)	(-0.920)
$LDoutMigr^h_{t-1}$	1.621**	1.798**	0.672***
	(1.984)	(2.220)	(2.620)
Δemp_t	-0.109***	-0.107***	-0.059***
	(-5.048)	(-4.878)	(-4.730)
$part_t$	0.233***	0.239***	0.101***
	(6.563)	(6.879)	(6.930)
ser_t	0.066	0.073	0.002
	(1.258)	(1.397)	(0.785)
man_t	0.001	-0.001	-0.040***
	(0.056)	(-0.020)	(-3.550)
cos_t	0.021	0.035	0.100***
	(0.413)	(0.610)	(3.071)
$AR(1)$			[0.000]
$AR(2)$			[0.850]
Hansen J			[0.292]
C-Stat. instr. for levels			[0.258]
C-Stat. external instr.			[0.968]

Notes: the dependent variable is u_t). Model in columns 1 and 2 are estimated by QMLE, model in column 3 is estimated by System-GMM. Asymptotic t statistics in parenthesis. $*$, $**$ and $***$ denote significance at the 1, 5 and 10 per cent levels respectively. Time dummies and interactions between time dummies and the South dummy included in all models. $AR(1)$ and $AR(2)$ are the Arellano and Bond tests for first and second-order serial correlation; Hansen J is the over-identification test; C-statistics are difference-in-Hansen statistics (H_0: exogenous). Number of obs.: 824.

Table 5: Model 4S: Dynamic spatial panel data specification. Short and long run effects

		Inverse distance		Exponential inverse distance			
			QMLE			System-GMM	
Variables		Short run	Long run	Short run	Long run	Short run	Long run
$LDinMigr^h_{t-1}$	ADE	-0.398	-0.609	-0.406	-0.624	-0.397	-1.055
	AIE	-0.031	-0.180	-0.010	-0.126	0.000	-0.530
	ATE	-0.430	-0.789	-0.416	-0.750	-0.397	-1.586
$LDoutMigr^h_{t-1}$	ADE	1.663**	2.555**	1.789**	2.778**	0.672**	1.786**
	AIE	0.130**	0.764**	0.045**	0.588**	0.000	0.898**
	ATE	1.793**	3.319**	1.834**	3.366**	0.672**	2.685**

Notes: $*$, $**$ and $***$ denote significance at the 1, 5 and 10 per cent levels respectively. ADE direct marginal effect, AIE indirect marginal effect, ATE average total effect (ADE+AIE).