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Sectoral shifts, diversification and regional unemployment: evidence from local labour systems in Italy

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Abstract[♥]

Using Local Labour Systems (LLSs) data, this work aims at assessing the effects of sectoral shifts and industry specialization patterns on regional unemployment in Italy over the years 2004-2008, when huge worker reallocation caused by changes in the international division of labour occurred. Italy represents an interesting case study because of the high degree of spatial heterogeneity in local labour market performance and the well-known North-South divide. Furthermore, the presence of strongly specialized LLSs (Industrial Districts, IDs) allows us to test whether IDs perform better than highly diversified urban areas thanks to the effect of agglomeration economies, or *viceversa*. Building on a semiparametric spatial auto-regressive framework, our empirical investigation documents that sectoral shifts and the degree of specialization exert a negative role on unemployment dynamics. By contrast, highly diversified areas turn out to be characterized by better labour market performances.

Keywords: Unemployment, sectoral shift, diversification, spatial dependence, nonparametrics

JEL codes: C14, C21, L16, R23

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1. Introduction

The ongoing process of international relocation of manufacturing activities towards Eastern European low-labour-cost regions and towards other emerging countries (such as China, India and Brazil) has been contributing to modify the European map of interregional product specialization, with old member states (EU-15 countries) being progressively more specialized in the service sector and the twelve newly accessed countries gradually specializing in manufacturing activities. The reallocation of labour resources within the enlarged Europe may have generated significant turmoil in local labour markets, with backward areas being particularly exposed to this structural change due to their persistent weaknesses: low industrial diversification, high specialization in low skilled labour intensive activities, low attractiveness to foreign direct investment, economic dependence on more developed regions and poverty traps (Caroleo and Pastore, 2010).

A number of studies have analyzed the effects of sectoral shifts and industry specialization patterns on local labour market performances and, especially, local unemployment (Lilien, 1982; Samson, 1985; Newman and Topel, 1991; Chiarini and Piselli, 2000; Krajnyak and Sommer, 2004; Newell and Pastore, 2006; Ferragina and Pastore, 2008; Robson, 2009, among others). The present study contributes to this literature by focusing on Italian Local Labour Systems (LLSs), over the most recent period (2004-2008), when huge worker reallocation mainly caused by changes in the international context (*in primis*, through foreign direct investments in the manufacturing sector from Western to Eastern European countries; see Basile et al. 2011) has occurred.

Given the well-known North-South divide, Italy represents an interesting case-study: most of Southern LLSs are expected to suffer more than others from structural change due to their traditional concentration of employment in industries where new competitors specialize and lack of automatic adjustment mechanisms (Contini and Trivellato, 2006). The case of Italy is also particularly interesting because of the presence of strongly specialized LLSs, known as Industrial Districts (IDs). While the Portfolio hypothesis (Simon, 1988; Simon and Nardinelli, 1992) and Jacobs' (1969) theory would suggest that, thanks to their high degree of diversification, urban areas should buffer better adverse shocks than specialized LLSs, the Industrial Districts theory (Marshall, 1890; Becattini, 1991) posits that highly specialized areas may perform better than others due to the presence of agglomeration economies.

The objective of this study is therefore twofold: a) analyze the effects of sectoral shifts and of specialization patterns on local labour market performance, using LLSs over the years 2004-2008; b) compare the relative performance of specialized LLSs (Industrial districts) and of urban areas. To this aim, we develop a methodological framework which innovates with respect to the existent literature along several dimensions. First, the case of Italy has never been studied before; second, we propose the use of semiparametric estimates to jointly model possible overlapping effects of Jacobsian and Marshallian economies; third, we control for spatial clustering, which is also quite a novelty in this literature.

Building on a semiparametric spatial auto-regressive framework, our empirical investigation documents that sectoral shifts and the degree of specialization exert a negative role on unemployment dynamics. By contrast, urban and highly diversified areas turn out to be characterized by better labour market performance.

The structure of the work is as follows. In Section 2 we review the relevant literature. Section 3 illustrates data and variables used in the econometric analysis.

Section 4 presents the econometric framework and our main empirical findings. Conclusions follow.

2. Review of the literature

Since Lilien (1982) a growing body of literature has focused on structural change as a key factor to explain spatial disparities in labour market performance. Economic integration processes and changes in technology are widely recognized as major sources of structural change which are likely to produce - on both advanced and backward regions - massive reallocation of labour resources (sectoral shifts) leading to growing regional unemployment, because labour that is displaced from declining industries takes time to be absorbed into the new expanding sectors of the economy.

Based on the assumption that sectoral shifts are a consequence of idiosyncratic shocks hitting some sectors/regions more than others, a number of studies (Samson, 1985; Barbone, Marchetti and Paternostro, 1999; Newell and Pastore, 2006; Krajnyak and Sommer, 2004; Robson, 2009) have confirmed the evidence firstly documented in Lilien (1982) according to which cross-industry dispersion of employment growth rates (measured by the Lilien's index) positively affects aggregate unemployment rates over time.

According to the criticism raised by Abraham and Katz (1986), however, regional unemployment differentials are mainly caused by common aggregate shocks rather than by idiosyncratic disturbances and the observed spatial variability in sectoral shifts is mainly due to the asymmetric consequences of the same aggregate shocks. In order to capture the effects of aggregate disturbances, a number of studies have included a measure of industrial diversity (such as, for instance, Herfindhal or Gini indexes) along with the Lilien's indicator (Newman and Topel, 1991; Chiarini and Piselli, 2000; Robson, 2009) in the econometric specification. It is widely recognized indeed that common shocks may generate asymmetric effects across industries: in fact, regions that are highly specialized in low-sensitive industries are expected to exhibit low vulnerability to aggregate disturbances; and *viceversa*. Conversely, more diversified economies should be more able to absorb the adverse labour market effects of common shocks through inter-sectoral mobility, as the portfolio hypothesis suggests (Simon, 1988; Simon and Nardinelli, 1992; Elhorst, 2003; Ferragina and Pastore, 2008).

Jacobs (1969) had already reached similar conclusions, by arguing that sectoral diversification may offer more job opportunities and, thus, reduce the unemployment rate of a region. An alternative hypothesis indicates specialization rather than diversity as a mechanism leading to local (urban) growth, however. According to Marshall (1890), workers are better protected from business uncertainty and demand shocks if located in a region with a large local base in their own industry. The local concentration of firms within the same industry gives rise to a greater number of employment opportunities to dismissed workers. In ultimate analysis, whether specialization or diversity are more beneficial for local labour market dynamics is an empirical question whose answer depends on the time period of the analysis, on the way phenomena are measured, on which industry is considered, at which level of (sectoral and territorial) aggregation the analysis is carried out and on the methodology adopted (see Beaudry and Schiffauerova, 2009, for a critical review).

3. Data and measurement

3.1 The spatial unit of analysis

Empirical studies on regional unemployment disparities usually adopt administratively defined areas (such as regions and provinces, i.e. NUTS-2 and NUTS-3 regions) within which labour market relevant policy measures can be taken by planning authorities (Elhorst, 2003). While this strategy has the advantage of data availability for these regions, its main drawback usually consists in having to cut and subdivide functionally linked labour market areas, which often do not follow administrative boundaries (Isserman et al., 1986). Disregarding the functional interdependencies of some areas can have serious repercussions on the estimation of theory-based labour market models (Openshaw, 1984, among others).

Arbitrariness in boundaries and huge heterogeneity in size are commonly viewed as the main problems related to the use of administratively defined areas. On the grounds of those shortcomings, functional labour market regions are usually preferred.[1] The most common variable used to define functional labour market regions is the level of commuting to the core region (see, for example, ISTAT, 1991). In particular, according to the evidence from the last census of population (year 2001), the territory of Italy has been divided by ISTAT (Italian National Institute of Statistics) into 686 LLSs on the basis of working-day commuting areas. The algorithm defines self-contained

[1] There are several drawbacks with this concept in practical modelling situations, however. Functionally defined regions may be under the planning authority of several governmental institutions which makes the formulation of the relevant policy variables a rather difficult task. A second disadvantage is constituted by the arbitrariness of the cut-off points for the region defining variable. See Elhrost (2003) on this point.

labor markets in terms of worker mobility as in the case of US Core Based Statistical Areas and French "*zones d'emploi*".

Moreover, ISTAT provides a taxonomy of LLSs, according to their degree of specialization and their population density. Thus, we can distinguish among eight categories of LLSs (namely non specialized, nsp; urban, urb; port, por; tourism, tou; agriculture, agr; textile, tex; other Made in Italy, omi; heavy manufacturing, hma). ISTAT also categorizes LLSs according to whether or not they constitute an ID. Accordingly, we are able to identify 156 IDs in Italy, as Table 1 shows. This piece of information turns out to be of relevance for our analysis: while the degree of urbanization and specialization allows us to put into a test the effect of Jacobsian economies on local labour market performance, the possibility of distinguishing between IDs and other LLSs allows us to assess the role of Marshallian economies on unemployment rate dynamics at a very fine territorial level.

Table 1

3.2 Measure of labor market performance and their main determinants

Regional labour market performance is measured here in terms of unemployment rate dynamics as in Overman and Puga (2002) and Niebuhr (2003), among others. We use ISTAT data to construct our dependent variable, $y_i = \left(\ln u_{2008} - \ln u_{2004}\right)/4$, which measures the average 2004-2008 growth rate of the *i*-th LLSs ($i = 1, 2, ..., N = 686$) unemployment rate, u_i ($\ln$ the natural logarithmic transformation). Figure 1 reports the density estimates of LLS unemployment rates in 2004 and 2008 relative to the national average, while Figures 2A and 2B show the quartile spatial distribution of unemployment rates in 2004 and 2008. These graphs give strong evidence of the existence of two clusters of LLSs in both years: a cluster of high-unemployment LLS is located in the South, while a group of low unemployment rates is located in the North. Figure 2C reports the quartile distribution of regional unemployment growth rates. Despite the clear picture emerging from the maps in Figures 2A and 2B, we document a strong heterogeneity across spatial units in terms of unemployment rate dynamics.

Figures 1 and 2

Explanatory variables used in the empirical analysis are measures of sectoral shift, sectoral specialization, initial conditions (the level of unemployment rate at the beginning of the sample span), labour supply-demand mismatch and population density. Here is an overview of these variables constructed using ISTAT data.

Sectoral shifts. We measure sectoral shifts by computing the Lilien's index of variance in industry employment growth as $lil_i = \left[\sum_{s=1}^{S} \left(x_{si} / x_i \right) \left(\Delta \ln x_{si} - \Delta \ln x_i \right)^2 \right]^{1/2}$, where x_{si} is the regional employment in industry $s = 1, 2, ..., S = 43$, x_i is the total regional employment and Δ denotes the first difference operator. High values of lil_i are expected to increase unemployment growth rates, especially for those LLSs economically weaker than others. The expected sign for lil_i is, thus, positive. The choroplet map in Figure 3A reports the quartile distribution of Lilien's indicator computed for the period 2004-2008. Confirming evidence reported in Contini and Trivellato (2006), our data show a concentration of high values of the index in the South of Italy, indicating a strong vulnerability of this area to the structural change occurred in the economy.

Figure 3

Specialization. On the grounds of the criticism put forward by Abraham and Katz (1986), a proper modeling approach needs to disentangle sectoral shifts and aggregate disturbances. This implies that lil_i captures "genuine" sectoral shifts only when a measure of the degree of industrial specialization is also included in the set of regressors (Neumann and Topel, 1991). As a measure of specialization, we use the log of the Gini index ($\ln G_i$), where $G_i = \frac{1}{S}\left[2\left(\frac{\sum_{s=1}^{S}(S+1-s)x_{si}}{\sum_{s=1}^{S}x_{si}}\right)-1-S\right]$, where x_{si} is the regional employment in industry s indexed in non-decreasing order. The quartile distribution of the Gini index suggests that Southern LLSs are characterized by a lower diversification (Figure 3B). As discussed in the previous Section, the Jacobsian approach predicts that the variety of industry within a geographic region is likely to raise the probability for dismissed workers to find employment in other sectors. Similarly, the *portfolio* theory (Simon and Nardinelli, 1992) posits that diversified urban areas should better absorb negative idiosyncratic shocks thanks to inter-industry externalities. An opposite effect of specialization is predicted by the Marshallian view of local growth: specialization is expected to better protect workers from business uncertainty and demand shocks, suggesting a negative effect of specialization measures on unemployment rates dynamics (the higher the local base of a given industry, the lower the growth of unemployment rate). Thus, the ultimate effect of specialization on unemployment rate dynamics is ambiguous and should be object of empirical scrutiny.

Initial conditions and supply-demand mismatch. In order to control for local labour market conditions, we include the (logarithm of the) unemployment rate at the beginning of the period, $\ln u_i$, as well as an indicator of the supply-demand mismatch, Δeld_i, measured as the difference between employment growth rate and labor participation growth rate. The expected sign for both regressors is negative. Higher initial conditions are expected to lower growth rates; labour demand above labour supply implies a decline in unemployment.

Population density. A further candidate explanatory variable is population density, den_i, measured as the ratio between population and square kilometers. Large and dense urban labour markets are expected to exhibit higher degree of efficiency in the matching process: more job-seekers and job offers lead to faster matching and lower unemployment (Elhorst, 2003). On the other hand, population density may capture amenities of large LLSs, which might induce congestion effects and, thus, higher unemployment (Niebuhr, 2003).

4 Econometric analysis

4.1 Model specification

In modeling regional unemployment dynamics, we resort to a flexible approach which simultaneously allows for nonlinearities and spatial dependence. Nonlinearities in the relationship between unemployment growth and its main determinants are likely to occur. Focusing, for instance, on the relationship between unemployment dynamics and the degree of diversification (specialization), following (Simon and Nardinelli, 1992) we should expect a negative (positive) effect of diversification (specialization). However, this expected effect may be soften or even reversed if Marshallian externalities are at work, i.e. once a certain threshold of the degree of specialization has been reached.

Nonlinearities could be captured by a polynomial regression model. We instead use a semiparametric methodology, since it is much more flexible than any parametric specification. By using a particular version of the semiparametric model that allows for additive components, we are able to obtain graphical representation of the relationship between unemployment dynamics and LLSs characteristics. Additivity ensures that the effect of each of the model predictors can be interpreted net of the effect of the other regressors, as in linear multiple regression. A typical semiparametric additive model (AM) is specified as follows:

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \ldots + \varepsilon_i \qquad (1)$$

where ε_i is a vector of independently, identically (*iid*) and normally distributed errors, $\varepsilon_i \sim iidN(0, \sigma_\varepsilon^2)$, $f_j(\cdot)$ are unknown smooth functions of the covariates, X_i^* is a vector of strictly parametric components and α^* is the corresponding parameter vector. For our analysis, we employ the methodology proposed by Wood (2006) to estimate AMs with spline based penalized regression smoothers which allows for automatic and integrated smoothing parameters selection via Generalized Cross Validation (GCV).[2]

The assumption of *iid* error in Model (1) is however too restrictive in our case. Spatial dependence may occur because of either agglomeration effects related to the demand linkages across nearby areas (Overman and Puga, 2002) or unobserved heterogeneity clustered in space (LeSage and Pace, 2009; Niebuhr, 2003), so that omitting spatial autocorrelation may lead to misleading estimates and inference.

In order to control for spatial interaction effects, Model (1) has to be augmented by including the spatial lag of the dependent variable, $y_i^{\square} = \sum_{j \neq i} w_{ij} y_j$, on the right hand side of the AM, leading to a Spatial Autoregressive AM (SAR-AM):

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[2] For a comprehensive discussion of the methodology used to estimate AMs, see Basile and Girardi (2010) and Basile et al. (2011).

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \rho y_i^{*} + \ldots + \varepsilon_i \qquad (2)$$

where ρ is the spatial autocorrelation parameter and w_{ij} is the element of a spatial weights matrix which summarizes the interaction between regions i and j.[3]

It is worth noticing that when the data generating process is non-stationary, the evidence of spatial dependence may be induced by the presence of spatial trends so that, after removing them, test statistics may reveal the absence of spatial autocorrelation or a random dispersion pattern (Diggle and Ribeiro, 2007). Spatial trend in the data can be properly captured by including in the model a nonparametric smooth interaction between latitude and longitude, $f\left(lat_i, lon_i\right)$.[4]

Finally, because of the feedbacks between y_i and its spatial lag term, y_i^*, enters endogenously into equation (2). Accordingly, we apply the two-step "control function" approach (Blundell and Powell, 2003). In the first step, the following auxiliary semiparametric regression is considered

$$y_i^{*} = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + h(Z_i) + \ldots + \upsilon_i$$

where Z_i is a set of conformable instruments and υ_i is a sequence of random variables satisfying $E(\upsilon_i \mid Z_i) = 0$.[5] Moreover, if Z_i and ε_i are independent, then it follows that

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[3] Throughout the paper, we use a *knn* (*k-nearest-neighbours*) matrix with $k = 5$. The results are robust to the alternative choices of *k*.

[4] While rarely considered for modelling economic data, spatial and spatio-temporal trends are widely included in biological models using generalized additive models (see, for example, Augustin et al. 2009).

[5] Mimicking the two-stage least square procedure for the estimation of linear SAR model proposed by Kelejian and Prucha (1998), we include in the set of instruments the first and second order spatial lags of all exogenous or predetermined variables.

$E(\varepsilon_i \mid \upsilon_i, Z_i) = E(\varepsilon_i \mid \upsilon_i)$ and, thus, $E(\varepsilon_i \mid y_i^{\square}) \neq 0$ when $E(\varepsilon_i \mid \upsilon_i) \neq 0$. The second step consists of estimating an AM of the form:

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \rho y_i^{\square} + f_4(\hat{\upsilon}_i) \ldots + \varepsilon_i \qquad (3)$$

Furthermore, as the employment growth rate and the participation growth rate have common components with the dependent variable by construction, a second endogeneity problem is likely to emerge for Δeld_i. Therefore another first step is estimated and the corresponding residual vector is introduced as an additional regressor in the second step.

4.2 Results

Table 2 reports the estimation results and diagnostics tests for our empirical model applied to analyze the spatial effects characterizing unemployment dynamics in Italian LLSs. After considerable experimentation, we have opted for a regression model which admits two additional terms, $\hat{\upsilon}_1$ and $\hat{\upsilon}_2$, representing the estimated residuals from two distinct first step estimations for the spatial lag of the dependent variable and for excess labour demand growth rate, respectively.

Table 2

Estimates for Model 1 provide strong evidence of spatial dependence: the $y_i^{\square}$ term is statistically significant and signals that neighboring units exhibit a higher degree of spatial contagion than do units located far apart even controlling for the presence of a spatial trend. All terms but *lil* and *den* enter nonlinearly, as suggested by the estimated degrees of freedom (*edf*). Furthermore, $y_i^{\square}$ and Δeld turn out to be strongly endogenous, since the two smooth terms $f(\hat{v}_1)$ and $f(\hat{v}_1)$ are statistically significant.

As for the choice of the set of instruments, diagnostics tests point out that the null of excludability of the instruments for the first steps is strongly rejected.[6] Finally, the specification is able to explain about 90 percent of cross-sectional variation in unemployment rates.

On the ground of these findings, we specify a regression model where the linearity constraint is imposed for lil and den. In line with our theoretical priors, we document that sectoral shifts worsen labour market performance: *ceteris paribus*, labour pushed out from declining industries has not been absorbed into the other sectors leading to an increase (or to a relatively lower reduction) in unemployment rates in those areas where labour relocation phenomena have taken place. Moreover, the positive coefficient of population density suggests that unemployment dynamics tends to be rather unfavourable in highly agglomerated LLSs, as previously documented by Niebuhr (2003) for the case of European regions.

The graphs in Figure 4A-4C show the fitted univariate smooth functions (solid line) for Model (2), alongside Bayesian confidence intervals (shaded gray areas) at the 95 percent level of significance (see Wood, 2004). In each plot, the vertical axis displays the scale of the expected (standardized) values of unemployment growth rates, while the horizontal one reports the scale of initial conditions (Figure 4A), excess demand growth rates (Figure 4B) and specialization (Figure 4C). The contour plot in Figure 4d shows the joint effect of latitude and longitude, $f(lat, lon)$.

Figure 4

Italian provinces with a higher initial unemployment are more likely to reduce unemployment rates than other provinces up to a threshold (equal to 2.5 and

[6] The results of the first steps are available upon request.

corresponding to around 12 percent). After such a maximum level, $\ln u$ has no effect on unemployment growth, since the confidence intervals include the horizontal axis. As expected, high excess labour demand growth rate lowers almost monotonically regional unemployment growth. Furthermore, increasing specialization seems to exert detrimental effects on local labour market performances. The relationship between specialization and unemployment growth is strongly nonlinear, however. For low specialized LLSs, our results are fully consistent with the idea that inter-sectoral mobility helps absorb adverse labour market shocks (Simon and Nardinelli, 1992; Ferragina and Pastore, 2008) and that sectoral diversification may offer more job opportunities and, thus, improve local labour market performance (Jacobs, 1969). After a certain threshold of specialization, however, Marshallian externalities gain relevance and mitigate the previous pattern, so that the ultimate effect of specialization on unemployment growth is not statistically significant in highly specialized territorial units. Finally, the spatial trend surface reveals a clustering of highly expected unemployment growth rates in the South not captured by the explanatory variables.

Finally, the Moran I plot (Figure 5) illustrates that the relationship between residuals (horizontal axis) and their spatial lag (vertical axis) is nonlinear and not statistically significant at the usual confidence levels, suggesting that our empirical model is able to remove spatial dependence.

Figure 5

4.3 Extension

In an effort to better assess unemployment growth in Italian LLSs, we exploit the taxonomy provided by ISTAT in order to analyze to what extent population density and the degree of specialization affect local labor market performances. As a preliminary step, Table 3 shows some descriptive statistics for Italian LLSs taking into account both pieces of information and reports the unemployment rate at the beginning period (2004) and the average unemployment growth rate over the sample span covered in the analysis (2004-2008). The last row of the Table collects national average figures.

Table 3

Three main remarks ensue. *First*, those entities of reference belonging to groups with a starting unemployment rate above 10 percent have experienced a reduction in unemployment rates greater than the national average. *Second*, LLSs without a clear specialization pattern have exhibited the strongest decline in unemployment rates. *Third*, as for highly specialized industrial areas (textile, heavy manufacturing and other Made in Italy productions) IDs have recorded a relatively better labour market performance with respect to their no-IDs counterparts.

In order to better understand those dynamics, Table 4 collects the results from the analysis aimed at testing if the difference in means across groups for unemployment rate changes is statistically significant. We observe that some groups (non-ID areas specialized in textile as well as regions specialized in other Made in Italy productions) appear to be less performing than non-specialized areas (the reference category), with the remaining groups showing no statistically significant deviations from the reference category.

Table 4

Now, it turns out to be particularly interesting to assess whether Model 2 is able to fully capture these differences in the unemployment performance of the various groups of LLSs. Accordingly, in Model 3 we augment the set of regressors employed for the estimation of previous regression models with the inclusion of the dummy variables used for the analysis of variance (with non-specialized areas as reference category). Thus, Model 3 takes into account not only the overall degree of specialization of a LLSs (through $\ln G$) but also where (how) that region specializes (through the set of dummy variables). Furthermore, since the degree of urbanization is captured by urb, we exclude the continuous variable $dens$ from the regressors.

Table 5

Estimation results in Table 5 document that our empirical framework allows to capture the heterogeneity emerging from the analysis of variance: all dummy variables turn out to be not statistically significant at the usual confidence levels, but $tnID$. This implies that the conditional mean does not vary across groups, with the exception of highly specialized non-ID regions in textile productions, which are randomly distributed in space and thus do not exhibit clear spatial pattern, as Figure 6 shows.

Figure 6

5 Conclusions

In this work we present an empirical framework to assess the effects of sectoral shifts and industry specialization patterns on regional unemployment applied to Italian LLSs data over the years 2004-2008. We argue that Italy represents an interesting case-study not only for the huge dispersion across space in unemployment rates due to her well-known North-South divide but also for the presence of strongly specialized LLSs (Industrial Districts, IDs). Understanding cross-sectional variation and assessing the role of possible intra-sectoral spillovers driven by agglomeration forces are indeed issues of particular relevance when analyzing local labour market performances.

Three main features characterize our setup. *First*, the chosen territorial units allow a detailed territorial approach and are constructed according to economic criteria instead of administrative ones. *Second*, we focus on a period during which huge worker reallocation caused by changes in the international context has occurred. The ensuing process of structural change may have indeed insightful implications for local labour market performance, since they are likely to differ according to the forces which can be at work. *Third*, the use of spatial econometric techniques along with nonparametric methods allows us to capture spatial contagion phenomena, spatial non-stationarity and spatial heterogeneity (nonlinearities or parameter heterogeneity).

In order to explain the cross-sectional variation in unemployment rate dynamics we assess the role of several potential determinants of local labour market performances, including measures of sectoral shifts and specialization, initial conditions, supply-demand mismatch and population density. Building on a semiparametric spatial auto-regressive framework, our econometric results document that local labour market performances are characterized by significant differences across space. We also find that that sectoral shifts and the degree of specialization exert a negative role on unemployment dynamics. Conversely, highly diversified areas turn out to be characterized by more favourable unemployment dynamics.

In an effort to sharpen our understanding of how local labour market performances vary across spaces, we also try to compare the performance of IDs with respect to other LLSs so as to take into account not only the overall degree of specialization of a certain spatial unit but also where (how) that region specializes. Results from the analysis of variance point out that some groups (non-ID areas specialized in textile as well as regions specialized in other Made in Italy productions) appear to be less performing than non-specialized areas. Controlling for a number of possible determinants of unemployment dynamics and allowing for spatial dependence and nonlinearities, our empirical framework is able to capture such a heterogeneous pattern except for highly specialized non-ID regions in textile productions. A fuller explanation of the reasons behind the relatively worse performance in terms of unemployment growth rates for those LLSs is left for future research.

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Table 1 – Types of LLSs

Definition		Type	Observation	
			Freq.	Share
Not specialized		*nsp*	220	32.1
Urban		*urb*	46	6.7
Port		*por*	26	3.8
Tourism		*tou*	82	12.0
Agriculture		*agr*	24	3.5
Textile	no IDs	*tex-noID*	35	5.1
	IDs	*tex-ID*	65	9.5
Other Made in Italy	no IDs	*omi-noID*	57	8.3
	IDs	*omi-ID*	75	10.9
Heavy Manufacturing	no IDs	*hma-noID*	44	6.4
	IDs	*hma-ID*	12	1.7
Total LLSs			686	100.0

Table 2 – Estimation results

	Model 1		Model 2	
	Parametric terms (β and p values)			
Intercept	-1.581*** (0.000)		-1.821*** (0.000)	
lil	.		0.510* (0.056)	
den	.		0.548** (0.022)	
$y^{\square}$	0.297*** (0.000)		0.294*** (0.000)	
	Nonparametric terms			
	F test and p values	Edf	F test and p values	edf
$f(\ln u)$	30.647*** (0.000)	3.249	30.280*** (0.000)	3.258
$f(\Delta eld)$	85.760*** (0.000)	3.975	86.250*** (0.000)	3.976
$f(\ln G)$	5.944*** (0.000)	3.601	5.580*** (0.000)	3.555
$f(lil)$	3.351* (0.068)	1.000	.	
$f(den)$	4.011** (0.023)	1.500	.	
$f(lat, lon)$	13.710*** (0.000)	6.512	13.670*** (0.000)	6.535
$f(\hat{v}_1)$	9.816*** (0.000)	2.268	10.000*** (0.000)	2.279
$f(\hat{v}_2)$	27.901*** (0.000)	3.957	28.200*** (0.000)	3.957
R^2 adj.	0.916		0.916	
GVC score	2.329		2.331	
F test – first step (Wy)	137.27*** (0.000)		137.27*** (0.000)	
F test – first step (Δeld)	26.788*** (0.000)		26.788*** (0.000)	

Notes: the dependent variable is the average growth rate of regional unemployment rate over the period 2004-2008. The total number of observations is 686. A 5NN spatial weights matrix has been used. F tests are used to investigate the overall ("approximate") significance of smooth terms. *edf* (effective degrees of freedom) reflect the flexibility of the model. $\hat{v}_1$ and $\hat{v}_2$ refer to the residuals of the first step for $y^{\square}$ and Δeld, respectively. *P*-values are in parentheses.

Significance levels: (***) 1% or less; (**) 5%; (*) 10%.

Table 3 – Descriptive statistics by LLSs type

Definition		Type	u	Δu
Not specialized		*nosp*	13.32	-2.92
Urban		*urb*	4.93	-1.57
Port		*port*	12.54	-3.83
Tourism		*tur*	6.87	-2.42
Agriculture		*agr*	12.21	-2.41
Textile	no IDs	*tnID*	9.13	-0.84
	IDs	*tID*	6.53	-2.07
Other Made in Italy	no IDs	*onID*	4.88	-0.64
	IDs	*oID*	4.43	-1.08
Heavy Manufacturing	no IDs	*hnID*	4.08	-2.08
	IDs	*hID*	7.54	-2.80
Total LLSs			8.89	-2.18

Table 4 – Estimation results

Intercept	-2.925*** (0.000)
urb	1.346 (0.105)
por	-0.912 (0.391)
tou	0.501 (0.450)
agr	0.513 (0.642)
tex-noID	2.083** (0.026)
tex-ID	0.852 (0.239)
omi-noID	2.283*** (0.003)
omi-ID	1.845*** (0.007)
hma-noID	0.118 (0.889)
hma-ID	1.181 (0.437)

Notes: the dependent variable is the average growth rate of regional unemployment rate over the period 2004-2008. The total number of observations is 686. *p*-values are in parentheses.

Significance levels: (***) 1% or less; (**) 5%; (*) 10%.

Table 5 – Estimation results

	Model 3	
	Parametric terms (β and p values)	
Intercept	-1.795*** (0.000)	
lil	0.477* (0.079)	
$y^{\square}$	0.274*** (0.000)	
urb	-0.076 (0.812)	
por	0.327 (0.346)	
tou	-0.079 (0.736)	
agr	-0.165 (0.621)	
tex-noID	0.601** (0.043)	
tex-ID	-0.038 (0.883)	
omi-noID	0.186 (0.503)	
omi-ID	0.101 (0.709)	
hma-noID	0.074 (0.794)	
hma-ID	-0.277 (0.556)	
	Nonparametric terms	
	F test and p values	edf
$f(\ln u)$	27.241*** (0.000)	3.366
$f(\Delta eld)$	90.531*** (0.000)	3.978
$f(\ln G)$	3.724*** (0.006)	3.370
$f(lat, lon)$	12.382*** (0.000)	6.465
$f(\hat{v}_1)$	11.285*** (0.000)	2.296
$f(\hat{v}_2)$	25.828*** (0.000)	3.954
R^2 adj.	0.915	
GVC score	2.386	
F test - first step (Wy)	137.27*** (0.000)	
F test - first step (Δeld)	26.788*** (0.000)	

Notes: see Table 2.

Figure 1 – Density estimates of relative unemployment rates

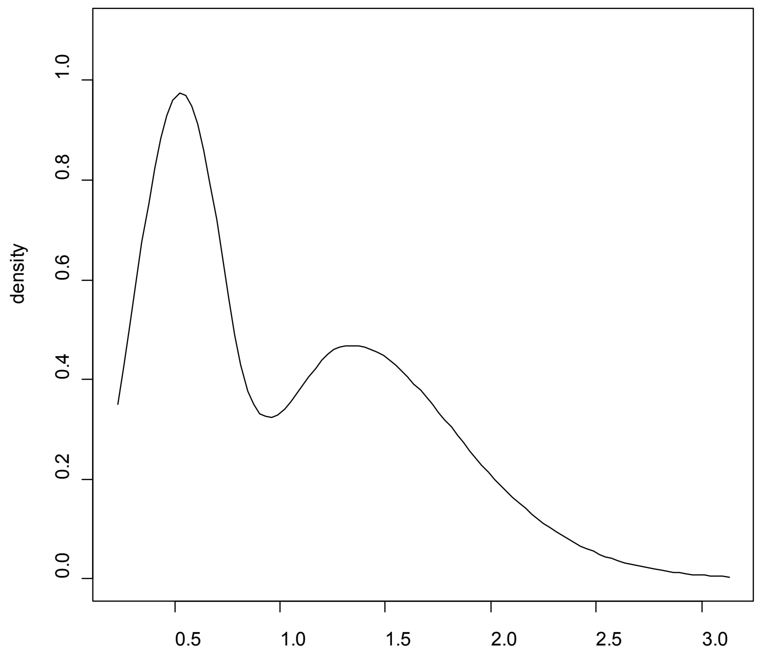
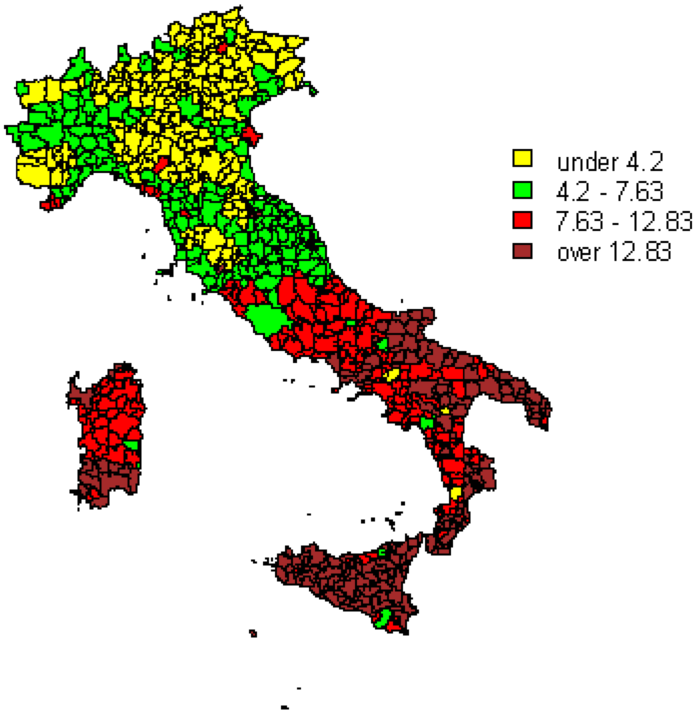
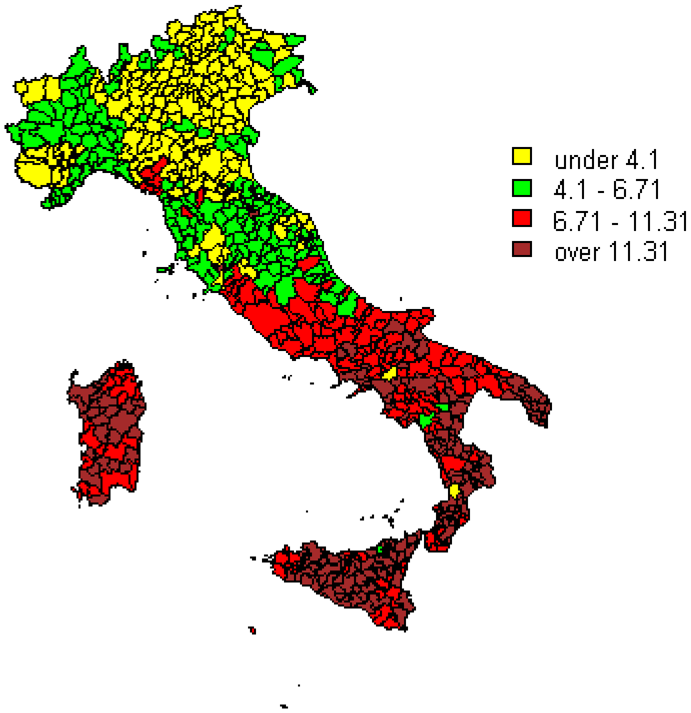


Figure 2 – Choroplet maps of unemployment rates (quartile distribution)

A. 2004



B. 2008



C. Growth rate (2004-2008)

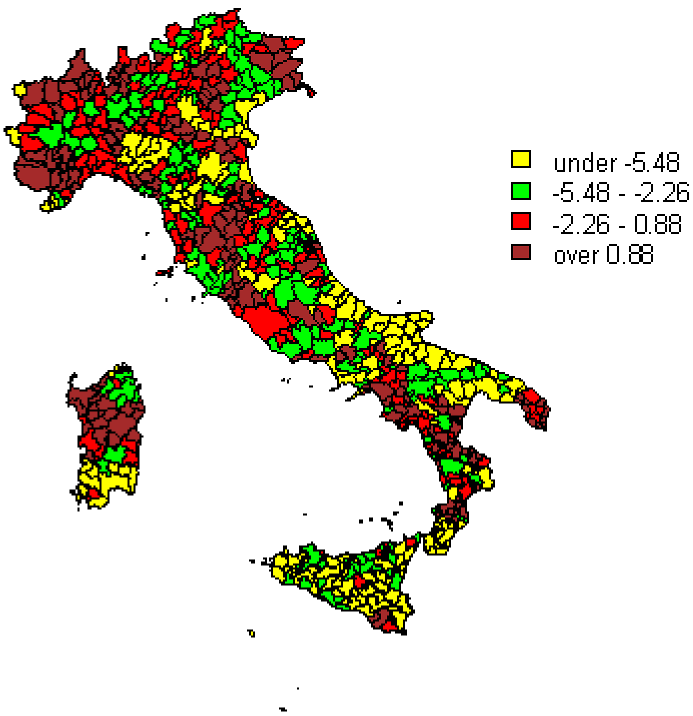
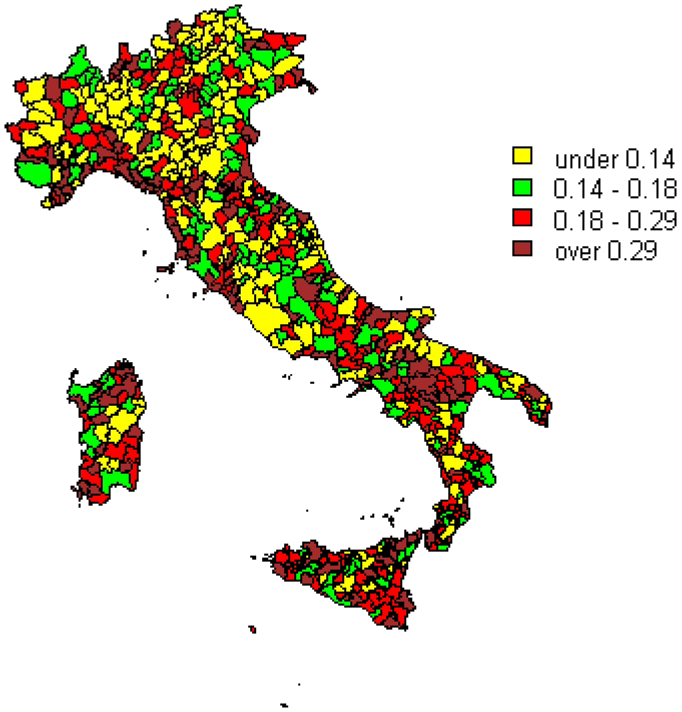


Figure 3 – Choroplet map of Lilien's indicator and Gini index

A. Lilien



B. Gini

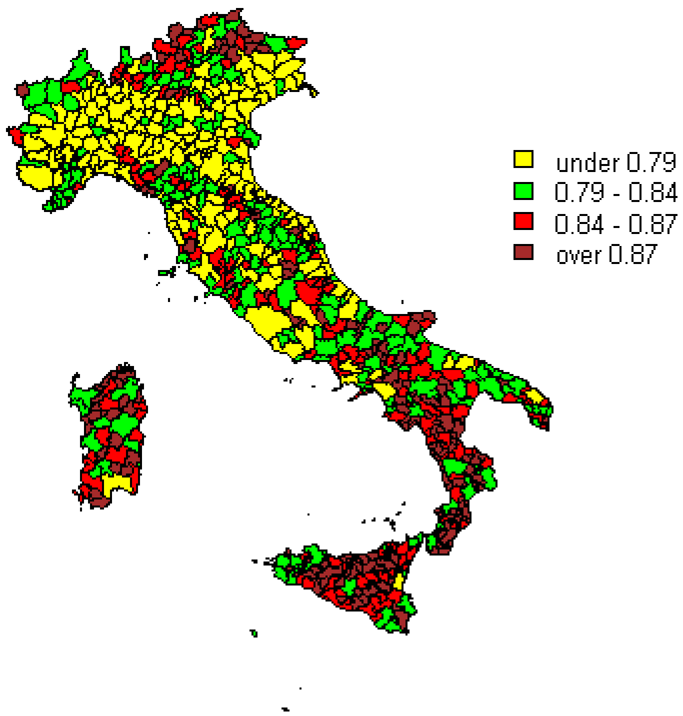
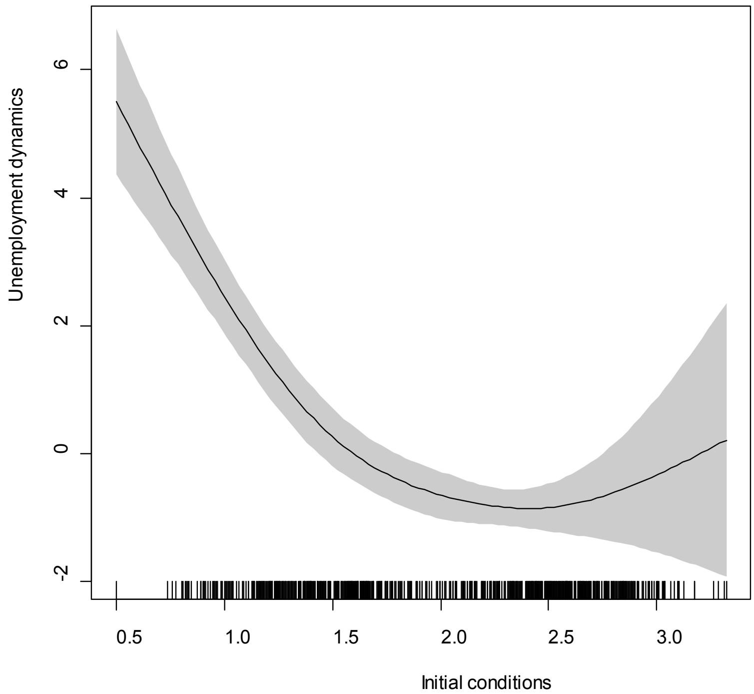


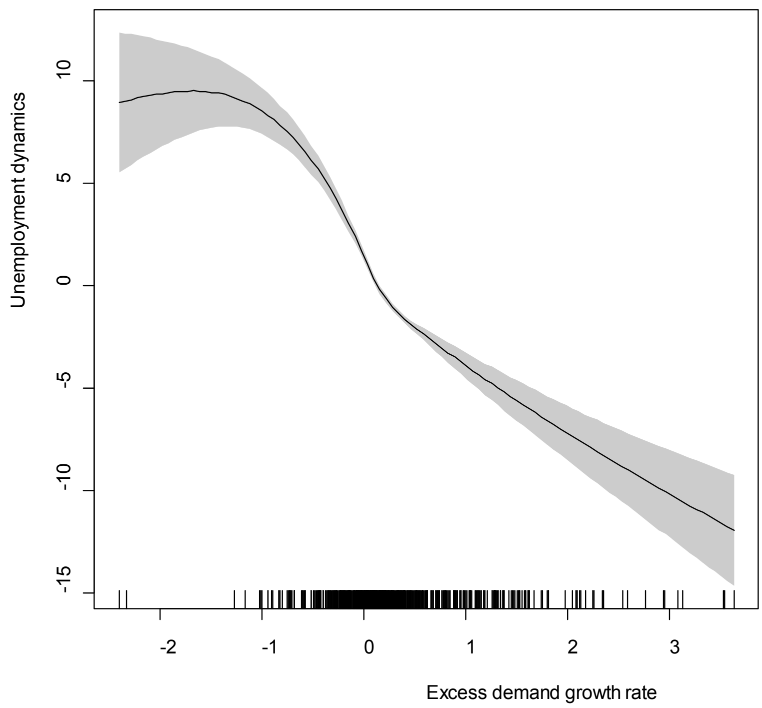
Figure 4 – Partial effects of smooth terms

A. Initial conditions



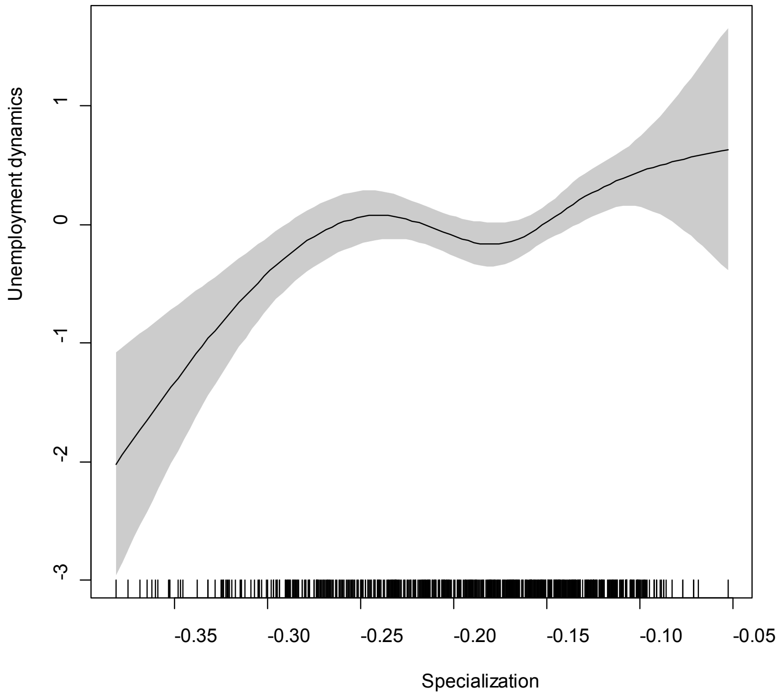
Note: The vertical axis displays the scale of the expected (standardized) values of unemployment growth rates, while the horizontal one displays the scale of initial conditions.

B. Excess demand growth



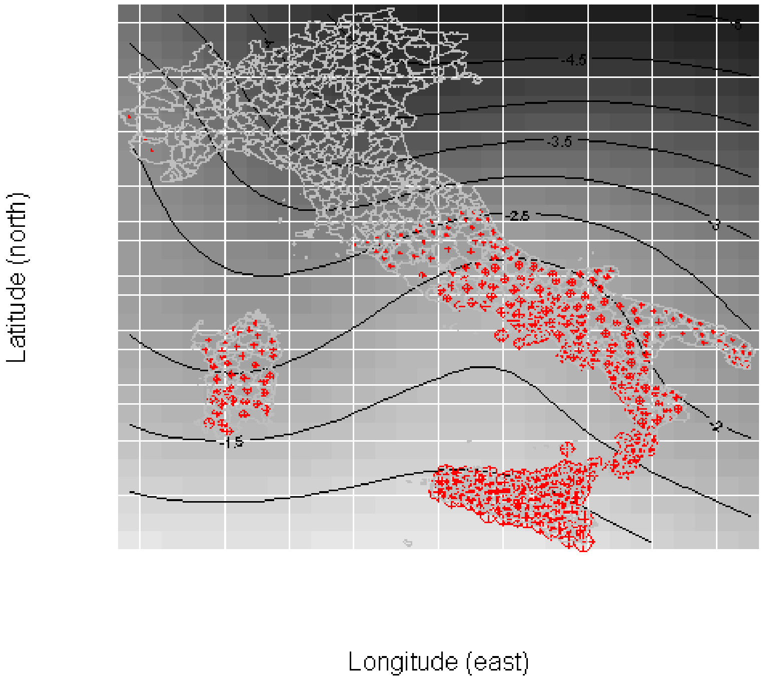
Note: The vertical axis displays the scale of the expected (standardized) values of unemployment growth rates, while the horizontal one displays the scale of excess demand growth rate.

C. Specialization



Note: The vertical axis displays the scale of the expected (standardized) values of unemployment growth rates, while the horizontal one displays the scale of specialization.

D. Latitude and longitude



Note: The graph displays the joint effect of latitude and longitude.

Figure 5 – Moran I Plots

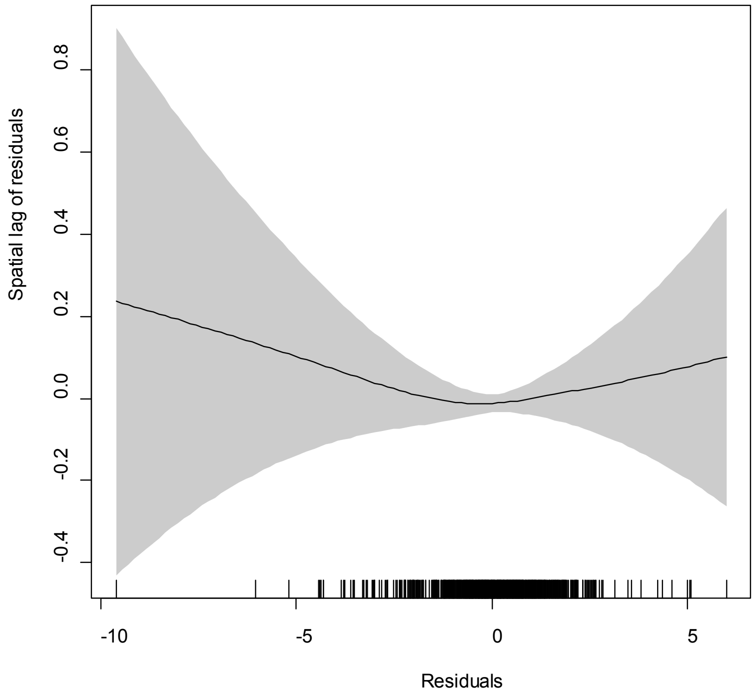


Figure 6 – Textile LLS

Appendix

Variables description and sources

Variable	**Description**	**Source**
$\Delta \ln u_i$	Unemployment growth rate	ISTAT
$\ln u_i$	Log of unemployment rate	ISTAT
Δeld_i	Supply-demand mismatch	ISTAT
$\ln G_i$	Log of Gini index	ISTAT
lil_i	Lilien index	ISTAT
den_i	Population density	ISTAT