Regional unemployment traps in Italy:

assessing the evidence

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Abstract

The ongoing restructuring of the Italian labor market has been leading to a decrease of the national unemployment rate albeit a severe polarization of regional unemployment has emerged. Using longitudinal regional unemployment data at NUTS-3 level, the ergodic distribution reveals indeed the formation of a cluster of Southern regions caught in a high unemployment trap. Simulation exercises, based on the estimation of parametric and nonparametric unemployment growth models for panel data, document that excess of labour supply (mismatch), migration outflows (brain drain) and spatial proximity determine the observed bimodality in the long-run density.

Keywords: Unemployment, Ergodics, Spatial dependence, nonparametrics.

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1. Introduction

Lowering unemployment is a policy mission typically challenged at a national level. Only in the textbook case of full efficient markets, however, where equilibrating forces of capital and labour mobility and changes in relative prices are fully at work, no significant spatial unemployment disparities *within* country would exist. In the real world, instead, national averages are likely to hide large regional differences in unemployment rates (Pissarides and McMaster, 1990; Blanchard and Katz, 1992; Decressin and Fatas, 1995; Elhorst, 1995; Taylor and Bradley, 1997; Kostoris-Padoa-Schioppa and Basile, 2002; Overman and Puga, 2002; Bande and Karanassou, 2007). Aside from academic disputes, divergence in unemployment patterns within national boundaries entails welfare losses due to a downward spiral effect for backward regions, which tend to suffer typically from a net loss of population, reduced demand for locally produced goods and services and regional brain drain (selective out-migration of high-skilled workers) (Elhorst, 2003).

This paper aims at tackling the issue at stake focusing on regional unemployment dynamics in Italy at a very fine territorial level (103 provinces or NUTS-3 regions) over the 1995-2007 years.[1] The case of Italy is peculiar since the ongoing restructuring of the domestic labor market has been leading to a reduction of the nation-wide unemployment rate in the presence of remarkable (and persistent) regional disparities (Faini et al., 1997; Prasad and Utili, 1998; Alesina et al., 1999; Cannari et al., 2000; Brunello et al., 2001, Kostoris-Padoa-Schioppa and Basile, 2002). Although the national unemployment rate dropped substantially over the last

[1] NUTS is an acronym for "Nomenclature of Territorial Units for Statistics". In this classification, NUTS-1 means aggregation of regions (like North-West or South), while NUTS-2 means Basic Administrative Units (regions like Piemonte or Basilicata) and NUTS-3 corresponds to sub-regions (provinces like Firenze or Venezia).

decade (from 11.2 percent in 1995 to 6.1 in 2007), there still exists indeed a strong dichotomy between Northern and Southern regions, with the South/North unemployment rate ratio moving from 2.3 in 1995 to 2.7 in 2007, after reaching its maximum (3.3) in 2001. An even more critical picture emerges from a provincial perspective: the ergodic distribution of unemployment rates displays a process of polarization with the formation of a cluster of provinces caught in a high unemployment trap.

In an effort to disentangle the causative (macroeconomic) determinants of the shape of the ergodic distribution of the provincial unemployment rates, we propose a framework which innovates along several dimensions with respect to the existent literature. *First*, we employ models for panel data in the presence of spatial dependence (Elhorst, 2009) in place of simpler cross-section methods as in Overman and Puga (2002), among others. *Second*, we allow for possible nonlinearities by specifying semiparametric formulations of the regression models along the lines suggested by Ullah and Mundra (2001) and Mundra (2005) among others. *Third*, based on a two-step approach (Basile, 2009), we use the predictions from a number of parametric and nonparametric regressions to simulate end-period unemployment levels so as to match the shape of the ergodic distribution obtained from actual data. The results clearly suggest that the joint (nonlinear) effect of excess of labor supply, migration outflows and spatial dependence is responsible for the observed polarization with a cluster of regions doomed in a high unemployment equilibrium.

The layout of the paper is the following. Section 2 illustrates some stylized facts on the labour market dynamics in Italy. Section 3 presents the set of candidate causative determinants of regional unemployment growth along with the methodological framework. Section 4 discusses the estimation results as well as the simulations carried out to replicate the long run distribution observed from actual data. Concluding remarks follow.

2. Regional labor market dynamics in Italy: selected stylized facts

Using the most recent official data, we focus on the years 1995-2007, during which a number of institutional reforms aimed at enhancing the flexibility in the domestic labour market took place.[2] While the performance of labour market indicators at the national level (especially the declining trend of the unemployment rate - from 11.2 percent in 1995 to 6.1 in 2007) has been understood by politicians as unambiguous evidence supporting the effectiveness of those reforms, there is scant economic and political debate on the dynamics of the unemployment rates at a more disaggregate level. Apparently encouraging national figures do not guarantee that regional unemployment rate disparities have been decreasing, however.[3] Thus, it may be the case of exacerbating polarization (i.e. fostering the dichotomy between Northern and Southern regions) even in the presence of declining national-wide unemployment rates.[4]

As Figure 1 shows, the South/Centre-North unemployment rate ratio (histograms) has indeed increased from 2.3 in 1995 to 3.2 in 2000 due to substantially invariant unemployment rates in the South (roughly 18 percent - solid line) coupled by a declining pattern in the Centre-

[2] A comprehensive discussion of the various institutional reforms introduced to improve the flexibility in the Italian labour market is reported in Cipollone and Guelfi (2006) and in ISAE (2007).

[3] In 2004 the Italian National Institute of Statistics (ISTAT) applied new definitions of "employed" and "unemployed" so as to comply with the European rules for the labour force survey. In the paper, unemployment figures as well as other labour market indicators for years before 2004 are based on reconstructed series provided by ISTAT and Prometeia.

[4] In the Italian case, it is customary to distinguish between Southern regions, or interchangeably Mezzogiorno (namely, Campania, Abruzzo, Molise, Basilicata, Calabria, Puglia, Sicilia and Sardegna) and Central-Northern regions (namely, Valle d'Aosta, Piemonte, Lombardia, Trentino Alto Adige, Friuli Venezia Giulia, Veneto, Liguria, Emilia Romagna, Marche, Toscana, Lazio and Umbria).

North (from 8 to 6 percent - dashed line). Over the current decade, instead, we observe a sort of "convergence" between the two areas, which has led to a ratio of 2.7 in 2007.

Figure 1

In order to deeply understand the process of convergence/divergence of regional unemployment dynamics, we use data at the NUTS-3 level (provinces). Local G^* spatial autocorrelation indices (Ord and Getis 1995) document the existence of two clusters of provinces in 1995 and 2007 (Figure 2): a cluster of high-unemployment regions (black color) is located in the South, while a group of Northern provinces is characterized by negative standardized G_i^* scores (grey color). Remaining provinces (white color) are those with a non-significant value of G_i^*.[5]

Figure 2

We also compare the univariate densities of provincial relative unemployment rates in 1995 (solid line) and in 2007 (dashed line) as well as the long-run, or ergodic, distribution (heavy solid line) computed by estimating conditional density functions and related transition matrices, using actual data (Figure 3a) and their logarithmic transformation (Figure 3b).[6]

Figure 3

The snapshot density displays an unimodal right-skewed distribution of provincial unemployment rates in 1995, with a higher density for values lower than the national average

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[5] In our context, G_i^* is a measure of local clustering of unemployment rates around region *i*. If high (low) values of *x* tend to be clustered around *i*, the standardized G_i^* will be positive (negative). In order to compute local G_i^* indices, we have used 5-nearest neighbours (5-NN) spatial weights matrix. Under the null, the standardized G_i^* statistics is asymptotically normally distributed (Ord and Getis 1995).

[6] The relative unemployment rate at a NUTS-3 level is computed as the observed unemployment rate for each province demeaned by the national average at each point in time.

(Figure 3a).[7] The distribution of provincial unemployment in 2007 appears markedly different. We observe a vanishing of the mass around the national average and a corresponding tendency towards polarization, with the main peak much more pronounced than in 1995 and a second lower peak emerged at 1.5 times the national average. In the long run (i.e. according to the shape of the ergodic distribution), the regional unemployment disparities do not override.[8] Measuring unemployment rates in logs, the univariate density in 1995 still appears unimodal (but not skewed), with the mode close to the national average. By contrast, a clearer bimodality (twin peaks) comes into view in 2007.[9] The tendency towards polarization seems to be confirmed by the shape of the ergodic distribution, according to which spatial units are more likely to exhibit very low and/or very high unemployment rates rather than intermediate rates in the long-run. Thus, a group of provinces appears to be caught in a high unemployment trap.

Figure 4 displays the cluster of entrapped provinces (in grey), identified as those with unemployment rates in 2007 higher than or equal to 1.5 times the national average

[7] For the univariate density estimates we applied a local linear estimator with variable bandwidth selected by generalized cross-validation (Loader, 1996).

[8] The ergodic distribution has been computed using the transition matrix extracted from a conditional density estimate as suggested by Johnson (2005). A local linear density estimator with variable bandwidth has been used to estimate the conditional density function (Hyndman and Yao 2002).

[9] Following Fiaschi and Lavezzi (2007), we have tested the bimodality of the univariate distributions by applying the bootstrap procedure as suggested by Efron and Tibshirani (1993). The p-value of this test is equal to 0.282 (0.494 for the variable in logs) in 1995 and to 0.020 (0.002 for the variable in logs) in 2007, indicating the rejection of the null of unimodality only for the last year.

(corresponding to the second mode in the density in Figure 3a).[10] Asymptotic and bootstrap based tests for the equivalence of the sample means indicate that high initial conditions, negative net migration rates and sectoral composition characterize the entrapped regions as compared to the Southern average (Table 1). Moreover, they are very close in space, suggesting that spatial proximity (neighboring effects) may have affected their labor market performance.

Figure 4 and Table 1

3. Assessing regional unemployment dynamics: a spatial panel data approach

3.1. The econometric framework

We use longitudinal data for 103 NUTS3 Italian regions and four periods (1995-1998, 1998-2001, 2001-2004 and 2004-2007) to estimate the determinants of regional unemployment dynamics. Our starting point is the following parametric specification:

$$y_{it} = \beta X_{it} + \alpha_i + \varepsilon_{it} \qquad i = 1,...,N = 103; \qquad t = 1,...,T = 4 \qquad (1)$$

where i denotes the cross-sectional dimension and t indexes time; $y_{it} = \Delta u_{it}$ measures the three-year dynamics of the provincial unemployment rate, u_{it}; X_{it} is a vector of covariates; β is a vector of fixed unknown parameters associated to the covariates, ε_{it} is an independently and identically distributed (*iid*) error term for i and t with zero mean and variance σ^2, while α_i denotes a spatial specific effect so as to control for all space-specific time-invariant variables whose omission could bias the estimates.

[10] They are all Southern provinces (23 out of 36): Napoli, Salerno, Bari, Taranto, Brindisi, Lecce, Potenza, Cosenza, Catanzaro, Reggio Calabria, Trapani, Palermo, Messina, Agrigento, Caltanissetta, Enna, Catania, Siracusa, Sassari, Nuoro, Oristano, Crotone, Vibo Valentia.

In keeping with the existent empirical literature, the dynamics of regional unemployment rates is likely to depend on two main groups of factors: a) local economic structures and b) local labor market dynamics.[11] The first set of regressors includes initial conditions (the logarithm of the unemployment rate at the beginning of each period, $\ln u_{it}$), the industry mix (the logarithm of the share of manufacturing and services employment on total employment at the beginning of each period, $\ln man_{it}$ and $\ln ser_{it}$, respectively)[12], human capital defined as skill-composition of regional labor forces (the logarithm of the share of adults with upper secondary education at the beginning of each period, $\ln hc_{it}$), agglomeration externalities (the logarithm of total employment per km^2 at the beginning of each period, $\ln dens_{it}$), labor productivity (the logarithm of the total real value added over total employment ratio at the beginning of each period, $\ln prod_{it}$).[13] The second set of variables controls for migration rate (the average net migration balance/total population ratio over each time period, $migr_{it}$) and supply-demand mismatch (the average employment growth rate less the labor participation growth rate over each time period, Δeld_{it}).

[11] Elhorst (2003) gives a comprehensive description of the variables included in recent empirical analyses on regional unemployment differentials.

[12] Notice that a finer classification would be advisable for this kind of analysis as pointed out by Elhorst (2003). Unfortunately, more articulated sectoral data are only recorded over decades (Census data) and, thus, cannot be used for our purposes.

[13] In order to take account of the wage setting conditions, only labour productivity (the denominator of the unit labour cost) is used. Such a choice stems from a two-fold consideration: first, data on real wages (and so on unit labour costs) are only available at NUTS-2 level; second, the Italian wage-setting is still highly centralized (see Basile and De Benedictis, 2008).

The expected sign for $\ln u_{it}$, $\ln hc_{it}$, $\ln dens_{it}$, $\ln prod_{it}$, $\ln man_{it}$, $\ln ser_{it}$ and Δeld_{it} is negative: according to the standard concept of convergence, higher initial conditions imply lower growth rates; highly skilled workers are likely to be more efficient in job search and are less likely to be laid off; agglomeration forces produce significant changes in unemployment (inversely) related to the distribution of production activities (Epifani and Gancia, 2005); efficiency wages argumentations predict a (nonlinear) negative relationship between labor productivity and unemployment (Basile and De Benedictis, 2008). As for the industry mix, economic intuition suggests that regions specializing in declining economic sectors (such as agriculture) are suspected to exhibit larger structural unemployment rates than provinces with production based on manufacturing or services (Elhorst, 2003). Finally, the effect of an excess of labor demand over labor supply growth on the dynamics of the unemployment rate is negative almost by definition.

No clear-cut predictions can instead be made on the effects of the migration rate. Relying on the neo-classical view of homogenous labour, workers moving towards prosperous regions may help to reduce regional differences in unemployment (through a reduction of the pool of job seekers in initially high-unemployment regions and an increase of it in the host regions), leading thus to a positive effect of $migr_{it}$ (Blanchard and Katz, 1992). To the extent that labour is instead not homogenous and that migration propensity increases sharply with education (Greenwood, 2009), we can expect a negative effect of migration on the dynamics of regional unemployment. The brain drain process leads indeed to reduce the share of people with higher probability to find a job in the regions of origin of migration (Eggert *et al*. 2007). Thus, assessing the ultimate effect of $migr_{it}$ is mainly an empirical issue.

3.2 Including spatial interaction effects

Empirical literature on regional economics has recently shown a growing interest in the possibility to test for spatial interaction (or spatial dependence) effects in standard static linear panel data models (Elhorst, 2009; Kapoor et al., 2007). Furthermore, the above discussed stylized facts in Section 2 give pervasive evidence of spatial clustering in provincial unemployment rates. Finally, spatial autocorrelation may also act as a proxy for omitted variables clustered in space (Niebuhr, 2002).

Two customary specifications are the spatial lag and the spatial error models. The spatial lag or spatial autoregressive (SAR) model includes the dependent variable observed in neighbouring units as an additional regressor with respect to model (1):

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \beta X_{it} + \alpha_i + \varepsilon_{it} \qquad (2)$$

where δ is the spatial autoregressive coefficient and $W = \{w_{ij}\}_{i \neq j}$ is a pre-specified non-negative square matrix of order *N* collecting spatial weights, w_{ij}, which describe the spatial arrangement of the units in the sample. Model (2) can be conceived as the equilibrium outcome of a spatial process where the value of the dependent variable for one spatial unit is jointly determined with that of the neighbouring regions (Anselin *et al*., 2006). In such a specification, the unemployment rate dynamics in a given location will be affected not only by its exogenous characteristics (e.g. the migration rate) and by its idiosyncratic shocks (ε_{it}), but also by those in all other regions through the inverse spatial transformation $\left(I - \delta W\right)^{-1}$.

The spatial error model (SEM) relaxes the assumption of *iid* errors by allowing for their correlation across space. Using the same notation as above, the SEM can be written as:

$$y_{it} = \beta X_{it} + \alpha_i + \phi_{it} \qquad (3)$$

$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij} \phi_{jt} + \varepsilon_{it}$$

where ϕ_{it} denotes the spatially autocorrelated error term and ρ the spatial autocorrelation coefficient. The SEM specification is consistent with a situation where omitted determinants are spatially auto-correlated and unobserved shocks spread all over the system through a spatial multiplier mechanism.

The choice between fixed effects (FE) and random effects (RE) for models (2) and (3) must be conducted by means of standard Hausman's specification tests. The choice between SAR and SEM could rely on robust Lagrange multiplier (LM) tests.[14] Notice, however, that models (2) and (3) are nested in a more general specification known as the unconstrained spatial Durbin model (SDM) whose reduced form implies the existence of substantive spatial externalities:

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \beta X_{it} + \gamma \sum_{j=1}^{N} w_{ij} X_{jt} + \alpha_i + \varepsilon_{it} \qquad (4)$$

The hypothesis H_0: $\gamma=0$ can be tested to assess whether SDM collapses to the SAR, while the 'common factor' hypothesis H_0: $\gamma+\delta\beta=0$ can be used to verify whether model (4) reduces to the SEM.

Estimation of models (2)-(4) can be carried out through maximum likelihood (ML) or two-stage least square/generalized method of moments (2SLS/GMM) techniques. Both methods assume that ε_{it} are *iid* for all *i* and *t*, but only ML estimators rely on the assumption of normality of the errors. A second crucial difference between the two approaches is that δ and ρ are bounded from below and above using ML by the Jacobian term in the log-likelihood function, while they

[14] Elhorst provides a Matlab routine to estimate the spatial FE and the spatial RE models, including robust Lagrange multiplier (LM) tests to choose the best specification.

are unbounded using 2SLS/GMM.[15] An advantage of using 2SLS/GMM consists of the possibility to properly model endogeneity issues (Kelejian and Prucha 1998): in particular, the first-difference (FD) 2SLS estimator allows using weakly exogenous instrumental variables, while the 2SLS estimation of the FE model leads to inconsistent estimation of β's if the instruments are not strongly exogenous.

3.3 The role of nonlinearities

In specifications (1)-(4) we treat all terms as globally linear. Such a restriction may lead to biased estimates of the parameters if the data generating process obeys a more articulated specification. Both FD and FE nonparametric and semiparametric estimators have been recently proposed so as to take jointly into account of unobserved cross sectional heterogeneity and nonlinearities in the slope parameters (Li and Ullah, 1998; Ullah and Roy, 1998; Ullah and Mundra, 2001; Mundra, 2005). A semiparametric version of model (4) is:

$$y_{it} = \alpha_i + X_{it}^{*}\beta^{*} + \delta\sum_{j=1}^{N} w_{ij} y_{jt} + f_1\left(x_{1it}, \sum_{j=1}^{N} w_{ij} x_{1jt} \right) + f_2\left(x_{2it}, \sum_{j=1}^{N} w_{ij} x_{2jt} \right) + \ldots + \varepsilon_{it} \qquad (5)$$

where $f_j(..)$ are unknown smooth functions of the covariates, X_{it}^{*} is a vector of strictly parametric components and β^{*} the corresponding parameter vector. For each *k*-th smooth term, the estimated function $\hat{f}_k(..)$ reveals possible nonlinearities in the effect of x_k. As in Basile

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[15] The Jacobian term leads to the standard condition that $1/\omega_{min} < \delta < 1/\omega_{max}$, where ω_{min} and ω_{max} denote the minimum and maximum eigenvalue of the matrix *W* describing the spatial arrangement of the units in the sample.

(2008, 2009), the semiparametric SDM is specified so as to include smooth interactions between local conditions and their spatial lags.[16]

Correcting for the endogeneity of the spatial lag term as well as of other explanatory variables calls for an approach different from the 2SLS, however. In particular, Blundell and Powell (2003) have proposed to extend the "control function" method to additive nonparametric models in order to account for endogeneity issues.[17] The application of the control function approach to the semiparametric settings described above consists of two steps. Considering, for the ease of exposition, only the endogeneity of the spatial lag of the dependent variable, the first step consists of an auxiliary nonparametric regression as:

$$\sum_{j=1}^{N} w_{ij} y_{jt} = \alpha_i + X_{it}^{*}\beta^{*} + f_1\left(x_{1it}, \sum_{j=1}^{N} w_{ij} x_{1jt}\right) + f_2\left(x_{2it}, \sum_{j=1}^{N} w_{ij} x_{2jt}\right) + h(Z_{it}) + \ldots + \upsilon_{1it} \quad (6)$$

where Z_{it} is a set of conformable instruments and υ_{1it} a random variable satisfying $E(\upsilon_{1it} \mid Z_{it}) = 0$. Moreover, if Z_{it} and ε_{it} are independent, then it yields that $E(\varepsilon_{it} \mid \upsilon_{1it}, Z_{it}) = E(\varepsilon_{it} \mid \upsilon_{it})$ and, thus, $E(\varepsilon_{it} \mid \sum_{j=1}^{N} w_{ij} y_{it}) \neq 0$ when $E(\varepsilon_{it} \mid \upsilon_{1it}) \neq 0$. The second step consists of estimating an additive model of the form:

$$y_{it} = \alpha_i + X_{it}^{*}\beta^{*} + \delta \sum_{j=1}^{N} w_{ij} y_{jt} + f_1\left(x_{1it}, \sum_{j=1}^{N} w_{ij} x_{1jt}\right) + f_2\left(x_{2it}, \sum_{j=1}^{N} w_{ij} x_{2jt}\right) + \ldots + \hat{\upsilon}_{1it} + \varepsilon_{it} \quad (7)$$

[16] Wood (2000, 2006) has recently proposed a method to estimate semiparametric additive models with penalized regression smoothers which allows for automatic and integrated smoothing parameters selection. He has also implemented this approach in the R package *mgcv*.

[17] See Basile (2009) for a recent application and a detailed discussion.

Obviously, in the presence of a number of candidate endogenous terms (for instance, $migr$ and Δeld), different first steps like in (6) - *mutatis mutandis* - are estimated and the corresponding residuals $\hat{\upsilon}_{it}$'s are introduced as additional regressors in the second step (7).

4. Empirical evidence

4.1. Estimation results

Table 2 reports the econometric results of a number of alternative parametric specifications. Panel A and B collect the estimated coefficients and the main diagnostic tests, respectively. The results for the FE estimates are presented in column (1).[18] The effect of initial conditions is negative and statistical significant, suggesting some conditional convergence of regional unemployment rates. The coefficient on employment density confirms the hypothesis of a positive effect of agglomeration economies on regional labour markets dynamics (Epifani and Gancia, 2005). As expected, a higher excess labour demand growth rate lowers regional unemployment dynamics. Moreover, FE estimates advise that Italian provinces with a higher initial share of employment in service sectors are more likely to reduce the unemployment rate than the other provinces, *ceteris paribus*. Also the migration rate has a negative impact on regional unemployment growth, suggesting that the brain drain effects (Eggert et al., 2007) dominate over the neoclassical argumentations (Blanchard and Katz, 1992). Finally, the remaining covariates ($\ln man$, $\ln prod$, $\ln hc$) do not exert any significant role.

[18] Hausman's test for the consistency of the random effects (RE) estimator provides evidence in favour to the FE estimator (see Table 2). The results of a F test confirm the joint significance of fixed spatial effects. Full estimation details are available upon request.

Including spatial interaction effects. LM tests on the residuals from model (1) clearly indicate the existence of sizable spatial dependence, calling for resorting to spatial econometric tools. Columns (2) and (3) report the estimates of FE-SAR and FE-SEM specifications.[19] The main conclusions from the FE model (Column 1) are largely confirmed, except for $\ln hc$ which turns out to be significant and negative signed. In contrast, the coefficient on $\ln ser$ becomes very weakly significant. Furthermore, there is strong evidence of spatial dependence, as documented by the significance of both Wy - the matrix form of the term $\sum_j w_{ij} y_{jt}$ in equation (2) - and $W\hat{\phi}$ - the matrix form of the term $\sum_j w_{ij}\phi_{jt}$ in equation (3). In order to discriminate between the alternatives, robust LM tests have been applied. The results favour choosing the SEM over the SAR and to conclude that only random shocks diffuse across economies, while there are no substantive spatial labour market externalities. This conclusion would be misleading, however. The common factor test indicates indeed that the restriction implied by the SEM specification can be rejected at 1 percent level and, thus, the unconstrained SDM (column 4) appears to be a more satisfactory specification. The estimation results of the SDM support previous conclusions and document significant effects for three exogenous spatially lagged terms ($W\ln u$, $W\ln hc$, $W\Delta eld$). Finally, the coefficient on the endogenous term *Wy* signals the presence of global spatial *spillover* in the labour market: the exogenous characteristics of province i (for example, its level of out-migration) or an idiosyncratic *shock* in that province do not only influence the

[19] Hausman's specification tests work again in favour of the FE model both in the case of SAR and SEM (see Table 2). For the estimation of SAR and SEM, we have used the 5-nearest neighbours (5-NN) spatial weights matrix. The results from using alternative matrices based on 10- and 15-NN are similar. Full estimation details are available upon request.

unemployment dynamics in that location, but affect also the outcome of all other regions with an intensity that decreases with distance (Anselin, 2004).

Controlling for endogeneity. The ML procedure used to estimate the previous models can take into account the bias generated by the presence of the endogenous term Wy, under the assumption of strict exogeneity of the other regressors. In our case, however, the exogeneity assumption for $migr$ and Δeld (and thus for their spatial lags) might be too strong. The decision to migrate depends indeed on the observed unemployment rate, generating a possible simultaneity problem. Furthermore, as the employment rate and the participation rate have common components with the dependent variable by construction, a second endogeneity problem is likely to emerge. In order to correct such biases, a FE-2SLS estimation is employed by using a large set of external instruments.[20] Column (5) reports the FE-2SLSL results of our preferred parametric specification where not significant variables have been excluded from the model for the sake of parsimony. Hausman's tests confirm the endogeneity only of Wy and Δeld terms.[21] Although the estimation results are qualitatively similar with respect to the FE-SDM (ML), the spatial autocorrelation coefficient δ gets larger and reaches an amount almost similar to the one estimated in Overman and Puga (2002) for the case of European regions. Furthermore, in the FE-2SLS, all spatial lags of the exogenous variables are estimated with more precision, so as now also $Wmigr$ is significant.

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[20] Namely, the second order spatial lags of the strictly exogenous variables included in the model, the one-period time lag of the strictly exogenous variables and two strictly exogenous variables not included in the model (the log of the share of population aged 15-64 and the log of the real disposable income at the beginning of each period).

[21] The lack of evidence of endogeneity for $migr$ can be rationalized on the grounds of possible temporal lags between the dynamics of regional unemployment and the individual decision to actually move. In other words, this variable can be considered predetermined rather then endogenous.

Table 2

A semiparametric specification. In the SDM specification discussed above the variables measuring the local characteristics and those of the spatial neighbours enter in an additive and linear form. In order to properly capture interaction effects and to relax unnecessarily restrictive assumptions on the functional form, we estimate a semiparametric version of the SDM in Table 2. After considerable experimentation, we impose the linearity constraint for Wy, $\ln dens$ and $\ln hc$, while we estimate non-parametrically the joint effect of $f\left(\ln u, W \ln u\right)$, $f\left(migr, Wmigr\right)$ and $f\left(\Delta eld, W\Delta eld\right)$. As Table 3 shows, all terms but $\ln hc$ turn out to be significant (at least at the 10 percent level) and the edf clearly indicates nonlinear effects for $f\left(\ln u, W \ln u\right)$ and $f\left(\Delta eld, W\Delta eld\right)$. The same set of instruments employed to estimate the parametric FE-2SLS has been used to apply the control function approach. The significance of the first-step residuals from the auxiliary regressions for Wy and Δeld ($\hat{\upsilon}_{1it}$ and $\hat{\upsilon}_{2it}$, respectively) indicate traces of endogeneity for those terms. Finally, the AIC and the adjusted R^2 confirm a sizable gain with respect to the linear parametric counterpart.

Table 3

Figure 5 reports the perspective plots for the bivariate partial smooth terms. In each plot, the vertical axis displays the scale of the expected values of provincial unemployment rate dynamics, while the two axes of the horizontal plane report the scale of initial conditions, net migration rate and excess labour demand and of their correspondent spatial lags, respectively. Taking into account the effect of the interaction between $\ln u$ and $W \ln u$ allows to better qualify the convergence process: provinces with very high initial unemployment rates appear to be penalized by the proximity of spatial units with similar initial conditions (this is the case of the entrapped provinces identified in Section 2); conversely, in the case of regions with low initial conditions surrounded by other low unemployment regions the proximity effect is weaker. Thus, it emerges a strong asymmetry in the effect of local spillovers depending on the level of initial conditions. Perspective plots for migration rates and excess demand growth read similarly. Notice, however, that the proximity effect turns out to be substantially symmetric in the case of $migr$, while local spatial spillovers in the case of Δeld mostly matter for province experimenting negative rates of excess labour demand. All in all, these results inform that spatial clustering is a key factor in explaining regional unemployment disparities especially for lagging provinces.

Figure 5

4.2. Behind the unemployment trap: some simulations

This Section reports the results of ergodic distributions computed by using fitted values from a number of competing specifications. We have firstly estimated five specifications: A) a parametric model with only structural variables (namely, $\ln u$, $\ln man$, $\ln ser$, $\ln prod$, $\ln dens$, $\ln hc$); B) a parametric model with only $migr$ and Δeld; C) a parametric model encompassing A) and B); D) the parametric model C) augmented with the spatial interaction effects (Wy and all spatial lags of the exogenous regressors); E) a semiparametric version of model D).[22] Next, we extracted the predictions $\hat{y}$ (i.e. the expected growth rate of the unemployment rate) from each specification so as to estimate conditional densities as follows:

[22] As we are interested in explaining the intra-distribution dynamics in unemployment rates, we use predicted values from pooling estimations in order to preserve between variation.

$$f_{\tau}\left(\ln\left(u+\tau\hat{y}u\right)\middle|\ln u\right) \quad (8)$$

where u and $\tau = 3$ denote initial conditions and the temporal window of each period, respectively. Figure 6 reports the 'conditioned' ergodic distributions obtained from (8) (heavy solid lines) and the 'unconditioned' ergodic distribution (solid lines).

Figure 6

The ergodic distribution obtained from model A) is unimodal and left skewed, pointing out an unsatisfactory ability of structural variables in predicting actual unemployment rates. Even though sizable biased, the shape of the ergodic distribution simulated under model B) demonstrate that the bimodality observed in the unconditioned ergodic distribution can be partially ascribed to spatial heterogeneity in net migration rates and excess labour demand growth. Simulations based on model C) (which includes all regressors from previous specifications) are analogous to the one from model B) and confirms the scarce role of structural characteristics in explaining the occurrence of multiple equilibria. Including spatial interaction effects (model D) markedly improves the overlapping of the two long-run distributions: the twin-peaks property of the unconditioned long-run distribution is more satisfactorily replicated, albeit the probability mass around the mean value is still over-estimated. The semiparametric specification allows capturing with remarkable precision the process of vanishing of the probability mass around the national average together with a better matching of the actual shape of the right-hand side of the ergodic distribution (where the high-unemployment trap emerges).

All in all these findings give support to previous conclusions according to which spatial spillovers are relevant factors when interpreting regional disparities in unemployment rates. We also document that the occurrence of a high unemployment trap is determined not only by 'bad luck' (spatial proximity of provinces with high unemployment rates), but also by a mismatch in changes of labour market supply and demand schedules as well as by brain drain-induced migration outflows. A possible interpretation of our results is that the role of supply-demand mismatches in the labour market origins from the divergence between the wage-setting mechanism and the actual heterogeneous local labour market conditions. As for migration, it seems that the neoclassical re-equilibrating framework depicted by Blanchard and Katz (1992) is dominated by a selective process, where most qualified workers – who are more likely to find a job – move across space.

5. Concluding remarks

Using Italian regional unemployment data at NUTS-3 level over the years 1995-2007, the ergodic distribution reveals the formation of a cluster of Southern provinces caught in a high unemployment trap. In order to identify the causative determinants of the shape of the long-run distribution, we follow a two-step approach: first, we estimate a number of parametric and nonparametric spatial auto-regressive unemployment growth regression models for regional panel data; second, we use the predictions from those regressions to simulate end-period unemployment levels so as to match the shape of the ergodic distribution obtained from actual data. Simulation results document that excess of labour supply (mismatch) and migration outflows (brain drain) are primarily responsible for the observed bimodality in the long-run density.

From a methodological perspective, our results might inform about the relevance of working with disaggregate data in place of average figures at the national level. Masking huge spatial disparities among provinces, country averages may lead to misleading interpretations of the dynamics of unemployment patterns in Italy. Furthermore, empirical analyses which neglect the role of spatial externalities are doomed to be, at least, partial. Our findings document indeed that excess of labour supply and migration outflows in a certain spatial unit are relevant in explaining unemployment dynamics not only in that specific province, but also in all other provinces through a propagation mechanism which magnifies spatial disparities. From a normative perspective, we may conclude that national labour market policies put into action over the last decade (Cipollone and Guelfi, 2006; ISAE, 2007), even though effective in reducing the Italian average unemployment rate, did not prove to be suitable in lowering regional unemployment disparities.

In the light of the ongoing global economic downturn, the evidence of a cluster of entrapped provinces suggests that fiscal policy actions (like reductions of the labour cost in lagging areas) are required in the short-run so as to avoid that the consequences of the crisis exacerbate such a spatial dualism. Our results also suggest that policy interventions over a longer time horizon should provide a proper environment to increase the demand of skilled workers even in provinces entrapped in a high-unemployment equilibrium. While mobility of skilled workers may act as an automatic stabilizer of demand-supply mismatch in the short-run, long lasting outflows of qualified workforce will have detrimental effects on the productive structure of Southern areas. In this respect, an effort to fulfil the targets of the Lisbon Strategy in terms of expenditure in innovation and research activity appears to be a key factor so as to enhance the absorption of qualified workers in both advanced areas and lagging regions.

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Figure 1 – Unemployment rates

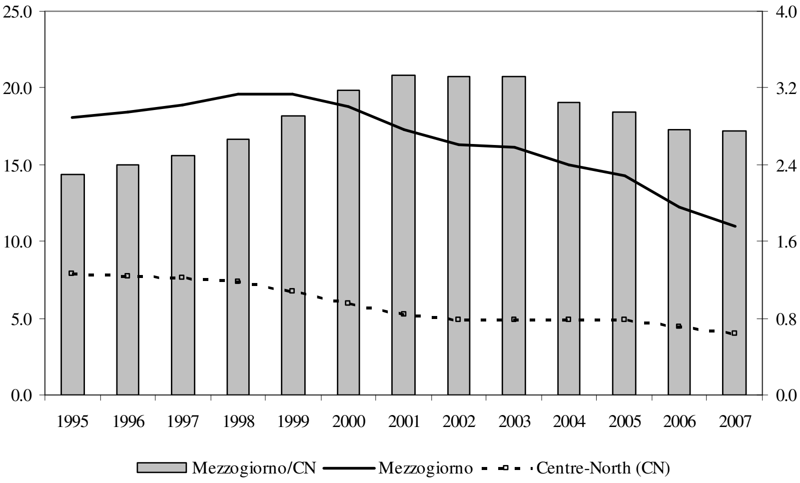
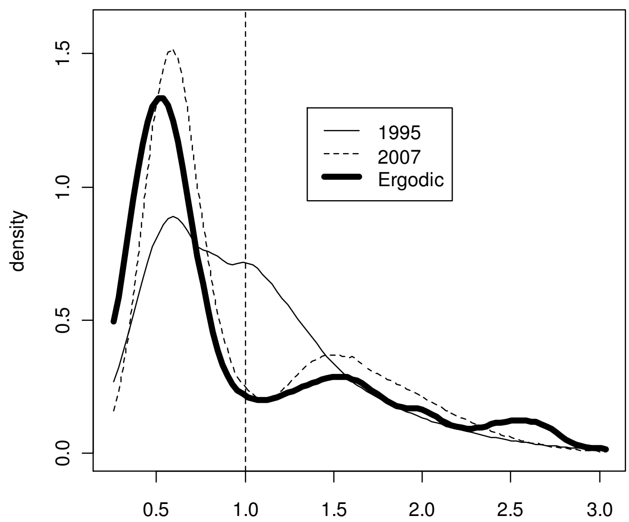


Figure 2 – Local G* statistics of relative unemployment rates

Figure 3 Density and ergodic distributions

a) Unemployment rate



b) log of unemployment rate

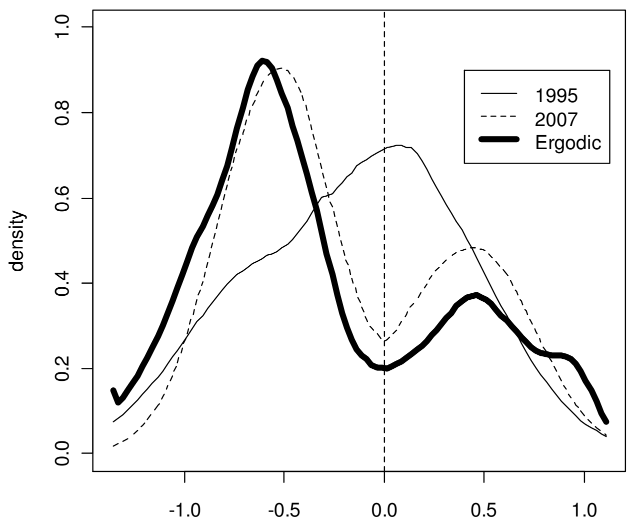


Figure 4 Entrapped provinces

Figure 5 – Nonparametric estimates

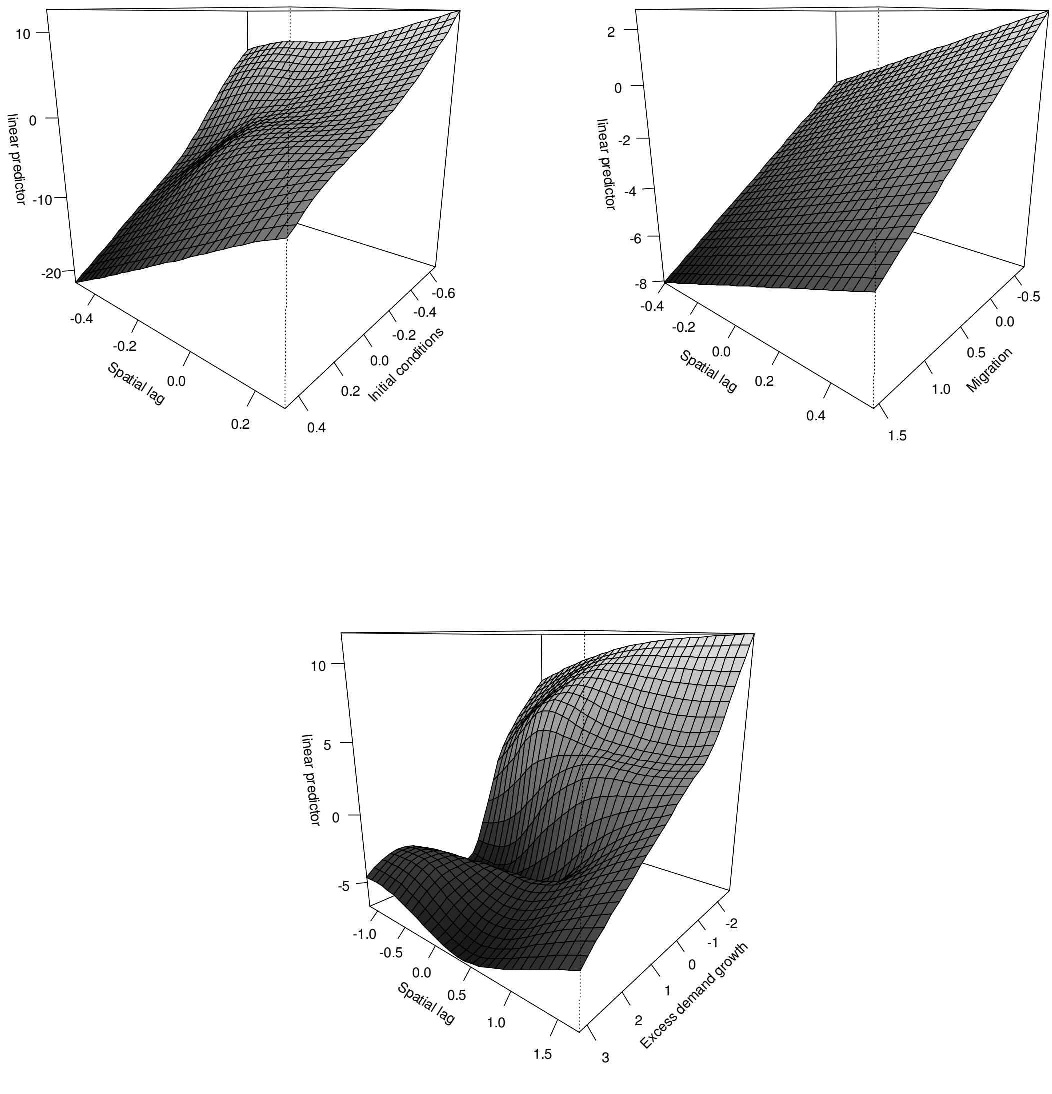
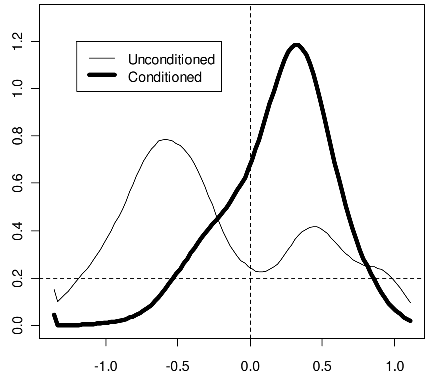
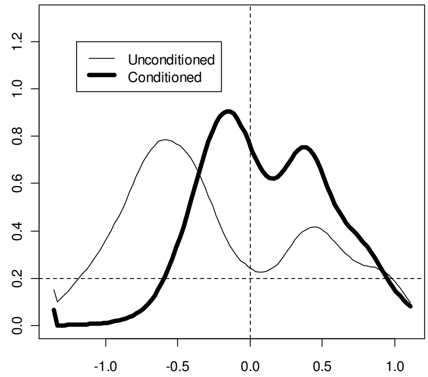


Figure 6 Conditioned ergodic distributions

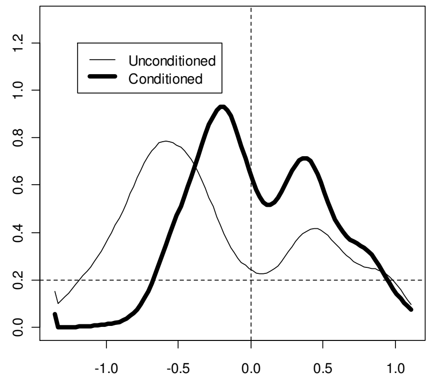
A. Model with structural variables alone



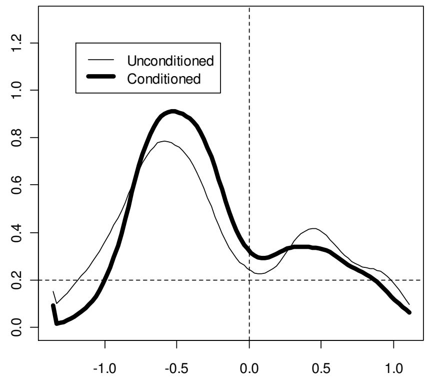
B. Model with migration and excess labour demand growth alone



C. Model A + B



D. Model C plus spatial dependence



E. Nonparametric version of Model D

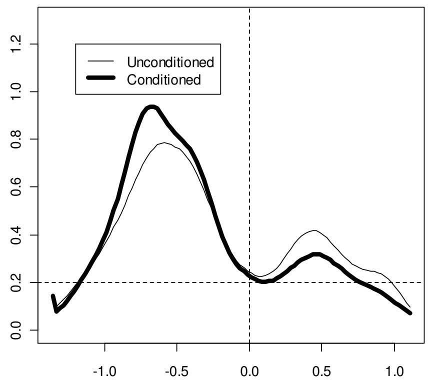


Table 1 – Mean values of the variables for different groups of provinces

	Entrapped provinces		South without entrapped		Italy without entrapped	
	Mean	*Std.dev.*	*Mean*	*Std.dev.*	*Mean*	*Std.dev.*
Δu	-2.224	7.513	-3.191	7.503	-3.267	9.180
$\ln u$	2.842^{*+}	0.285	2.524	0.297	1.826	0.537
$migr$	-227.398^{*+}	350.366	141.061	421.895	613.485	463.739
Δemp	0.861	1.760	0.382	1.899	1.101	1.666
$\ln \cos$	2.077^{+}	0.214	2.119	0.132	1.972	0.198
$\ln agr$	2.457^{+}	0.510	2.585	0.475	1.811	0.828
$\ln man$	2.428^{*+}	0.316	2.774	0.343	3.089	0.422
$\ln ser$	4.200^{*+}	0.08	4.087	0.107	4.098	0.134
Δpr	0.224^{+}	1.844	-0.170	1.741	0.729	1.536
$\ln hc$	-4.137^{+}	0.166	-4.155	0.170	-4.463	0.235
$\ln prod$	3.620^{+}	0.071	3.601	0.089	3.767	0.107
$\ln dens$	3.864^{+}	0.810	3.721	0.543	4.215	0.767

Notes: Δu measures the three-year dynamics of the regional unemployment rate; $\ln u$ is the logarithm of the unemployment rate at the beginning of each period; $\ln man$, $\ln ser$, $\ln cos$ and $\ln agr$ are the logarithms of the shares of manufacturing, services, construction and agriculture employment on total employment at the beginning of each period, respectively; $\ln hc$ is the logarithm of the share of adults with upper secondary education at the beginning of each period ; $\ln dens$ is the logarithm of total employment per km^2 at the beginning of each period; $\ln prod$ is the logarithm of the total real value added over total employment ratio at the beginning of each period; $migr$ is the average net migration balance/total population ratio over each time period; Δemp and Δpr are the average employment growth rate and average the labor participation growth rate over each time period, respectively; * indicates significant mean difference from the rest of the South while + indicates significant mean difference from the rest of the country

Table 2 – Econometric results of parametric models

Panel A

	(1) FE	(2) SAR-FE	(3) SEM-FE	(4) SDM-FE	(5) SDM-FE
	WG-OLS	MLE	MLE	MLE	2SLS
$\ln u$	-16.518 (0.000)	-13.824 (0.000)	-15.398 (0.000)	-15.934 (0.000)	-27.140 (0.000)
$W \ln u$				7.887 (0.010)	25.219 (0.000)
$\ln man$	-3.240 (0.434)	1.314 (0.701)	-5.389 (0.152)	-4.433 (0.165)	
$W \ln man$				10.763 (0.126)	
$\ln ser$	-25.233 (0.013)	-18.155 (0.017)	-12.951 (0.122)	-6.100 (0.450)	
$W \ln ser$				-17.070 (0.296)	
$\ln prod$	-1.701 (0.897)	2.847 (0.765)	-8.733 (0.417)	-3.138 (0.756)	
$W \ln prod$				-28.359 (0.076)	
$\ln dens$	-19.268 (0.007)	-18.303 (0.001)	-21.883 (0.001)	-20.116 (0.000)	-21.311 (0.017)
$W \ln dens$				8.748 (0.427)	
$\ln hc$	0.138 (0.965)	-3.748 (0.094)	-5.780 (0.022)	-8.704 (0.006)	-9.701 (0.106)
$W \ln hc$				10.003 (0.019)	
$migr$	-2.456 (0.016)	-3.578 (0.000)	-3.376 (0.001)	-3.022 (0.001)	-3.717 (0.009)
$Wmigr$				2.673 (0.109)	4.973 (0.037)
Δeld	-5.249 (0.000)	-4.725 (0.000)	-4.850 (0.000)	-4.839 (0.000)	-2.120 (0.026)
$W \Delta eld$				1.637 (0.013)	3.020 (0.006)
Wy		0.392 (0.000)		0.541 (0.000)	0.965 (0.000)
$W\hat{\phi}$			0.608 (0.000)		

(*continues*)

Table 2 – Econometric results of parametric models

Panel B

	(1) FE	(2) SAR-FE	(3) SEM-FE	(4) SDM-FE	(5) SDM-FE
	WG-OLS	**MLE**	**MLE**	**MLE**	**2SLS**
R-squared adj.	0.654	0.667	0.550	0.689	0.798
Log-likelihood	-1,239	-1,190	-1,180	-1,171	
AIC	2,494	2,398	2,378	2,376	
Hausman's test (RE vs. FE)	109.0 (0.000)	-87.6 (0.000)	-108.1 (0.000)	-74.7 (0.000)	
Common factor test (LR)		18.942 (0.015)			
LM test no spatial lag	152.704 (0.000)				
Robust LM test no spatial lag	25.735 (0.0.00)				
LM test no spatial error	161.738 (0.000)				
Robust LM test no spatial error	34.769 (0.000)				
Sargan test					23.882 (0.092)
Hausman's endogeneity test (Wy)					-0.478 (0.005)
Hausman's endogeneity test (Δeld)					-3.833 (0.000)
F test -first step 1 (Wy)					333.180 (0.000)
F test -first step 1 (Δeld)					96.162 (0.000)

Notes: the dependent variable is $y_{it} = \Delta u_{it}$ is the average growth rate of regional unemployment rate. The total number of observations is 412, the number of regions is 103 and the number of periods is 4. Heteroskedasticity-robust *p*-values are in brackets. A 5NN spatial weights matrix has been used for SAR, SEM and SDM models.

Table 3 – Econometric results of semiparametric models

	SDM-FE	
Parametric terms	β	edf
Wy	0.761 (0.000)	
$\ln dens$	-11.710 (0.055)	
$\ln hc$	-4.770 (0.148)	
$\hat{v}_1$ (Wy)	-0.257 (0.053)	
$\hat{v}_2$ (Δeld)	-2.233 (0.003)	
Nonparametric terms	F tests	
$f_1(\ln u, W \ln u)$	6.799 (0.000)	10.170
$f_2(migr, Wmigr)$	4.009 (0.012)	2.000
$f_3(\Delta eld, W\Delta eld)$	6.427 (0.000)	17.600
Diagnostics		
F test -first step 1 (Wy)	57.584 (0.000)	
F test -first step 2 ($migr$)	13.211 (0.000)	
Adj. R-squared	0.844	
Deviance	86.1	

Notes: the dependent variable is $y_{it} = \Delta u_{it}$ is the average growth rate of regional unemployment rate. The total number of observations is 412, the number of regions is 103 and the number of periods is 4. F tests are used to investigate the overall ("approximate") significance of smooth terms. *edf* (effective degrees of freedom) reflect the flexibility of the model. Adj. R-squared is the determination coefficient adjusted for the degrees of freedom. Deviance is the percentage of explained deviance. $\hat{v}_1$ and $\hat{v}_2$ refer to the residuals of the first step for Wy and for $migr$ respectively. F test-first steps indicate the tests for the joint significance of additional instruments in the corresponding first steps of the model. Bayesian *p*-values are in brackets.