INDUSTRY STRUCTURE AND EMPLOYMENT GROWTH: EVIDENCE FROM SEMIPARAMETRIC GEOADDITIVE MODELS

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Abstract *- Using Local Labor Systems (LLSs) data, we assess the effect of the local productive structure on employment growth in Italy during the period 1981-2008. Italy represents an interesting case study because of the high degree of spatial heterogeneity in local labor market performances and of the presence of strongly specialized LLSs (industrial districts). Building on semiparametric geoadditive models, our empirical investigation allows us to identify important nonlinearities in the relationship between local industry structure and local employment growth, to assess the relative performance of industrial districts and to control for unobserved spatial heterogeneity.*

Key-words: SEMIPARAMETRIC GEOADDITIVE MODELS, INDUSTRY STRUCTURE, INDUSTRIAL DISTRICTS, EMPLOYMENT DYNAMICS

Classification JEL: R11, R12, C14

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1. INTRODUCTION

Following the broad literature started by Glaeser *et al*. (1992) and Henderson *et al*. (1995)[1], in this paper we analyze the effect of many factors characterizing the local industry structure (such as the presence of Marshallian and urbanization externalities) on employment growth in Italy. Previous studies on the Italian case (i.a., Mameli *et al*., 2008; Paci and Usai, 2008, Cainelli and Leoncini, 1999) report a negative impact of specialization (notwithstanding the strong anecdotal evidence of the economic success of *industrial districts*, the places where Marshallian externalities are magnified) and a positive effect of diversification on local employment growth. Only Forni and Paba (2002) find a positive impact of both factors. Moreover, it emerges a negative effect of local competition and of scale economies and a positive effect of population density.

We claim that the results of previous studies may suffer from a number of model mis-specifications. First, most of them use the location quotient to measure the effect of Marshallian externalities disregarding that specialization has a positive effect on productivity and, under certain conditions (inelastic product demand), this may lead to a reduction (rather than an increase) of labor demand (Cingano and Schivardi, 2004). However, specialization alone cannot explain the economic success of Italian industrial districts. As a matter of fact, several socio-economic factors (such as mutual trust and *coopetition*[2]) have contributed along with “working on similar things" to determine the “industrial atmosphere" theorized by Marshall as well as by several Italian economists (e.g. Becattini, 1987; Becattini *et al*., 2003; Bellandi, 2007). In a nutshell, in order to assess the existence of Marshallian externalities, we need to bear in mind that this kind of external economies are more likely to occur within industrial districts than anywhere else. Therefore, we suggest to verify directly the relative performance of industrial districts using information on their presence in the territory.

Second, most of the previous studies disregard the existence of nonlinearities in the relationship between industry structure and employment growth, although it is widely recognized in the literature that economic growth behaviors are characterized by strong nonlinearities (Henderson *et al*., 2012). Some authors (i.a. De Lucio *et al*., 2002, Viladecans-Marsal, 2004, and Illy *et al*., 2011) allow for nonlinearities by introducing quadratic terms in their models. Although this is the easiest way to deal with such a nonlinearity in a parametric framework, it is only one of several possible nonlinear parameterizations. Indeed, nonlinearities can be better accommodated in a semiparametric frame-

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[1] See also, i.a., Henderson (1997), Combes (2000), Rosenthal and Strange (2004), de Groot *et al*. (2009), Melo *et al*. (2009). For a recent review of the literature, see Beaudry and Schiffauerova (2009).

[2] Generally speaking, coopetition is a business strategy based on a combination of cooperation and competition. It is derived from an understanding that business competitors can benefit when they work together. Basic principles of coopetitive structures have been described in game theory. A coopetition approach can be adopted to study a model of district formation (see, e.g., Soubeyran and Weberm, 2002).

work, where the actual shape of the partial effect can be assessed using smooth functions.

Third, most of previous studies carried out in Italy as well as in many other countries do not control for unobserved spatial heterogeneity when specifying the local economic growth model. Part of this heterogeneity is *time invariant* and can be captured by geographical dummies included in the econometric model. One can think, for example, to the role of "*natural advantages*" of local areas in affecting their growth performances (Krugman, 1993; Ellison and Glaeser, 1999). There are, however, other sources of *time varying* unobserved spatial heterogeneity that cannot be captured by simple geographical dummies. One can think about the presence of localized *spillover* and the consequences of the *Modifiable Areal Unit Problem* (MAUP).

Using census data for 686 Local Labor Systems (LLS) in Italy for both manufacturing and services and for three different periods (1981-1991, 1991-2001, 2001-2008), we contribute to existing literature by a) assessing the presence of nonlinearities in the relationship between industry structure and local-sector employment growth, b) assessing the relative performance of industrial districts and c) controlling for both *time invariant* and *time varying* unobserved spatial heterogeneity.

To this aim, we develop a methodological framework which innovates with respect to the existent literature along several dimensions. First, we use a semiparametric model which allows us to identify smooth nonlinear effects of the growth predictors. Second, we include in our model a dummy variable, *ID*, which takes value 1 if the LLS belongs to an industrial district and zero otherwise. Specifically, we distinguish between the within-sector and the between-sector *ID* effects. We also consider potential endogeneity of this dummy variable using instrumental variable (IV) methods. Third, exploiting the longitudinal dimension of our data set, we include in our model a geoadditive component (a smooth interaction between latitude and longitude) for each time period which permits us to control also for time-varying unobserved spatial heterogeneity.

Controlling for endogeneity with instrumental variables, our empirical findings confirm that industrial districts have performed better than the other LLSs during the sample period, thus corroborating the hypothesis that Marshallian externalities exert a positive role on local employment growth. Regression results also highlight a hockey stick-shaped relationship between specialization and local employment growth: net of the industrial districts' effect, a higher specialization increases productivity and reduces, under the assumption of inelastic product demand, labor demand. However, after a certain threshold, location economies exhaust their effect on productivity and, thus, on employment so generating a nonlinear relationship between specialization and employment growth. In line with previous evidence and corroborating Jacobs' theory, diversification boosts employment growth in manufacturing and reduces it in services. Allowing for nonlinearities and in keeping with theoretical predictions, we find a hump-shaped relationship between population density and local employment growth in the case of services: the positive effect of overall population density fades as the density of economic activities reaches some threshold value, after which congestion costs overcome agglomeration externalities. In the case of manufacturing the effect of density is monotonically negative. Non-linear effects are also evident for local competition and average firm size. Finally, the inclusion of a smooth spatial trend surface allows us to control for spatial heterogeneity.

The remainder of the paper is organized as follows. Section 2 describes our modeling strategy. Section 3 provides information about data and variables. The results are presented and discussed in section 4. Conclusions are reported in section 5.

2. MODELING REGIONAL EMPLOYMENT GROWTH

2.1. A log-linear specification

Combes (2000) analyzes the relationship between industry structure and local employment growth by estimating the following log-linear reduced form:

$$\begin{aligned} y_{r,s,t} = {} & \beta_0 + \beta_1 \, log\left(spe_{r,s,t-\tau}\right) + \beta_2 \, log\left(div_{r,s,t-\tau}\right) \\ & + \beta_3 \, log\left(den_{r,t-\tau}\right) + \beta_4 \, log\left(size_{r,s,t-\tau}\right) \\ & + \beta_5 \, log\left(comp_{r,s,t-\tau}\right) + \gamma_s + \delta_t + \varepsilon_{r,s,t} \end{aligned} \quad (1)$$

where $y_{r,s,t}$ is the employment growth rate of sector s in site r computed over a given period (between $t-\tau$ and t); $spe_{r,s,t-\tau}$, $div_{r,s,t-\tau}$, $den_{r,t-\tau}$, $size_{r,s,t-\tau}$ and $comp_{r,s,t-\tau}$ are the explanatory variables computed at the initial period $t-\tau$ and corresponding respectively to specialization, diversity, population density, average size of plants and local competition; β_0-β_5 are the parameters associated to the intercept and to the explanatory variables expressed in log terms; γ_s is a sector fixed effect; δ_t is a temporal fixed effect; and $\varepsilon_{r,s,t}$ is an error term assumed to be iid.[3]

The variable spe should capture external economies occurring among firms producing similar goods or services and operating in the same area. According to the Marshall-Arrow-Romer theory (the MAR-theory), formalized by Glaeser *et al*. (1992), within-sector pecuniary (static) and non-pecuniary (dynamic) externalities (knowledge spillovers) are the main sources of local

[3] Starting from a similar specification, Paci and Usai (2008) and Mameli *et al*. (2008) extend the model by introducing other explanatory factors, such as human and social capital. However, they conclude that the baseline model (1) does not suffer from omitted-variable problems. On the basis of these evidences and because of the lack of complete information on further explanatory variables for the whole sample period, we do not consider additional factors in our empirical analysis.

growth.[4] These external economies are known as *localization* or *specialization externalities* and are often measured with the degree of *sectoral specialization* of the region. Therefore, according to the MAR-theory, the higher the degree of specialization of the region in a specific industry, the higher the growth rate in that particular industry within that region.

From a different perspective, Jacobs (1969) argues that the most important sources of pecuniary and non-pecuniary economies are external to the industry within which the firm operates. She suggests diversity rather than specialization as a mechanism leading to economic growth: a diverse sectoral structure increases the chances of interaction, generation, replication, modification and recombination of ideas and applications across different industries; moreover, a diverse industrial structure protects a region from volatile demand and offers it the possibility of switching between input substitutes. *Urbanization* or *Jacobs externalities* are measured with the degree of *sectoral diversification* (div) of the local production structure. According to Jacobs theory, the higher the degree of diversification of the region, the higher its growth rate.

Empirical evidence provided by a large amount of studies in support of the Marshall and Jacobs theories yields mixed results. Beaudry and Schiffauerova (2009) review 67 studies and discuss their basic results. According to them, almost half of these studies report both MAR and Jacobs externalities. Both specialized and diversified local industrial structures may therefore be conductive to local economic growth. In line with this interpretation, Duranton and Puga (2000, p. 553) observe that there is "a need for both large and diversified cities and smaller and more specialized cities". Although positive evidence for both types of externalities is reported, many of these studies also find negative impacts. However, the negative influence is observed much more often for Marshallian externalities than for Jacobs externalities (only in 3 per cent of all the studies).

Besides the degree of specialization and diversification, the two alternative theories (MAR and Jacobs) also relate regional growth performances to the level of local competition, $comp$. According to the MAR-theory, "local monopoly is better for growth than local competition, because local monopoly restricts the flow of ideas to others and so allows externalities to be internalized by the innovator" (Glaeser *et al*., 1992, p. 1127). Porter (1990) supports the Marshallian specialization hypothesis in identifying intra-industry spillovers as the main source of knowledge externalities but suggests that local competition rather than monopoly favors growth in specialized geographically concentrated industries. In line with Porter, Jacobs (1969) also suggests that a more competitive environment is more conductive to innovation and therefore to growth.

According to Beaudry and Schiffauerova (2009), only 25 studies attempt to detect the three types of externalities: specialization, diversity and competi-

[4] In MAR-Theory, static externalities refer to cost reductions deriving from the creation of a specialized labor market pooling and from the presence of specialized suppliers, while dynamic externalities refer to knowledge spillovers which occur when knowledge crosses the boundaries of a firm, improving the innovation activity of other firms.

tion. Porter's view on competition is most often supported in conjunction with Jacobs' prediction on the positive effect of diversity. For the case of Italy, Paci and Usai (2008) find a positive effect of market power (i.e. a negative effect of local competition) on local employment growth. Mameli *et al*. (2008) find a negative effect of local competition when using 2-digit sectoral level data and a positive effect of local competition when using 3-digit sectoral level data.

Urbanization economies are not only driven by the degree of diversity of an economy, but also by the overall density of economic activity, *den*. Ciccone and Hall (1996) argue that an increase in economic density involves the accessibility to a broader supply of local public services and a higher local demand and this may foster local growth. However, a larger size of the local economy also entails congestion effects (including higher land prices, higher crime rates, environmental pollution, traffic jams and excess commuting), so that agglomeration diseconomies may dominate. In other words, regions tend to grow faster if, *ceteris paribus*, agglomeration economies overcome congestion costs. Combes (2000) reports, for example, a negative effect of urbanization economies on urban growth in the manufacturing sector. Mameli *et al*. (2008) report evidence of a positive linear effect of population density, while in Paci and Usai (2008) the effect of population density is positive for the whole sample (including both manufacturing and services) and null for the manufacturing sectors.

Finally, the presence of scale economies means that larger is the size of a plant (*size*) better it is possible to exploit fixed costs. This is the case, for example, in monopolistic competition models. A large size could be source of a more detailed division of labor, promoting specialization and productivity growth. However, a large firm size can lead to an increase in costs, for example owing to the more difficult and slow information flow or related to managerial incapability. Mameli *et al*. (2008) find a negative effect of scale economies when using data at 2-digit sectoral level (in line with Paci and Usai, 2008) and a positive effect of scale economies when using data at 3-digit sectoral level.

2.2. Critical issues

Equation (1) is used in many empirical studies on local employment growth. However, we claim that this specification suffers from three types of problems. The first critical issue concerns the effect of Marshallian externalities, captured by the location quotient (or Balassa index), *spe*. The evidence of a negative effect of the specialization on employment growth observed in most of the studies on the Italian case contrasts with the strong anecdotal evidence of the economic success (also in terms of job creation) of *industrial districts*, the places where Marshallian externalities are magnified (Becattini and Dei Ottati, 2006; Becchetti *et al*., 2007; Sforzi, 2007). In fact, these empirical studies overlook the fact that a higher specialization first has positive effects on productivity and, under certain conditions (such as inelastic sectoral demand, labor-saving technical change, in-homogeneous and non-perfectly mobile labor, variable capital stock) this may lead to a reduction (rather than an increase) of labor demand (Cingano and Schivardi, 2004). In particular, as discussed by Combes, Magnac and Robin (2003), when the demand in the industry is inelastic, the increased product demand due to the reduction of the price deriving from the increased productivity cannot compensate the reduced labor demand per unit of output. Therefore, we should expect a negative (rather than a positive) effect of specialization on employment growth.[5]

On the other hand, it is important to recognize that a negative effect of specialization would not preclude a positive effect of district economies on employment growth. Indeed, specialization *per se* cannot capture the role of district externalities (Becattini, 1979). The essence of the "industrial atmosphere" discussed by Marshall does not simply consist of "working on similar things", but it also depends on a number of other factors, such as the prevalence of small and medium sized firms often involving family ties, a high degree of mutual trust and tolerance among economic actors and other socioeconomic factors which contribute to determine the social capital of the region. Additionally, the industrial districts' structures are supported by an infrastructure tailored to the particular needs of the district's industry. This includes educational infrastructure as well as financial services, technical support, and trade associations. Thus, in order to capture the effect of industrial districts externalities, a large number of socioeconomic variables should be included in the empirical model. However, this strategy is not always feasible because of the lack of relevant information, especially when, as in our case, the analysis covers a rather long time period. As it will be clarified in sub-section 2.3, to solve this problem, we exploit information on the presence of industrial districts in Italy.

The second critical issue concerns the possible existence of nonlinearities in the relationship between agglomeration economies and growth. For example, the prevalence of either positive or negative urbanization externalities may depend on the level of economic density (den) reached. Thus, one may expect the existence of a hump shaped relationship between local growth and total employment density: below a certain threshold of economic density positive urbanization externalities overcome congestion costs, while above the threshold congestion costs prevail. To explore this issue, one may insert a squared term of *den*. This strategy is adopted, for example, by De Lucio *et al*. (2002), Viladecans-Marsal (2004) and Illy *et al*. (2011). Although this is the easiest way to deal with such a nonlinearity in a parametric framework, it is only one of several possible nonlinear parameterizations. Indeed, nonlinearities can be better accommodated in a semiparametric framework, where the actual shape of the partial effect can be assessed using smooth functions.

Similar arguments can be raised to justify the existence of nonlinearities between employment growth and the other indicators of the local industry struc-

[5] More generally, we must recognize that agglomeration externalities should be captured measuring the impact of the indices of localization/diversification on productivity. As observed by Rosenthal and Strange (2004), the use of dependent variables different from productivity – such as, employment growth (Glaeser et al., 1992; Henderson et al., 1995), new firms formation (Carlton, 1983; Rosenthal and Strange, 2003), real wages (Wheaton and Lewis, 2002; Duranton and Puga, 2004; Combes *et al.*, 2011), rents (Dekle and Eaton, 1999) – suffers from one or more limitations.

ture. As for local competition (*comp*), we may expect that, starting from low levels of market power (high levels of competition), an increase of sectoral concentration fosters local economic growth because it allows externalities to be internalized by the innovator (in keeping with the MAR theory), while starting from high levels of local market power, a more competitive environment is more conductive to innovation and therefore to growth (in line with Porter and Jacobs). A non-monotonic effect of scale economies (*size*) can also be easily predicted: starting from low plant sizes, a larger plant size may boost economic growth, through a stronger division of labor; above a certain threshold, however, a larger plant size can lead to an increase in information and managerial costs.

A third possible mis-specification of model (1) concerns the possibility to control for unobserved spatial heterogeneity. The characteristics of the local industrial structure (degree of specialization, diversification, competition, density and scale economies) cannot capture all the spatial heterogeneity in employment growth rates. Regardless the role of economic factors, there are, indeed, “natural advantages" of local areas (Krugman, 1993; Ellison and Glaeser, 1999) affecting local growth performances. The marked unevenness of local development can be partly justified on the basis of space being not uniform: some areas are mainly agricultural systems and are scantly devoted to industrial and service activities; some others are plenty of mountains and are sparsely developed. A possible correlation between this unobserved spatial heterogeneity and the observed characteristics included in the model would generate an estimation bias. This kind of time invariant unobserved spatial heterogeneity might be controlled through the inclusion of geographical dummies (for example regional fixed effects), exploiting the longitudinal dimension of the data. There are, however, other sources of unobserved spatial heterogeneity which are time varying and, therefore, cannot be captured by spatial fixed effects. We can think, for example, about the presence of localized spatial spillovers (generated by labor mobility or information flows), or about the consequences of the so-called MAUP (*Modifiable Areal Unit Problem*) due to the arbitrary definition of geographical boundaries. Both spillovers and the MAUP generate *time-varying* spatial autocorrelation and spatial heterogeneity which cannot be captured by simple geographical dummies. As it will be clarified in the next sub-section, we use a geoadditive component (i.e. a smooth interaction between latitude and longitude) to capture both time-invariant and time-varying unobserved spatial heterogeneity.

All in all, in line with Briant *et al*. (2010), we argue that a number of model mis-specifications may have a much stronger impact on the econometric results than other issues related to the size and the shape of the geographical unit or to the level of sectoral aggregation adopted.

2.3. A semiparametric geoadditive model

Taking all of the above mentioned remarks into account, we propose an alternative specification of the empirical local employment growth model:

$$
\begin{aligned}
y_{r,s,t} = \beta_0 + \theta_1 ID_{r,s} + \theta_2 ID_{r,s'} \\
+ f_1\big(\log\big(spe_{r,s,t-\tau}\big)\big) + f_2\big(log\big(div_{r,s,t-\tau}\big)\big) \\
+ f_3\big(log\big(den_{r,t-\tau}\big)\big) + f_4\big(log\big(size_{r,s,t-\tau}\big)\big) \\
+ f_5\big(log\big(comp_{r,s,t-\tau}\big)\big) + \Sigma_t h_t\big(n_r, e_r\big) + \gamma_s + \delta_t \\
+ \varepsilon_{r,s,t}
\end{aligned}
\tag{2}
$$

where $ID_{r,s}$ is a dummy variable which takes value 1 if the region-sector (*r,s*) belongs to an industrial district specialized in the same sector (*s*) and zero otherwise; $ID_{r,s'}$ is a dummy variable which takes value 1 if the region-sector (*r,s*) belongs to an industrial district specialized in another sector (s') and zero otherwise; θ_1 and θ_2 are their associated parameters. The inclusion of these dummy variables allows us to assess the relative performance of industrial districts, net of specialization. Specifically, the two dummies permit us to distinguish between the within-sector and the between-sector *ID* effect, while the variable spe only captures the effect of specialization (positive on productivity and negative on employment).

f_k are unknown nonparametric smooth functions of the univariate terms[6]. They permit us to identify nonlinearities in the relationship between growth and industry structure without imposing any parametric polynomial form. Finally, h_t are nonparametric functions which allow us to estimate the smooth effect of the interaction between latitude (*northing*, *n*) and longitude (*easting*, *e*) of the region's centroid. The inclusion of this geoadditive component (or smooth spatial trend surface) for each time period permits us to control for both time invariant and time-varying spatial unobserved heterogeneity and, thus, to abstract from heterogeneity of the underlying space.[7]

2.4. The identification of the *ID* effect

Estimating the *causal* effect of industrial districts (*ID*) on employment growth without bias may be a very challenging identification task. First of all, since the *ID* "treatment" cannot be randomized across local areas (as it would be possible in a classical natural experiment), the identification of the *ID* effect requires the application of specific methodologies for the estimation of the Average Treatment Effect (ATE) (see, e.g., Wooldridge, 2002, chap. 18).[8] Assum-

[6] See Appendix 1a for a brief description of the method adopted to estimate the semi-parametric model. For further information, see Basile *et al.* (2013)

[7] Although geoadditive models are widely used in environmental studies and in epidemiology (see, i.a., Kammann and Wand, 2003; Augustin *et al*., 2009), they are rarely considered for modeling economic data, and, to the best of our knowledge, this paper presents their first application to the analysis of local employment growth.

[8] Let y_1 denote the outcome (the employment growth rate) with treatment (that is when *ID*=1) and y_0 the outcome without treatment (that is when *ID*=0). Because a region cannot be in both states over the same sample period, we cannot observe both y_0 and

ing "*ignorability of treatment"* – i.e. assuming that, conditional on the set of covariates, ID and the potential outcomes (y_0 and y_1) are independent[9], the estimated parameter $\hat{\theta}$ in our flexible model (2) still provides a consistent estimate of the average ID effect. In other words, the smooth functions of the covariates introduced in model (2) would operate as "control functions" (Van der Klaauw, 2002) for the correction of the omitted variable bias.[10]

As discussed in Wooldridge (2002), when we suspect failure of the "*ignorability-of-treatment"* assumption, we can use instrumental variable (IV) methods for estimating ATEs if a good instrument for treatment is available. In fact, there is good reason to suspect that the ID status is endogenously determined in growth equations, that is higher employment growth may be not only a consequence of Marshallian externalities but also its cause. Under specific socioeconomic conditions (such as mutual trust, family ties, a large number of small enterprises and so on), favorable employment growth in a sector within a region may induce other specialized workers and thus other small and medium sized firms belonging to the same or strictly related sectors to enter that region (the likelihood of matching within the local labor market increases), thus contributing to the creation of an industrial district. This reverse causality problem will lead to a spurious relationship between ID and employment growth and a correlation between the two variables does not necessarily imply causation. Accordingly, it is important to account for this potential endogeneity bias when estimating the effect of ID on employment growth in our semi-parametric regression framework.[11]

To implement the IV approach, we run two semiparametric first-stage probit equations (one for $ID_{r,s}$ and one for $ID_{r,s'}$) to estimate the probability for a local area to belong to an ID. In these probit equations we include all of the exogenous variables and a set of excluded instruments (see section 3.3). The fitted probabilities from the first-stage binary response models are then used as instruments for $ID_{r,s}$ and $ID_{r,s'}$ along with the exogenous covariates in the growth regression equation (see Angrist and Pischke, 2008, Sec. 4.6.1). Inference on the parameters is carried out through bootstrapping methods.

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y_1; in effect, the problem we face is one of omitted variable. The Average Treatment Effect is defined as $E(y_1 - y_0|X)$, where X is the vector of covariates.

[9] The idea underlying the "*ignorability of treatment*" assumption is this: if we can observe enough information (contained in the set of covariates) that determines treatment, then y_0 and y_1 might be mean independent of ID, conditional on the covariates. Loosely, even though y_0 and y_1 and ID might be correlated, they are uncorrelated once we partial out the covariates.

[10] The term "control function" used by Van der Klaauw (2002) in the Regression Discontinuity Design literature might confuse the reader with the notion of control function in endogenous regression. In that case a control function transform the problem of endogeneity to a one of omitted variables incorporating a function of residuals from a first stage to the reduced form.

[11] Simultaneity biases are ruled out for the other variables included in the model, since they are measured at the first year of each time period (1981, 1991 and 2001) and, thus, they can be considered as predetermined.

Alternatively, we can apply a control function approach, as suggested by Vella and Verbeek (1999). First, we compute the 'generalized residual' from the semiparametric first-stage probit equation (using the inverse Mill's ratio) and then we use it as an additional regressor in equation (2). The generalized residual may enter equation (2) as a smooth nonparametric function. Significance of this smooth term can be used as a test of endogeneity of *ID.*

3. DATA AND VARIABLES

3.1. Data

Following Mameli *et al*. (2008) and Paci and Usai (2008), the geographical unit of observation considered in the present analysis is the Local Labor System (LLS), a territorial aggregation of neighboring municipalities, identified on the basis of daily labor commuting flows as recorded in the censuses of the population and comparable from a statistical and geographical point of view (ISTAT, *Italian National Institute of Statistics*, 2001). LLSs cross regional and provincial administrative boundaries, leaving unchanged only municipalities boundaries, since municipalities are the basic unit of observation to survey daily labor commuting flows. Hence, LLSs seem to be a more suitable choice in terms of spatial units compared to the NUTS (*Nomenclature of Territorial Units for Statistics*) option in order to investigate the effects of agglomeration externalities on local employment growth. The number of LLSs in Italy has changed over time. We use the 2001 classification which identified 686 LLSs.

ISTAT categorizes LLSs according to whether or not they belong to an industrial district. In particular, ISTAT identifies industrial districts by means of an algorithm which requires the identification of: 1) the manufacturing LLS using a location quotient (LQ) based on employment; 2) the manufacturing LLS of small and medium enterprises (SMEs); 3) the main industry of the manufacturing LLS of SMEs. Finally, a manufacturing LLS of SMEs is defined as an *industrial district* if the following two conditions are met: a) the employment in SMEs of the main industry is more than half the total employment of the industry in firms of all sizes; b) the employment in small firms of the main industry is more than half the employment of medium-sized firms (see Sforzi, 2009, for further details).[12] Thus, ISTAT identifies 156 industrial districts in Italy. This piece of information turns out to be of relevance for our analysis: while the degree of urbanization and diversification allows us to put into a test the effect of Jacobs externalities on local labor market performance, the possibility of distinguishing between LLS belonging to an industrial district and other LLSs allows us to assess the role of Marshallian economies on employment dynamics at a very fine territorial level.

[12] Since ISTAT identifies industrial districts using threshold values of LQ and firm size, the dummy *ID* could pick up nonlinearities in the effect of *spe* and *size* more than the effect of Marshallian externalities. However, the inclusion of nonparametric terms for *spe* and *size* in our model specification allows us to correctly identify the *ID* effect.

Both manufacturing and service sectors are considered in our analysis. Many empirical studies on the local employment growth focus on the manufacturing sectors (Henderson *et al*., 1995; Forni and Paba, 2002; Cingano and Schivardi, 2004). However, modern economies are characterized by an increasing number of service activities that have become an important source of employment. Following the recent literature, we take into account this process of structural change in employment dynamics. We consider 15 sectors (subsections of ATECO91-NACE rev.1 classification)[13] (see Annex 2): 10 manufacturing sectors and 5 services sectors. The public sector is not included. Data on the number of employees and on the number of establishments (local units) in manufacturing sectors for the 686 LLS are taken from Italian Census of Industries and Services for 1981, 1991 and 2001. These data are obtained through the consultation of the Italian Statistical Atlas of Municipalities (*Atlante Statistico dei Comuni*). Data from the 2008 are taken from the Statistical Register of Active Enterprises (ASIA). Both sources of data are provided by ISTAT. Population and areas data come from ISTAT Population Census.

3.2. Variables

As in Combes (2000), each variable used in our empirical analysis is normalized by the value it takes at the national level for the considered sector: this allows us to control for unobserved time-varying industry effects. Thus, the dependent variable, $y_{r,s,t}$, is the difference between the annual employment growth rate of the *s*-th sector (*s*=1,...,10) in the *r*-th LLS (*r*=1,...,686) computed for three successive periods (1981-1991, 1991-2001 and 2001-2008) and the annual national employment growth rate of this sector during the same periods:

$$y_{r,s,t} = log(E_{r,s,t}/E_{r,s,t-\tau}) - log(E_{s,t}/E_{s,t-\tau}) \tag{3}$$

where E stands for employment, while t and $t-\tau$ correspond to the final year (1991, 2001 and 2008) and the initial year (1981, 1991 and 2001), respectively, of each period. Table 1a shows that employment decreased during the sample period in manufacturing while it increased in service sectors. We also detect a higher spatial heterogeneity in annual average growth performance in manufacturing than in services both among ID and non-ID LLS (Tables 1b and 1c).

All explanatory variables refer to the beginning of each period in a way consistent with the idea that agglomeration forces manifest their impact on regional growth after a consistent time lag (Combes, 2000). Specifically, we include five explanatory variables capturing the role of (1) specialization, (2) diversification, (3) density, (4) plant size and (5) local competition.

[13] Beaudry and Schiffauerova (2009), in their review of the literature, conclude that the probability to detect Jacobs externalities increases with the level of detail of industry classification, whereas the likelihood to detect MAR externalities appears less correlated with the industry aggregation level.

Table 1a. National annual average employment growth rates

NACE rev.1	1981-1991	1991-2001	2001-2008
Manufacturing			
DA	-0.149	-0.498	-0.313
DB-DC	-1.410	-2.703	-4.561
DD-DE	-1.157	-0.733	-3.432
DF-DG	-2.038	-1.485	-1.641
DH-DI	-2.057	0.318	-0.832
DJ	-1.121	0.681	-0.800
DK	-0.651	1.032	-3.056
DL	-0.605	-0.539	-6.079
DM	-1.808	-2.379	0.543
DN	0.122	0.014	6.678
Services			
G	0.659	-0.466	1.734
H	1.102	1.588	5.584
I	-0.237	0.623	0.804
J	2.581	0.324	0.236
K	6.202	6.446	4.435

Table 1b. Mean and standard deviations of LLS' annual average employment growth rates

NACE rev.1	1981-1991	1991-2001	2001-2008
Manufacturing			
DA	0.152	-0.133	0.185
	(3.865)	(3.285)	(4.261)
DB-DC	-2.214	-3.433	-6.776
	(7.425)	(7.287)	(9.517)
DD-DE	-1.196	-0.660	-2.224
	(3.495)	(3.242)	(4.585)
DF-DG	-1.016	0.834	-0.769
	(10.577)	(9.316)	(12.276)
DH-DI	-0.763	0.513	0.839
	(6.383)	(5.710)	(6.944)
DJ	0.965	1.845	0.304
	(4.780)	(4.242)	(5.075)
DK	0.784	2.470	-4.386
	(8.896)	(8.454)	(12.679)
DL	4.001	1.049	-9.405
	(10.402)	(7.859)	(14.887)
DM	0.949	0.401	0.749
	(10.426)	(10.928)	(16.509)
DN	2.555	0.396	12.116
	(9.252)	(7.570)	(12.061)
Services			
G	0.687	-1.091	1.758
	(1.247)	(1.445)	(1.486)
H	1.340	0.703	6.038
	(2.493)	(2.138)	(3.292)
I	0.092	-0.221	0.293
	(2.169)	(3.012)	(3.774)
J	3.830	1.040	-0.365
	(2.823)	(2.541)	(2.877)
K	7.536	5.202	4.932
	(3.076)	(2.616)	(2.946)

Notes: Standard Deviations in parenthesis.

Table 1c. Mean and standard deviations of LLS' annual average employment growth rates. *ID* vs. Non-*ID* LLS

NACE rev.1	1981-1991	1991-2001	2001-2008	1981 1991	1991-2001	2001-2008
Manufacturing		*Non-ID*			*ID*	
DA	0.10	-0.18	0.27	0.33	0.01	-0.12
	(4.04)	(3.20)	(3.93)	(3.19)	(3.55)	(3.25)
DB-DC	-2.89	-3.34	-6.87	0.07	-3.76	-6.48
	(7.74)	(7.70)	(10.28)	(5.71)	(5.72)	(6.37)
DD-DE	-1.26	-0.95	-2.37	-0.97	0.33	-1.73
	(3.64)	(3.32)	(4.76)	(2.93)	(2.75)	(3.91)
DF-DG	-1.40	0.60	-1.02	0.01	1.47	-0.06
	(10.71)	(9.78)	(12.40)	(10.19)	(7.91)	(11.94)
DH-DI	-0.46	0.02	1.15	-1.78	2.19	-0.23
	(6.66)	(6.02)	(7.26)	(5.26)	(4.09)	(5.66)
DJ	0.70	1.55	0.53	1.86	2.83	-0.45
	(5.07)	(4.44)	(5.35)	(3.51)	(3.30)	(3.91)
DK	0.42	2.29	-4.99	1.84	3.00	-2.54
	(9.58)	(9.39)	(13.81)	(6.45)	(4.77)	(8.03)
DL	3.98	0.75	-10.18	4.06	2.04	-6.82
	(11.10)	(8.24)	(14.68)	(8.15)	(6.41)	(15.34)
DM	1.71	0.91	0.19	-0.90	-0.97	2.34
	(10.65)	(10.96)	(17.33)	(9.65)	(10.79)	(13.88)
DN	3.57	0.31	13.04	-0.48	0.68	9.01
	(9.58)	(7.90)	(12.30)	(7.44)	(6.35)	(10.70)
Services		*Non-ID*			*ID*	
G	0.66	-1.23	1.74	0.77	-0.63	1.81
	(1.31)	(1.50)	(1.57)	(1.02)	(1.11)	(1.18)
H	1.38	0.53	6.07	1.22	1.30	5.92
	(2.59)	(2.21)	(3.34)	(2.15)	(1.75)	(3.12)
I	0.08	-0.46	0.24	0.12	0.60	0.48
	(2.26)	(3.10)	(4.03)	(1.81)	(2.57)	(2.72)
J	3.84	0.86	-0.51	3.79	1.64	0.11
	(2.88)	(2.58)	(2.95)	(2.62)	(2.32)	(2.57)
K	7.53	4.89	5.02	7.55	6.25	4.63
	(3.22)	(2.70)	(3.05)	(2.55)	(2.00)	(2.55)

Notes: Standard Deviations in parenthesis.

Following the main literature, in the first step of our empirical analysis (i.e. when we estimate the linear model (1)), we measure specialization externalities, $spe_{r,s}$ by means of the location quotient:

$$spe_{r,s} = \frac{E_{r,s}/E_r}{E_s/E} \tag{4}$$

This index measures the relative concentration of a sector in a LLS with respect to the average concentration of the same sector in Italy. Thus, the r-th LLS is specialized in the s-th sector if the value of $\mathrm{spe}_{r,s}$ is higher than 1, showing that in the LLS considered the weight of the sector is greater than its weight in the whole country. Values for $\mathrm{spe}_{r,s}$ lower than 1 are evidence of de-specialization.

According to arguments reported above, a higher level of $spe_{r,s}$ should yield a positive effect on productivity and, thus, a negative effect on employment growth.

In a second step of our empirical analysis (i.e. when we estimate the semiparametric model (2)), we try to capture the effect of industrial district (ID) externalities by directly including the dummy variable $ID_{r,s}$, on the basis of the consideration that specialization *per se* does not capture all the social-economic factors characterizing the industrial district atmosphere. We also include the dummy $ID_{r,s'}$ to evaluate the impact of industrial districts specialized in a given sector *s* into the employment growth rates of other sectors.

As it is common in the literature (e.g., Henderson et. al., 1995; Combes, 2000; Mameli *et al*., 2008; Paci and Usai, 2008; Illy *et al*, 2011), we measure Jacobs or diversification externalities by means of the inverse of the Hirschman-Herfindahl index normalized by the same variable computed at the national level:[14]

$$div_{r,s} = \frac{1/\sum_{s' \neq s}\left[E_{r,s'}/\left(E_r - E_{r,s}\right)\right]^2}{1/\sum_{s' \neq s}\left[E_{s'}/(E - E_s)\right]^2} \tag{5}$$

Own-industry employment is excluded so that the values of this indicator for the sectors in one LLS differ. A high value of $div_{r,s}$ means that the *r*-th LLS has a comparative advantage in a remarkable share of different sectors (i.e. its production structure is diversified). A low value of $div_{r,s}$ means that the *r*-th LLS is specialized in a few industries. Thus, a positive effect of $div_{r,s}$ would support Jacobs theory.

Total population density, $dens_r$, is used to measure the scale of urbanization externalities as in Mameli *et al*. (2008) and Usai and Paci (2008):

$$dens_r = \frac{P_r}{A_r} \tag{6}$$

where P_r indicates the population in the *r*-th LLS and A_r indicates the area in km^2. A positive effect of $dens_r$ implies that positive urbanization economies dominate over negative congestion effects.

Following Combes (2000) and Ó hUallacháin and Satterthwaite (1992), internal economies of scale, $size_{r,s}$, are measured by the normalized average plant size in the *s*-th sector located in the *r*-th LLS:

$$size_{r,s} = \frac{E_{r,s}/F_{r,s}}{E_s/F_s} \tag{7}$$

[14] Many alternative measures of Jacobs externalities have been used in the literature, for example the Gini index, the Ellison-Glaeser index and the Theil index (see, Beaudry and Schiffauerova, 2009).

where F indicates the number of local units (plants). A positive coefficient associated to $size_{r,s}$ indicates that the positive effect of a higher division of labor within the firm dominates over the negative effect of higher information and managerial costs.

Table 2. Descriptive statistics

	mean	*min*	*median*	*max*	*std.dev.*
Total					
log(*spe*)	-0.406	-6.000	-0.260	1.997	0.990
log(*div*)	-13.840	-15.570	-13.764	-13.000	0.422
log(*den*)	4.674	2.508	4.598	7.765	0.945
log(*size*)	-0.637	-3.994	-0.5261	2.913	0.772
log(*comp*)	5.846	2.014	5.813	9.891	1.138
Non-ID					
log(*spe*)	-0.388	-6.000	-0.258	1.995	1.035
log(*div*)	-13.831	-15.568	-13.761	-13.004	0.405
log(*den*)	4.610	2.508	4.514	7.765	0.972
log(*size*)	-0.703	-3.994	-0.597	2.913	0.833
log(*comp*)	5.947	2.014	5.912	9.891	1.134
ID					
log(*spe*)	-0.464	-5.839	-0.265	1.997	1.029
log(*div*)	-13.885	-15.396	-13.779	-13.025	0.460
log(*den*)	4.888	2.526	4.947	7.472	0.820
log(*size*)	-0.419	-3.994	-0.318	2.440	0.709
log(*comp*)	5.516	2.032	5.484	9.467	1.116

Table 3. Correlation matrix

	growth	*log*(*spe*)	*log*(*div*)	*log*(*den*)	*log*(*size*)	*log*(*comp*)
log(*spe*)	-0.306	1.000	0.097	0.002	0.631	-0.114
log(*div*)	-0.003	0.097	1.000	0.160	0.114	-0.287
log(*den*)	0.015	0.002	0.160	1.000	0.171	-0.458
log(*size*)	-0.250	0.631	0.114	0.171	1.000	0.014
log(*comp*)	-0.006	-0.114	-0.287	-0.458	0.014	1.000

We measure local competition, $comp_{r,s}$, using the following normalized Herfindahl index:

$$comp_{r,s} = \frac{\sum_{g=1}^{G}\left(\left(\frac{E_{r,s,g}/F_{r,s,g}}{E_{r,s}}\right)^2 * n_{r,s,g}\right)}{\sum_{g=1}^{G}\left(\left(\frac{E_{s,g}/F_{s,g}}{E_s}\right)^2 * n_{s,g}\right)} \tag{8}$$

where n is the number of firms and g indicates the size class of firms in terms of employees. Seven size classes are considered, namely: 1-5, 6-9, 10-19, 20-49, 50-99, 100-499 and more than 500 employees. A negative effect of $comp_{r,s}$ would support Porter's hypothesis, while a positive effect of $comp_{r,s}$ would support MAR theory.

Tables 2 and 3 report some descriptive statistics and the pairwise correlation matrix between explanatory variables.

The five explanatory variables mentioned above cannot capture all the spatial heterogeneity in the LLS' employment growth rates. As mentioned above, in our semiparametric approach, we directly control for the unobserved spatial heterogeneity by including the smooth interaction between latitude and longitude of the LLS' centroids.

3.3. Instrumental variables

As discussed above, the identification of the *ID* effect requires the use of instrumental variables. Following recent contributions to the literature on agglomeration economies (Combes *et al*., 2011; Di Giacinto *et al*., 2012), we use historical factors as sources of exogenous spatial variation of the likelihood of observing an industrial district in a specific LLS. At the same time we expect these factors will be uncorrelated with current employment growth in the LLS.

We have selected two groups of historical data to predict the *ID* status. The first one consists of long lags of specialization measures, indicating whether in the past the local area had those characteristics observed in 2001 for the Italian industrial districts, i.e. a specialization in traditional manufacturing sectors and/or in industrial machinery and a specialization in the small-size class (less than 10 employees) of firms. Precisely, we use data from the 1961 census to construct *a*) a dummy variable (*SpecIDsec*>1) taking value 1 if in 1961 the LLS was specialized in traditional and/or industrial machinery sectors, *b*) a dummy variable (*SpecSmallSize*>1) taking value 1 if in 1961 manufacturing firms within the LLS were specialized in the size class of less than 10 employees and *c*) the interaction between *a*) and *b*) (*Interaction*).

The second set of instruments consists of information on past dominations. According to several authors (see, i.a., Bagnasco, 1977; Trigilia, 1986, 2001; Becattini, 1987), the development of agglomerations of small and medium sized firms in the Third Italy over the 1970s represents the outcome of the interaction between social actors and institutions which have provided effective instruments for the regulation of social conflicts. Such interactions have favored the accumulation of social capital (*mutual trust* and *cooperation propensity*) which is the main factor characterizing the industrial atmosphere within industrial districts in Italy. More recently, Guiso *et al.* (2008) and Tabellini (2010) have also pointed out that the spatial distribution of entrepreneurial culture may reflect local differences in social capital endowment which affects the efficiency of local institutions. These authors have also suggested that different historical political traditions may have favored the accumulation of social capital which has improved the effectiveness of local institutions. According to Di Liberto and Sideri (2012), these factors may find their origin in the dominations that each geographical area in Italy has undergone in the past.

On the basis of these considerations, to isolate the exogenous variation in the spatial distribution of industrial districts, we rely on a set of data collected by Di Liberto and Sideri (2012) on the dominations which have governed each

Italian province over seven centuries before the creation of unified Italian State. More precisely, these data measure the number of years during which Italian provinces have been governed by one of the following dominations: *Normans*, *Swabian*, *Savoy*, *Papal*, *Anjou*, *Spain*, *Austria*, *Bourbon* and *Venice* (some provinces are classified as *Independent*). According to Di Liberto and Sideri (2012), the strong current spatial heterogeneity in the quality (efficiency, functioning) of local institutions (and more generally in the current local endowment of social capital) can be considered as “the result of the previous existence of highly heterogeneous formal institutions created by historical accidents across the Italian regions" and thus it is strongly affected by the duration of specific kinds of dominations which ruled a province before the process of Italian unification. These authors observe, for example, that during the XII century the South of Italy, after the Normans domination, was run by the Swabians, who have implemented important reforms (especially during the period of Federico II) reducing the influence of landowners, founding the University of Naples and creating a secular and well-ordered State. However, the succeeding dominations (Anjou, Aragonese and Bourbon) did not improve the educational system and supported a hierarchical political system which discouraged the formation of a confidence climate and the development of economic activities. On the contrary, during the XVI century part of the North-East of Italy was dominated by the Hasburg dynasty who managed to give their Empire a good administrative and bureaucratic organization, strong efficient judiciary system implementing several economic reforms in favor of industry.

To the extent that there is substantial persistence in the spatial distribution of industrial districts but local drivers of high employment growth today differ from those in the distant past, all these historical data represent good (i.e. exogenous) instruments and, thus, they remove any simultaneity bias caused by contemporaneous local shocks. This assumption can be defended by observing that the structure of the Italian economy and the technological paradigm predominating in the last thirty years are very different from those existing in the 1960s and 1970s when industrial districts emerged in Italy.[15]

4. ECONOMETRIC RESULTS

4.1. Evidence from log-linear models

We begin the econometric analysis by estimating the baseline log-linear model (1) which does not take into account nonlinear effects and spatial heterogeneity. The dependent variable is the local-sector average annual employment

[15] Specifically, we observe that the factors that stimulated industrial agglomerations in the past are not related to the current determinants of local employment growth. For example, advances in information and communication technologies (ICT) change the need for geographical proximity between knowledge users (Rallet and Torre 1999), and more in general, the diffusion of ICT provides opportunities for employees with offices in geographically dispersed locations to communicate, share and collaborate. For this reason, it is reasonable that face-to-face relationship are today less important in explaining agglomeration economies than in the past.

growth rate computed for the three successive periods (1981-1991, 1991-2001 and 2001-2008). Pooling the data by sector and by period, we estimate equation (1) using OLS (Ordinary Least Squares) and including time fixed effects (sectoral heterogeneity is controlled for by computing all the variables, except *den*, in deviation from national average, as described in Section 3) (Table 4). The analysis is repeated by pooling alternatively only manufacturing sectors and service sectors. Because all variables are in logarithms, coefficients can be interpreted as elasticities.[16]

Table 4. Log-linear model : basic specification

	Whole economy	*Manufacturing*	*Services*
Variables	*Coefficients (Robust s.e. in parentheses)*		
(Intercept)	3.840***	15.071***	-3.787***
	(1.101)	(2.121)	(0.699)
log(*spe*)	-1.292***	-1.322***	-1.460***
	(0.059)	(0.068)	(0.078)
log(*div*)	0.306***	1.006***	-0.195***
	(0.081)	(0.146)	(0.051)
log(*den*)	0.127***	-0.137**	0.308***
	(0.044)	(0.068)	(0.035)
log(*size*)	-0.679***	-0.702***	-0.153
	(0.079)	(0.089)	(0.094)
log(*comp*)	-0.105**	-0.146**	-0.100***
	(0.042)	(0.059)	(0.035)
No. of obs.	27,257	17,006	10,251
R^2_{adj}	0.074	0.070	0.122
RESET test	24.807	14.272	29.899
	[0.000]	[0.000]	[0.000]
Residual spatial het. 1981-91	10.880	6,932	8.329
	[0.000]	[0.000]	[0.000]
Residual spatial het. 1991-01	13.442	11,103	36.069
	[0.000]	[0.000]	[0.000]
Residual spatial het. 2001-08	1.658	1,890	9.621
	[0.109]	[0.054]	[0.000]

Notes: Dependent variable: Employment growth rate. All estimates includes time fixed effects. White-corrected standard errors in parenthesis. RESET test is a test for linearity. Time-varying residual spatial heterogeneity is tested by regressing the residuals on the smooth interaction between latitude and longitude (spatial trend surface) for each time period. Approximated F-tests and associated p-values for the significance of the spatial trend surfaces are reported.

[16] In order to estimate equation (1), Combes (2000) uses the sample selection regression model (Heckman, 1976) because plants smaller than 20 workers are not in his data set. In our case, this selection bias does not occur, since our data includes local units of all size classes, even those with just one worker. Nevertheless, within the group of manufacturing sectors, we had to exclude about 2,500 observations (i.e. 12% of the total number of observations in manufacturing) because in some LLS sectoral employment in manufacturing was equal to zero (in service sectors we had to exclude only 5 observations due to the same problem). Therefore, like in Combes (2000), for the whole economy and for manufacturing, we have also used a generalized tobit model including different geographical dummies in the selection (probit) equation. However, the coefficients and standard errors of the variables in the outcome equation turned out to be very close to the pooled-OLS results. Thus, we conclude that in our case the sample selection bias does not affect the consistency and the efficiency of our OLS results.

For the whole economy and for manufacturing sectors, OLS estimates indicate that, on average, the local-sector employment growth rate is negatively affected by the degree of specialization (spe) of the LLS in that sector and positively affected by the degree of diversification (div) of the LLS economy, corroborating Jacobs' theory and, apparently, confuting the MAR theory. In service sectors, both spe and div have a negative effect.[17]

The effect of population density (den) is positive for the whole economy and services, indicating that urbanization economies dominate over congestion costs, while it is negative and slightly significant for manufacturing. Therefore, according to linear estimation results, in Italy the positive effect of urbanization externalities dominates the negative effect of congestion costs in services but not in manufacturing.

Linear regression models also indicate a negative effect of *size* in the case of the whole sample and manufacturing sectors, which simply means that smaller plants tend to grow faster. This may reflect a firm's life cycle effect: new firms are in general of small size and are able to grow faster, whereas, once they have reached their optimal size, their employment stops expanding. The negative elasticity of $size$ would also mean that information spillover are more important for small firms and/or that adaptability and flexibility can be higher in small firms. Surprisingly, the effect of $size$ is not significant in the case of services. Finally, the effect of $comp$ is negative and significant for both manufacturing and services, apparently corroborating the Porter theory.

All in all, our econometric results for the log-linear model are very much in line with previous evidence reported for the case of Italy in studies which used LLS as territorial units of analysis (Paci and Usai, 2008; Mameli *et al.*, 2008). However, the results of nonlinearity (*RESET*) tests raise doubts about the capacity of the linear functional form to properly capture the data generating process. Moreover, by regressing the residuals on the smooth interaction between latitude and longitude for each time period, it emerges a significant time-varying residual spatial heterogeneity.[18] In conclusion, the diagnostics of the residuals suggest that the log-linear model is mis-specified due to the assumptions on the functional form and on spatial homogeneity. These assumptions are relaxed by estimating the geoadditive semiparametric model (2) as shown in the next section.

[17] To test for multicollinearity we computed the Variance Inflation Factors (VIF). This indicator has a minimum value of 1 (no multicollinearity) and no upper bound. A popular cut-off value of 10 is normally used to show that no multicollinearity is present. In our log-linear models, the VIF values are always lower than 2, thus we can safely rile out multicollinarity problems in our analysis.

[18] The spatial heterogeneity test applied for the residuals of the log-linear model (1) ($\hat{\varepsilon}_{it}$) is built by estimating the following equation: $\hat{\varepsilon}_{it} = \alpha + h_t(no_i, e_i) + u_{it}$. See Appendix 1a for the estimation method used. The significance of the smooth terms $h_t(no_i, e_i)$ would indicate the presence of unobserved spatial heterogeneity.

4.2. Evidence from semiparametric models

In Table 5 we report the estimation results of the semiparametric model (2) which includes the dummy variables $ID_{r,s}$ and $ID_{r,s'}$ to capture the average within-sector and between-sector “industrial district" effects, smooth univariate terms to identify possible nonlinear effects of agglomeration economies and the smooth interaction between latitude and longitude to control for unobserved spatial heterogeneity.

The coefficients associated to $ID_{r,s}$ and $ID_{r,s'}$ are always positive and significant, indicating that industrial districts perform better (in terms of job creation) than the other LLSs. This result is consistent with a huge amount of empirical evidence on the growth success of industrial districts in Italy. However, not surprisingly, the magnitude of the coefficient associated to $ID_{r,s'}$ is much higher in the case of manufacturing than in the case of services.

Table 5. Semiparametric geoadditive model

	Whole economy	Manufacturing	Services
Parametric terms	*Coefficients (s.e. in parentheses)*		
(Intercept)	0.328*** (0.063)	0.468*** (0.097)	0.067 (0.045)
$ID_{r,s}$	1.905*** (0.281)	2.210*** (0.346)	
$ID_{r,s'}$	0.172* (0.092)	0.399** (0.146)	0.195*** (0.067)
Non-parametric terms	*F test and edf (in square brackets)*		
f_1 (*log*(*spe*))	229.204*** [3.860]	132.286*** [3.732]	247.476*** [3.893]
f_2 (*log*(*div*))	20.962*** [2.481]	39.871*** [1.942]	12.108*** [2.053]
f_3 (*log*(*den*))	7.547*** [2.657]	2.167* [1.781]	32.368*** [3.204]
f_4 (*log*(*size*))	45.925*** [2.872]	32.663*** [2.896]	19.059*** [2.914]
f_5 (*log*(*comp*))	8.115*** [2.872]	6.348*** [2.400]	43.349*** [1.003]
$h_{1981}(no,e)$	7.190*** [7.190]	8.314*** [6.217]	8.547*** [11.184]
$h_{1991}(no,e)$	17.292*** [5.472]	11.667*** [5.308]	22.092*** [8.132]
$h_{2001}(no,e)$	1.851* [6.242]	2.109** [6.715]	9.160*** [11.306]
No. of obs.	27,257	17,006	10,251
R^2_{adj}	0.094	0.091	0.197
REML	85,784	56,815	23,734

Notes: Dependent variable: Employment growth rate. All estimates include time fixed effects. Time-varying residual spatial heterogeneity is tested by regressing the residuals on the smooth interaction between latitude and longitude for each time period. Approximated F-tests and associated p-values for the significance of the spatial trend surfaces are reported.

The middle part of Table 5 reports the *F*-tests for the overall significance of the smooth terms as well as their effective degrees of freedom (*edf*).[19] In order to avoid both mis-specification biases and the danger of over-fitting, we have controlled the degree of smoothness of each nonparametric term by penalizing wiggly functions in the model fitting through a quadratic penalty term. A smoothing parameter associated to the penalty function allows us to balance

[19] Each univariate nonparametric term, $f_k$is specified as a linear combination of known basis functions (we have used *P-spline basis* functions) with associated unknown parameters to be estimated (see Appendix 1a).

between bias and variance of the estimates.[20] The results of F-tests suggest that all univariate smooth terms enter significantly the model. The *edf* is a measure of the term's nonlinearity: if the *edf* is equal to one, a linear relationship cannot be rejected. Evidence reveals that the *edf* is equal to one only for $f_5(log(comp))$ in services. Finally, also the spatial trend surface $(h(n_r, e_r))$, approximated by a tensor product of penalized cubic regression splines, is highly significant in all sectors and in all periods, suggesting the presence of unexplained spatial heterogeneity in local employment growth.

Figures 1-5 portray the smoothed partial effects of univariate terms. The shaded areas highlight the 95 per cent credibility intervals (we have used Bayesian inference). The $log(spe)$-plot (Figure 1 - Panel A) confirms that, *ceteris paribus*, local areas with lower specialization in a sector tend to grow faster in that sector. However, the effect of specialization always appears to be nonlinear. In particular, we find a hockey stick-shaped relationship between specialization and local employment growth: a higher specialization increase local productivity and reduces, under the assumption of inelastic product demand, the labor demand. However, localization economies exhaust their effect on productivity and thus on employment growth after a certain threshold.

The effect of diversification is monotonically positive in manufacturing (Figure 2 - Panel A) in line with previous evidence and corroborating Jacobs' theory. For services, it emerges a nonlinear relationship: the effect of diversification is null up to a certain threshold, after which it turns to be negative.

Allowing for nonlinearities, we find a hump-shaped relationship between population density, *log*(*den*), and local employment growth (Figure 3 - Panel A) in the case of services: the positive effect of overall population density fades as the density reaches some threshold value, after which congestion costs overcome agglomeration externalities. This outcome is consistent with the hypothesis that a denser economic activity can exert a positive externality that promotes local growth, but when the level of agglomeration becomes too high, congestion costs kick in and gradually reduce the growth performance. In the case of manufacturing sectors the results suggest that negative congestion effect always prevails over the positive externality.

We also find evidence of a hump-shaped relationship between employment growth and *log*(*size*) (Figure 4 - Panel A): starting from low levels of *log*(*size*), an increase in plant size has a positive effect on growth due to, for example, a more detailed division of labor; after a certain threshold (that is starting from high values of *log*(*size*)), however, an increase in plant size has a negative effect on growth due to an increase in information and managerial costs. The log-linear model (Table 4) masks these nonlinearities and brings us to conclude for a negative effect of *log*(*size*) both in manufacturing and for a null effect of this variable in services.

[20] To estimate model (2), we have used the method described by Wood (2006) which allows for automatic and integrated smoothing parameters selection through the minimization of the *Restricted Maximum Likelihood* (*REML*). Wood has implemented this approach in the R package *mgcv*.

Figure 1. (A) Smooth effect of *spe*. (B) Smooth effect of *spe* with IV estimates

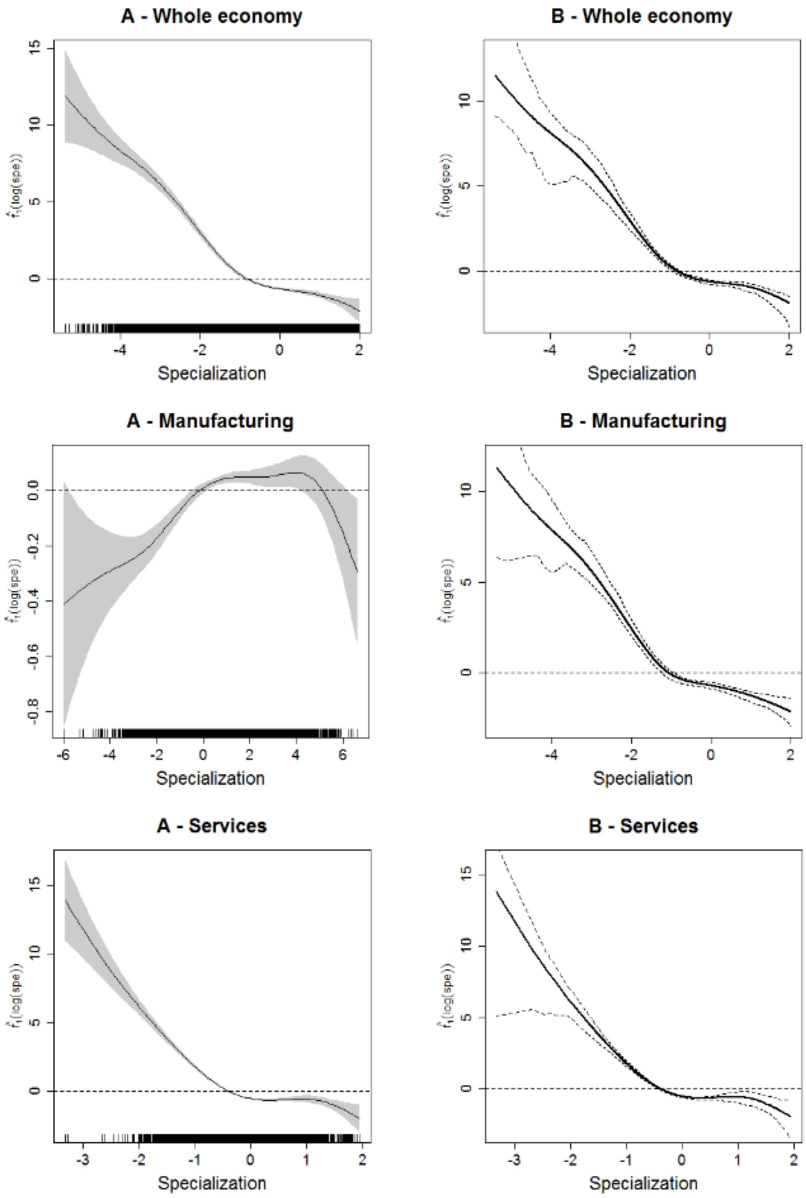


Figure 2. (A) Smooth effect of *div*. (B) Smooth effect of *div* with IV estimates

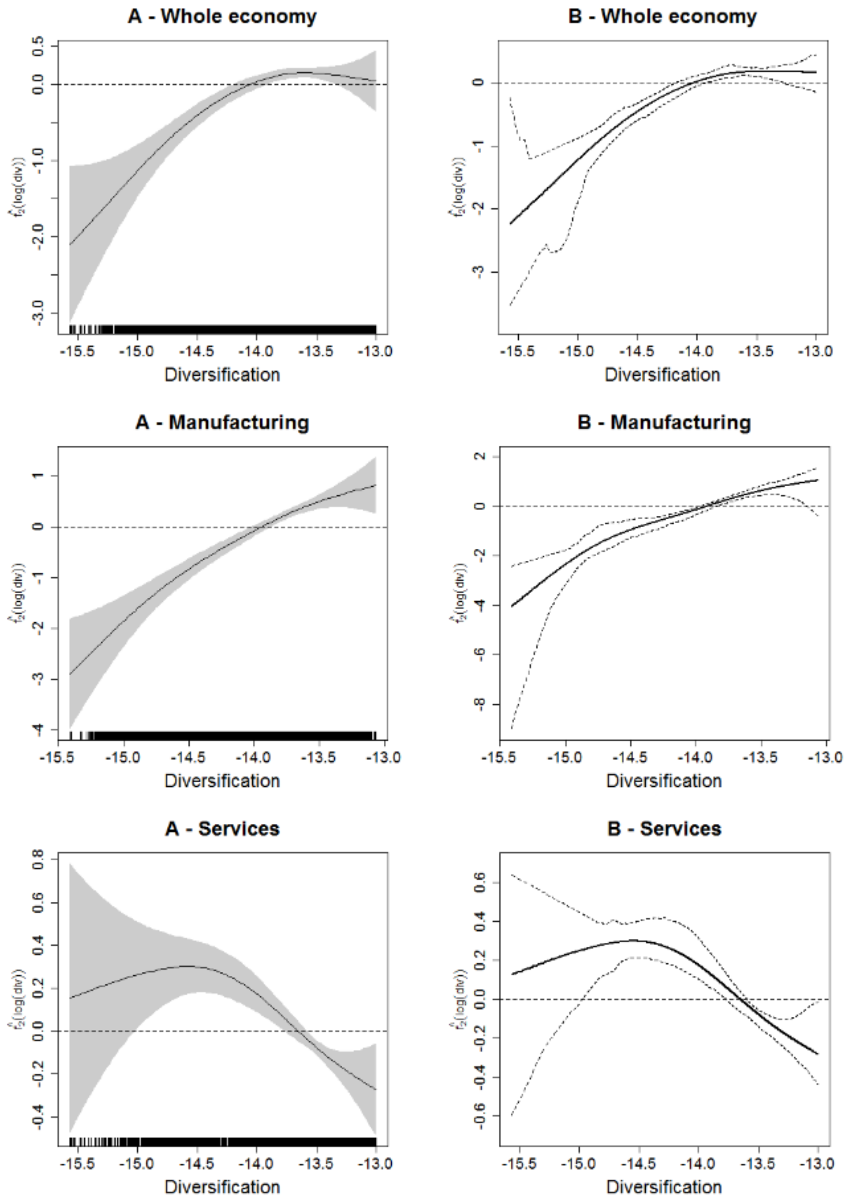


Figure 3. (A) Smooth effect of *dens.* (B) Smooth effect of *dens* with IV estimates

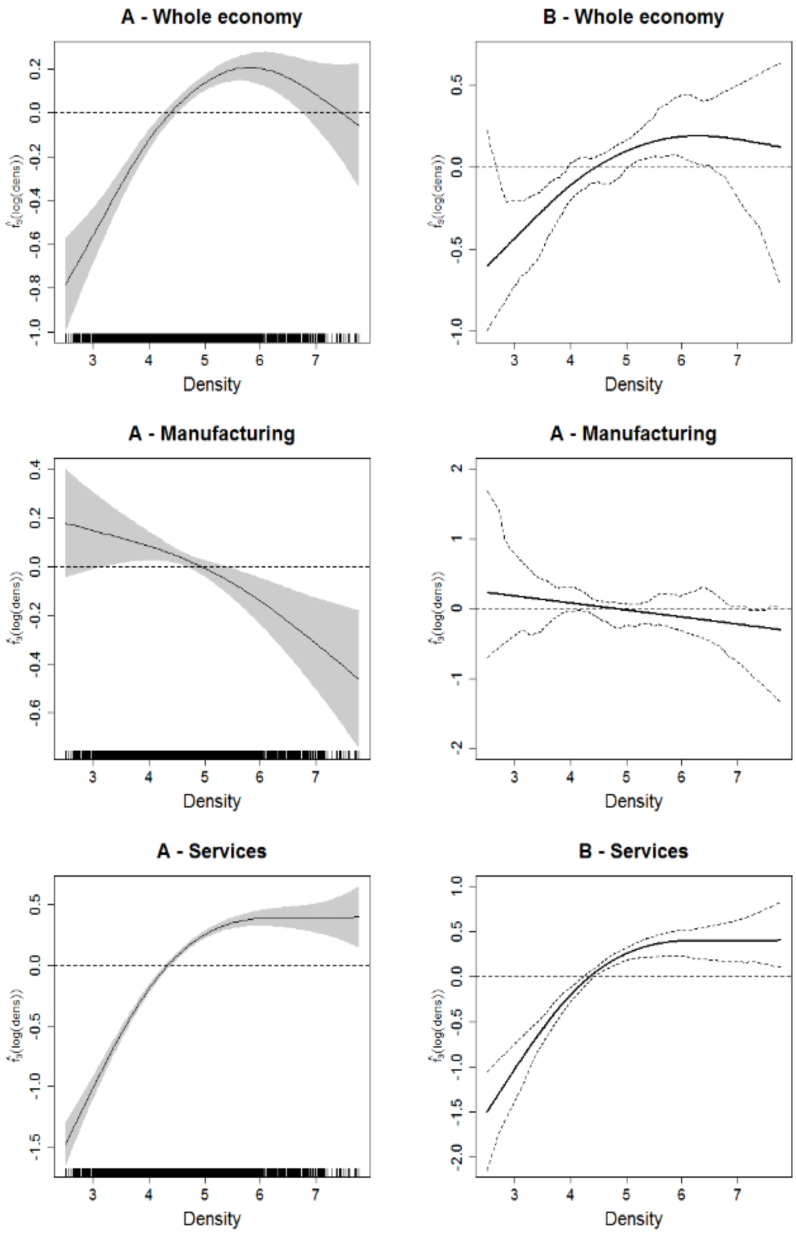


Figure 4. (A) Smooth effect of *size.* (B) Smooth effect of *size* with IV estimates

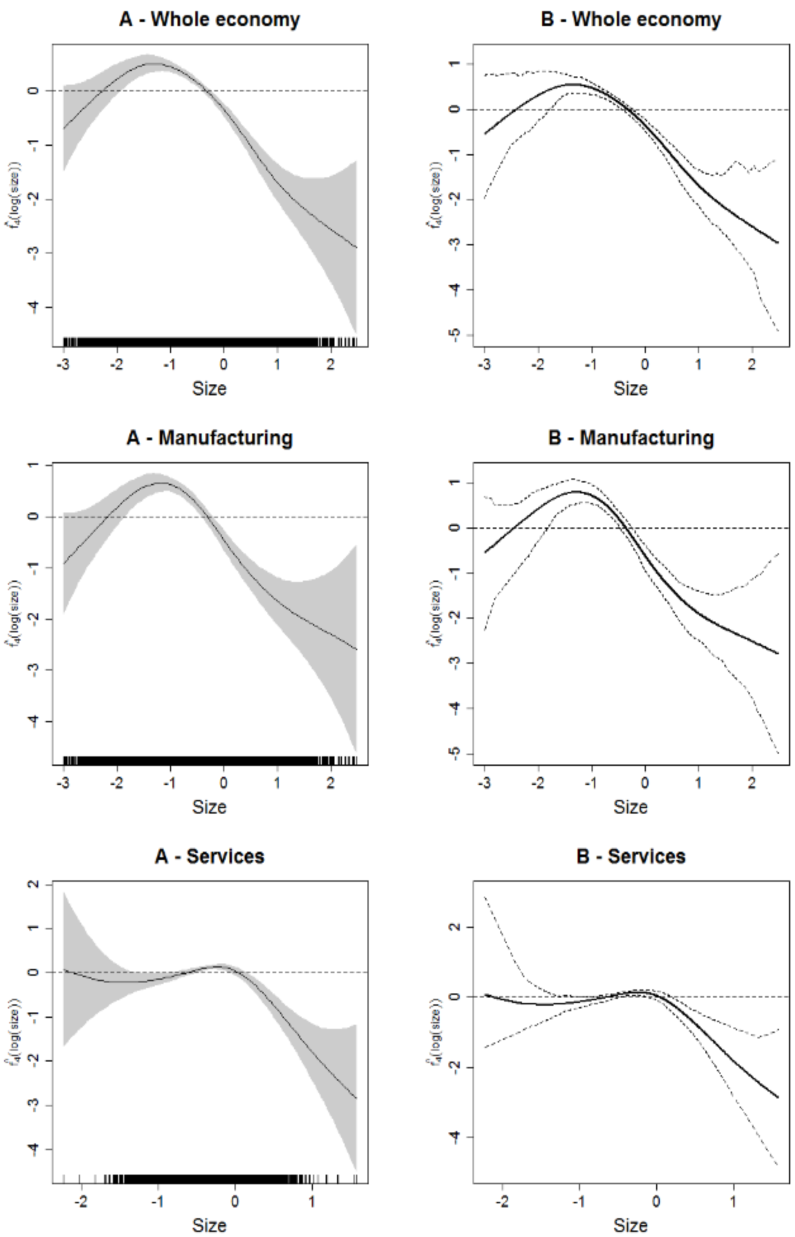


Figure 5. (A) Smooth effect of *comp.* (B) Smooth effect of *comp* with IV estimates

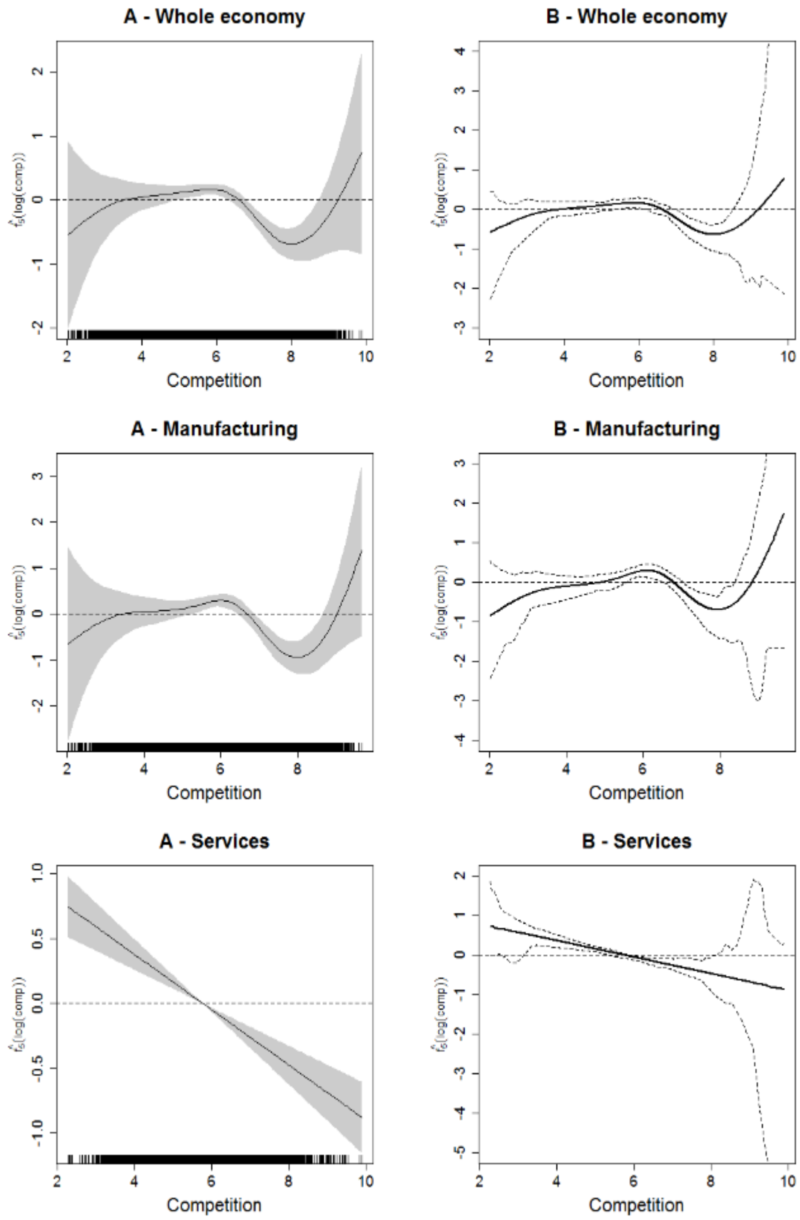
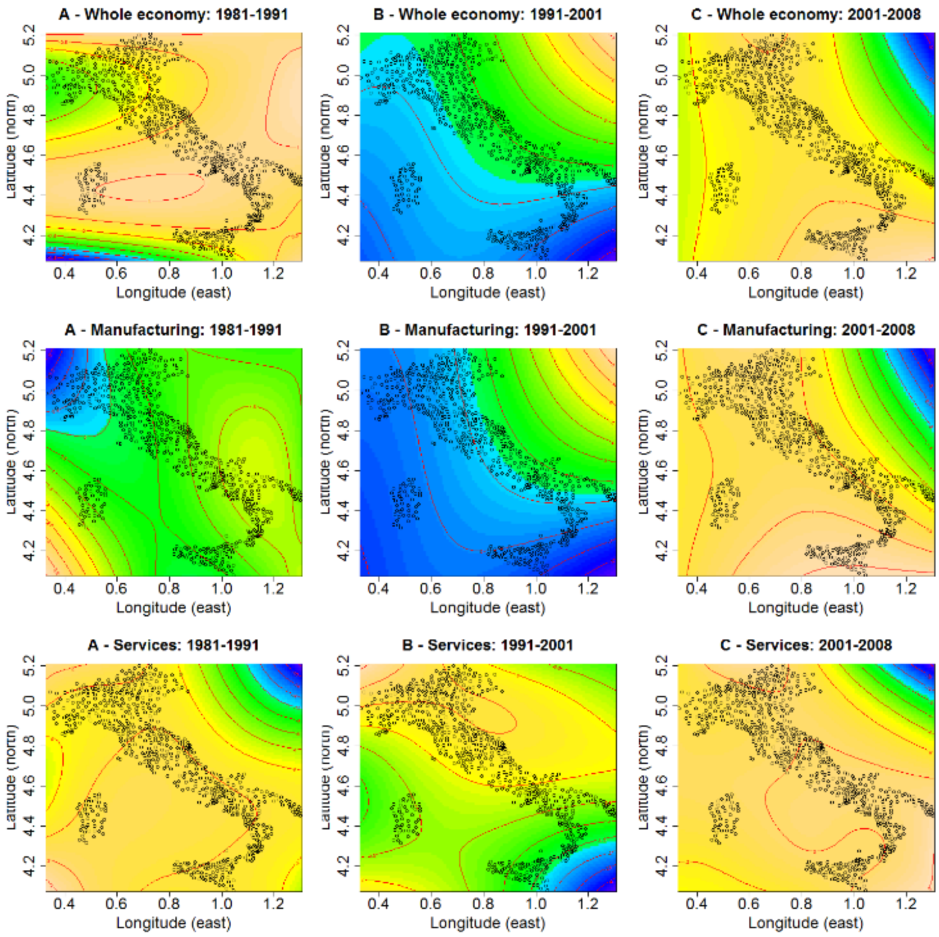


Figure 6. Geographical components of the geo-additive model for each time period



Notes: Contour lines for different values of the predicted employment growth rate in each LLS. X- and Y- axes mesure degrees of longitude and latitude, respectively.

The relationship between growth and *log*(*comp*) (Figure 5 - Panel A) is linear and negative in the case of services, indicating that local competition is always better for growth, in line with the Porter's theory. In the case of manufacturing, our semiparametric estimates provide evidence of a nonlinear relationship between growth and *log*(*comp*): starting from low levels of *log*(*comp*) (i.e. from high levels of local competition), an increase in market power has a positive effect on growth, corroborating the MAR theory; after a certain threshold (that is starting from high levels of *log*(*comp*)), a decrease of market power favors local growth. In other words, our results suggest that the validity of Jacobs-Porter hypothesis (according to which local competition is a driving force to urban growth) or of the MAR theory (according to which local competition is an obstacle to urban growth) depends on some cut off level reached by the degree of local competition.

Table 6. First stage: semiparametric probit model for $ID_{r,s}$

	Whole economy	Manufacturing
Parametric terms	*Coefficients (s.e. in parentheses)*	
SpecIDsec>1	0.822 (0.000)	0.753 (0.000)
SpecSmallSize>1	-0.195 (0.140)	-0.177 (0.160)
Interaction	0.560 (0.000)	0.5199 (0.000)
log(*Anjou*)	0.199 (0.000)	0.190 (0.000)
log(*Spain*)	0.043 (0.140)	0.040 (0.160)
log(*Bourbon*)	-0.358 (0.000)	-0.346 (0.000)
log(*Venice*)	0.069 (0.000)	0.073 (0.000)
Nonparametric terms	χ^2 *test and edf (in square brackets)*	
f_1 (*log*(*spe*))	5.409	5.239
f_2 (*log*(*div*))	4.224	4.299
f_3 (*log*(*den*))	3.740	3.608
f_4 (*log*(*size*))	4.649	4.475
f_5 (*log*(*comp*))	3.425	3.260
$h_{1981}(no, e)$	6.471	6.426
$h_{1991}(no, e)$	6.382	6.393
$h_{2001}(no, e)$	8.020	7.779
No. of obs.	27,257	17,006
REML	1,252	1,218

Table 7. First stage: semiparametric probit model for $ID_{r,s'}$

	Whole economy	Manufacturing	Services
Parametric terms	*Coefficients (s.e. in parentheses)*		
log(*Anjou*)	0.263 (0.000)	0.195 (0.000)	0.122 (0.240)
log(*Spain*)	0.021 (0.040)	0.051 (0.000)	0.029 (0.680)
log(*Bourbon*)	-0.408 (0.000)	-0.340 (0.000)	-0.238 (0.000)
log(*Venice*)	0.137 (0.000)	0.117 (0.000)	0.137 (0.000)
Non-parametric terms	χ^2 *test and edf (in square brackets)*		
f_1 (*log*(*spe*))	5.248	3.901	3.962
f_2 (*log*(*div*))	6.754	5.539	5.704
f_3 (*log*(*den*))	8.728	8.552	6.393
f_4 (*log*(*size*))	3.966	4.162	2.818
f_5 (*log*(*comp*))	3.666	3.324	2.751
$h_{1981}(no, e)$	21.773	17.516	11.588
$h_{1991}(no, e)$	21.726	13.169	11.775
$h_{2001}(no, e)$	21.527	13.075	12.264
No. of obs.	27,257	17,006	10,251
REML	10,129	6,029	3,821

Finally, Figure 6 displays the map of the geographical component in the geoadditive model – $h(n_r, e_r)$ – estimated for each sector and for each period. It shows that, after controlling for the most relevant variables and allowing for nonlinearities, some unexplained clusters of high (or low) employment growth still remain in some part of the country. In particular, it emerges some unexplained positive growth in the North-East over the middle period (1991-2001).

The results presented so far might be affected by a simultaneity bias and we select a sufficiently large number of instruments to endogenize the dummy variables $ID_{r,s}$ and $ID_{r,s'}$. The relevance of the instruments is well documented in Tables 6 and 7, which report the estimation results of the first stage semiparametric probit equations. To avoid the pitfalls of weak instruments, we drop insignificant instruments, but we also repeat the analysis by including the whole set of instruments in both first stages and see that this does not affects the coefficients of interest.

In Table 8 we report the results of the IV estimation of model (2). In the case of manufacturing sectors, the results confirm that the exogenous component of *ID* due to history and geography is strongly correlated with current local economic growth, after controlling for observed and unobserved spatial heterogeneity. As it is usual, the IV estimates of the dummy variables $ID_{r,s}$ and $ID_{r,s'}$ are larger in magnitude than the one estimated without control for the endogeneity bias. Surprisingly, for the sample of service activities, IV estimates do not confirm the evidence of a significant effect of industrial districts. The results for the nonparametric terms are very similar to those obtained without control for endogeneity (Figures 1-5 Panel B). For robustness check, we have also applied a control function procedure described in section 2.4. The results reported in Table 9 confirm the significance of $ID_{r,s}$ and $ID_{r,s'}$ in manufacturing, although the amount of the coefficients is lower.[21].

Table 8. Semiparametric geoadditive model – IV method

	Whole economy	Manufacturing	Services
Parametric terms	*Coefficients (bootstrap s.e. in parentheses)*		
$ID_{r,s}$	1.728 (0.000)	2.628 (0.000)	
$ID_{r,s'}$	0.896 (0.020)	1.753 (0.000)	0.120 (0.680)
Nonparametric terms	*F test and edf (in square brackets)*		
f_1 (*log*(*spe*))	5.439	5.174	5.344
f_2 (*log*(*div*))	2.793	3.113	2.499
f_3 (*log*(*den*))	2.260	1.007	3.501
f_4 (*log*(*size*))	4.102	4.272	4.095
f_5 (*log*(*comp*))	4.759	5.069	1.005
$h_{1981}(no, e)$	8.100	6.961	14.359
$h_{1991}(no, e)$	5.365	5.204	8.885
$h_{2001}(no, e)$	5.554	5.621	13.353
No. of obs.	27,257	17,006	10,251
R^2_{adj}	0.095	0.093	0.199
REML	85,780	56,805	23,735

[21] Both for IV and control function estimates, bootstrapped p-values are computed for the coefficients of $ID_{r,s}$ and $ID_{r,s'}$ following the procedure described in Appendix 1b.

Table 9. Semiparametric geoadditive model – CF method

	Whole economy	Manufacturing	Services
Parametric terms	*Coefficients (bootstrap s.e. in parentheses)*		
$ID_{r,s}$	0.681 (0.040)	1.732 (0.000)	
$ID_{r,s'}$	0.729 (0.060)	1.311 (0.020)	0.109 (0.620)
$gr_{r,s}$	0.764 (0.010)	0.271 (0.040)	
$gr_{r,s'}$	-0.390 (0.040)	-0.634 (0.060)	0.060 (0.780)
Nonparametric terms	*F test and edf (in square brackets)*		
f_1 (*log*(*spe*))	5.439	5.159	5.344
f_2 (*log*(*div*))	2.649	2.602	2.493
f_3 (*log*(*den*))	2.514	1.022	3.503
f_4 (*log*(*size*))	3.998	4.182	4.094
f_5 (*log*(*comp*))	4.716	5.070	1.005
$h_{1981}(no,e)$	8.062	6.886	14.401
$h_{1991}(no,e)$	5.521	5.168	8.847
$h_{2001}(no,e)$	5.559	5.665	13.349
N. of obs.	27,257	17,006	10,251
R^2_{adj}	0.093	0.093	0.200
REML	85,081	56,808	23,733

5. CONCLUSION

In this paper we have used a semiparametric geoadditive model to analyze the effect on employment growth of various factors characterizing the local productive structure in Italy: localization and urbanization externalities, local competition and internal scale economies. The flexibility of the semiparametric approach has allowed us to appreciate that some local characteristics have a nonlinear effect on employment growth. In particular, in keeping with theoretical predictions, the positive effect of urbanization externalities (captured by population density) appears to fade as the density of economic activities reaches some threshold value (in the case of service sectors). Moreover, it emerged a hump-shaped relationship between average firm size and local employment growth as well as between the level of local competition and employment growth. A higher diversification has a positive effect on employment growth in manufacturing sectors corroborating Jacobs theory and a nonlinear effect in services, while a higher specialization (computed with the location quotient) has a negative (albeit nonlinear) impact on employment dynamics. This last finding is consistent with idea that a higher specialization boosts local productivity and thus, under certain circumstances (such as inelastic product demand), reduces labor demand. Finally, the geoadditive model, which incorporates a smooth spatial trend surface, is able to capture residual spatial heterogeneity.

Net of the effect of specialization and average firm size, it has also emerged a *causal* positive effect of industrial district economies on employment growth. It would be a very hard task to capture district externalities through a single indicator, since the essence of this kind of external economies depends on a large number of socio-economic factors (mutual trust, co-operation propensity, presence of institutions that boost the formation and accumulation of social capital). In order to overcome this problem, we have exploited the information on the membership of LLSs to industrial districts (the places where Marshallian externalities are magnified). Thus, we have included in our model a dummy variable *ID*, indicating whether a LLS belongs or not to an industrial district. Empirical evidences (even after controlling for the potential endogeneity of the dummy *ID*) have confirmed that industrial districts have performed better than the other LLSs in manufacturing sectors, thus confirming that industrial district externalities exert a positive effect on local employment growth.

Obviously, our approach does not allow us to distinguish between the various channels through which industrial districts exert a positive effect on local employment dynamics. As it is well known, Marshallian externalities take the form of a more efficient *sharing* of indivisible facilities (e.g., local infrastructure), risks, and the gains from specialization (Duranton and Puga, 2004; Ellison *et al*., 2010). Moreover, industrial districts allow for a better *matching* between employers and employees, buyers and suppliers, partners in joint projects, or entrepreneurs and financiers. This can occur through both a higher probability of finding a match and a better quality of matches when they occur. Finally, industrial districts can facilitate *learning* about new technologies, new markets, or new forms of organization. Some of these mechanisms (e.g., matching) may have instantaneous effects, while others (e.g., learning) may take time to materialize. In other words, the dummy variable *ID* represents a *black box* and it allows us only to estimate the average net effect of the Marshallian externalities on growth, while the identification of the mechanisms of *sharing*, *matching* and *learning* requires the availability of microeconomic information (see, for example, Andini *et al*., 2012).

REFERENCES

Andini M., de Blasio G., Duranton G., Strange W.C., 2012, “Mashallian labor Market pooling: Evidence from Italy”, *Documents de Treball de lIEB* 2012/27.

Angrist, J.D., Pischke J., 2008, *Mostly Harmless Econometrics: An Empiricist’s Companion*, Princeton University Press.

Augustin, N., Musio, M., von Wilpert, K., Kublin, E., Wood, S. N., Schumacher, M., 2009, “Modeling spatio-temporal forest health monitoring data”, *Journal of the American Statistical Association*, 104, pp. 899-911.

Bagnasco, A., 1977, *Tre Italie. La problematica territoriale dello sviluppo italiano*, Il Mulino, Bologna.

Basile, R., Girardi, A., 2010, “Specialization and Risk Sharing in European Regions”, *Journal of Economic Geography*, 10(5), pp. 645-659.

Beaudry, C., Shiffauerova, A., 2009, “Who is right, Marshall or Jacobs? The localization versus urbanization debate”, *Research Policy*, 38(2), pp. 318-337.

Becattini, G., 1979, “Dal ’settore’ industriale al ’distretto’ industriale: alcune considerazioni sull’unità d’indagine dell’economia industrial”, *Rivista di economia e politica industriale*, 1, pp. 7-21.

Becattini, G., 1987, *Mercato e forze locali: il distretto industriale*. Bologna: il Mulino.

Becattini, G., Bellandi, M., Dei Ottati, G., Sforzi, F., 2003, *From industrial districts to local development. An itinerary of research*. Cheltenham: Edward Elgar.

Becattini G., Dei Ottati, G., 2006, “L’economia italiana negli anni novanta: un confronto tra aree di grande impresa e distretti industriali”, *Economia e Politica Industriale*, 1, pp. 5-24.

Becchetti L., De Panizza, A., Oropallo, F., 2007, “The role of agglomeration externalities in export and value added performance: evidence from the population of Italian firms”, *Regional Studies*, 41(5), pp. 601-621.

Bellandi, M., 2007, “Industrial Districts and Waves of Industrialization: A Rich and Contested Terrain”, *Scienze regionali*, 6(2), pp. 7-33.

Briant, A., Combes, P.P., Lafourcade, M., 2010, “Dots to boxes: Do the Size and Shape of Spatial Units Jeopardize Economic Geography Estimations?”, *Journal of Urban Economics*, 67(3), pp. 287-302.

Cainelli, G., Leoncini, R., 1999, “Externalities and long-term local industrial development: some empirical evidence from Italy”, *Revue d’Economie Industrielle*, 90, pp. 25-39.

Ciccone, A., Hall, R.E., 1996, “Productivity and the density of economic activity”, *American Economic Review*, 86, pp. 54-70.

Cingano, F., Schivardi, F., 2004, “Identifying the Sources of Local Productivity Growth”, *Journal of the European Economic Association*, 2, pp. 720-742.

Combes, P.P., 2000, “Economic structure and local growth: France, 1984-1993”, *Journal of Urban Economics*, 47, pp. 329-355.

Combes, P.P., Duranton, G., Gobillon, L., 2011, “The identification of agglomeration economies", *Journal of Economic Geography*, 11(2), pp. 253-266.

De Groot, H.L.F., Poot, J., Smit, M.J., 2009, “Agglomeration, innovation and regional development: theoretical perspectives and meta-analysis”. In: Capello, R., Nijkamp, P. (eds), *Handbook of regional growth and development theories*. Cheltenham: Edward Elgar, pp. 256-281.

De Lucio, J.J, Herce, J.A., Goicolea, A., 2002, “The Effects of Externalities on Productivity Growth in Spanish Industry”, *Regional Science and Urban Economics*, 32, pp. 241-258.

Di Giacinto, V., Gomellini, M., Micucci, G., Pagnini, M., 2012, “Mapping local productivity advantages in Italy: industrial districts, cities or both? “, *Temi di discussione Banca d’Italia*, 850.

Di Liberto, A., Sideri, M., 2012, “Past Dominations, Current Institutions and the Italian Regional Economic Performance”, *DEGIT Conference Papers c017-022*, DEGIT, Dynamics, Economic Growth, and International Trade.

Duranton, G., Puga, D., 2000, “Diversity and Specialisation in Cities: Why, Where and When Does it Matter?”, *Urban Studies*, 37(3), pp. 533-555.

Duranton, G., Puga, D., 2004, “Microfoundations of urban agglomeration economies”, In Vernon Henderson, J., Thisse, J-J (eds.) *Handbook of Regional and Urban Economics*, Vol. 4. Amsterdam: NorthHolland, pp. 2063-2117.

Eilers, P., Marx, B., 1996, “Flexible Smoothing with B-Splines and Penalties”, *Statistical Science*, 11, pp. 89-121.

Ellison, G., Glaeser, E.L., William, R.K., 2010, “What causes industry agglomeration? Evidence from coagglomeration patterns”, *American Economic Review*, 100(3), pp. 1195-1213.

Forni, M., Paba, S., 2002, “Knowledge Spillovers and the Growth of Local Industries”, *Journal of Industrial Economics*, 50, pp. 151-171.

Glaeser, E., Kallal, H., Scheinkman, J., Shleifer, A., 1992, “Growth in cities”, *Journal of Political Economy*, 100, pp. 1126-1152.

Guiso, L., Sapienza, P., Zingales, L., 2008, “Alfred Marshall Lecture Social Capital as Good Culture”, *Journal of the European Economic Association*, MIT Press, 6(2-3), pp. 295-320, 04-05.

Heckman, J. (1976), “The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models”, *Annals of Economic and Social Measurement*, 5, pp. 475-492.

Henderson, V., Kunkoro, A., Turner, M., 1995, “Industrial Development in Cities”, *Journal of Political Economics*, 103, pp. 1067-1090.

Henderson, V., 1997, “Externalities and Industrial Development”, *Journal of Urban Economics*, 42(3), pp. 449-470.

Henderson, D.J., Papageorgiou, C., Parmeter, C.F., 2012, “Growth Empirics without Parameters”, *The Economic Journal*, 122, pp. 125-154.

Illy, A., Schwartz, M., Hornych, C., Rosenfeld, M.T.W., 2011, “Local Economic Structure and Sectoral Employment Growth in German Cities”, *Tijdschrift voor economische en sociale geografie*, 102, pp. 582-593.

ISTAT, 2001, *Distretti industriali e sistemi locali del lavoro 2001*. Roma.

Jacobs, J., 1969, *The Economies of Cities*. New York: Random House.

Krugman, P. 1993, “First nature, second nature, and metropolitan location”, *Journal of Regional Science*, 33: pp. 129-144.

Mameli, F., Faggian, A., McCann, P., 2008, “Employment growth in Italian Local Labour Systems: issues of model specification and sectoral aggregation”, *Spatial Economic Analysis*, 3(3), pp. 343-360.

Markusen, A., 1996, “Sticky Places in Slippery Space: A Typology of Industrial Districts”, *Economic Geography*, 72, pp. 293-313.

Marshall, A., 1920, *Principles of Economics*. London: Macmillan.

Melo, P.C., Graham, D.J., Noland, R.B., 2009, "A Meta-analysis of Estimates of Urban Agglomeration Economies", *Regional Science and Urban Economics*, 39, pp.332-342.

Ó hUallacháin, B., Satterthwaite, M.A., 1992, "Sectoral growth patterns at the metropolitan level: an evaluation of economic development incentives", *Journal of Urban Economics*, 31, pp. 25-58.

Paci, R., Usai, S., 2008, "Agglomeration Economies, Spatial Dependence and Local Industry Growth", *Revue D'Economie Industrielle*, 123, pp. 1-23.

Porter, M.E., 1990, *The Competitive Advantage of Nations*. London: MacMillan.

Rosenthal, S.S., Strange, W.C., 2004, "Evidence on the Nature and Sources of Agglomeration Economies". In: Henderson, V., Thisse, J-C. (eds), *Handbook of Regional and Urban Economics: Cities and Geography*, Amsterdam: Elsevier, pp. 2119-2171.

Sforzi, F., 2007, "Il contributo dei distretti industriali al cambiamento dell'economia italiana", *Economia italiana*, pp. 79-103.

Sforzi, F., 2009, "The empirical evidence of industrial districts in Italy", In: Becattini, G., Bellandi, M., De Propris, L. (eds.). *A Handbook of industrial Districts*. Cheltenham: Edward Elgar, pp. 327-342.

Soubeyran, A. and Weber, S., 2002, "District formation and local social capital: a (tacit) co-opetition approach", *Journal of Urban Economics*, 52, pp. 65-92

Tabellini, G. (2010), "Culture and Institutions: Economic Development in the Regions of Europe", *Journal of the European Economic Association*, 8(4), pp. 677-716

Trigilia, C., 1986, *Grandi partiti e piccole imprese: comunisti e democristiani nelle regioni a economia diffusa*, Il Mulino, Bologna.

Trigilia, C., 2001, "Capitale sociale e sviluppo locale", in A. Bagnasco, F. Piselli, A. Pizzorno, C. Trigilia, *Il capitale sociale Istruzioni per luso*, Il Mulino, Bologna.

Van der Klaauw, W., 2002, "Estimating the Effect of Financial Aid Offers on College Enrollment: A Regression-Discontinuity Approach", *International Economic Review*, 43, pp. 1249-1287.

Viladecans-Marsal, E., 2004, "Agglomeration Economies and Industrial Location: City-level Evidence", *Journal of Economic Geography*, 4, pp. 565-582.

Wood, S.N., 2006, *Generalized additive models. an introduction with R*. Boca Raton. Florida: Chapman and Hall/CRC.

Wooldridge, J., 2002, *Econometric Analysis of Cross Section and Panel Data*. Massachusetts: MIT Press.

ANNEX 1. Semiparametric Geoadditive Models

The semiparametric geoadditive model estimated in this paper can be represented in a more general form as:

$$y_{it} = \mathbf{X}_{it}^{*'}\boldsymbol{\beta}^* + f_1(x_{1it}) + f_2(x_{1it}) + \cdots + \sum_t h_t(no_i, e_i) + \tau_t + \varepsilon_{it}$$
$$\varepsilon_{it} \sim iid\mathcal{N}(0, \sigma_\varepsilon^2) \quad i = 1, \dots, N \quad t = 1, \dots, T \tag{9}$$

where, for each spatial unit i=1,2,...,N and for each period t=1,2,...,T, y_{it} is a continuous response variable; $\mathbf{X}_{it}^{*\prime}\boldsymbol{\beta}^*$is a linear predictor for any strictly parametric component parametric component (including the intercept, all categorical covariates and eventually some continuous covariates), with $\boldsymbol{\beta}^*$ a vector of fixed parameters; with $\boldsymbol{\beta}^*$ being a vector of fixed parameters. $f_k(.)$ are unknown smooth functions of univariate continuous covariates capturing nonlinear effects of exogenous variables. The term $h(no_i, e_i)$ is a smooth spatial trend surface, i.e. a smooth interaction between latitude (*northing*) and longitude (*easting*). It allows us to control for unobserved spatial heterogeneity.[22] Finally, τ_t is a time fixed effect and ε_i are *iid* normally distributed random shocks.
Omitting the subscripts *it*, each *k-th* univariate term in equation (9) can be approximated by a linear combination of known basis functions $b_{q_k}(x_k)$:

$$f_k(x_k) = \sum_{q_k} \beta_{q_k} b_{q_k}(x_k)$$

with β_{q_k} unknown parameters to be estimated.

To reduce mis-specification bias, $q_k's$ must be made fairly large. But this may generate a danger of over-fitting. By penalizing 'wiggly' functions when fitting the model, the smoothness of the functions can be controlled. Thus, a measure of 'wiggliness' $J \equiv \boldsymbol{\beta}'\mathbf{S}\boldsymbol{\beta}$ is associated with each k smooth function, with **S** a positive semi-definite matrix. In this study, we have used P-spline basis functions and discrete penalties suggested by.

The penalized spline base–learners can be extended to two or more dimensions, such as $h_t(no_i, e_i)$, to handle interactions by using thin–plate regression splines or tensor products (Wood, 2006). In the case of a tensor product, smooth bases are built up from products of 'marginal' bases functions. For example:

$$h_t(no, e) = \sum_l \sum_m \beta_{l,m} b_l(no) b_m(e)$$

Given the bases for each smooth term, equation (9) can be rewritten in matrix form as a large linear model,

[22] Removing *unobserved spatial patterns* is a primary task, especially when the researcher considers spatial unobservables as potential sources of endogeneity, that is, when there is a suspected correlation between unobserved and observed variables.

$$y = X^*\beta^* + \Sigma_{q1}\beta_{1_{q1}} b_{1_{q1}}(x_1) + \Sigma_{q2}\beta_{2_{q2}} b_{2_{q2}}(x_2) + \cdots + \varepsilon = X\beta + \varepsilon \qquad (10)$$

where matrix $\mathbf{X}$ includes $\mathbf{X}^*$ and all the basis functions evaluated at the *x*'*s* covariate values, while $\boldsymbol{\beta}$ contains $\boldsymbol{\beta}^*$ and all the coefficient vectors, β_q, corresponding to the basis functions.

The estimation of model (10) can be based on the reparameterization of such a model in the form of a mixed model:

$$y = X\beta + ZU + \varepsilon \quad U \sim \text{i.i.d. } N(0, G) \quad \varepsilon \sim \text{i.i.d. } N(0, \sigma_\varepsilon^2 I) \qquad (11)$$

where G is a block–diagonal matrix, which depends on both $\sigma_{u_k}^2$ and σ_ε^2 variances. This model is a mixed model where β represents the parameters vector of fixed part and U are the random effects. The smoothing parameters are defined by the ratios $\theta_k = \frac{\sigma_\varepsilon^2}{\sigma_{u_k}^2}$.

This reparameterization consists in post-multiplying X and pre-multiplying β in model (10) by an orthogonal matrix resulting from the singular value decomposition of the penalty matrices S_k. Therefore, the type of penalizations determines the transformation matrix and, thus, the fixed and random effects obtained in the mixed model. The resulting coefficients associated with the fixed effects (β) are not penalized, while those associated with the random effects (U) are penalized. The penalization of random effects is given by the variance–covariance matrix of these coefficients.

Once the mixed model is defined, the parameters associated to fixed (β) and random effects (θ_k and σ_ε^2) can be estimated by using a ML algorithm. If the noise term follows a Gaussian distribution, the log–likelihood function is given by:

$$\log L(\beta, \theta_1, \ldots, \theta_K, \sigma_\varepsilon^2) = \text{constant} - \frac{1}{2} log|V| - \frac{1}{2}(y - X\beta)' V^{-1}(y - X\beta)$$

where $V = ZGZ' + \sigma_\varepsilon^2 I$ and the smoothing parameters θ_K are included in V.

However, the ML estimates are biased since this method does not take into account the reduction in the degrees of freedom due to the estimation of the fixed effects. The restricted maximum likelihood (REML) method can be used to solve the problem. The REML method looks for the linear combinations of the dependent variable that eliminates the fixed effects in the model. In this case the objective function to maximize is given by:

$$\log L_R(\theta_1, \ldots, \theta_K, \sigma_\varepsilon^2) = \text{constant} - \frac{1}{2} log|\mathbf{V}| - \frac{1}{2} log|\mathbf{X}'\mathbf{V}^{-1}\mathbf{X}|$$
$$- \frac{1}{2}\mathbf{y}'(\mathbf{V}^{-1} - \mathbf{V}^{-1}\mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1})\mathbf{y}$$

An estimation of the variance components parameters can be obtained after maximizing $log\ L_R(.)$. In a second step, the estimates of β and U are given by:

$$\hat{\beta} = (\mathrm{X}'\hat{\mathrm{V}}^{-1}\mathrm{X})\mathrm{X}'\hat{\mathrm{V}}^{-1}\mathrm{y} \qquad \hat{\mathrm{U}} = \hat{\mathrm{G}}\mathrm{X}'\hat{\mathrm{V}}^{-1}(\mathrm{y} - \mathrm{X}\hat{\beta})$$

Finally, the estimated values of the observed variable can be obtained as:

$$\hat{\mathrm{y}} = \mathrm{X}\hat{\beta} + \mathrm{Z}\hat{\mathrm{U}}$$

To build confidence (or better credibility) intervals for the estimated values, Wood (2006) has implemented a Bayesian approach. This strategy recognizes that, by imposing a particular penalty, we are effectively including some prior beliefs about the likely characteristics of the correct model. This can be translated into a Bayesian framework by specifying a prior distribution for the parameters β. Specifically, Wood (2006) shows that using a Bayesian approach to uncertainty estimation results in a Bayesian posterior distribution of the parameters

$$\beta|\mathrm{y} \sim \mathcal{N}\left(E(\hat{\beta}), \sigma_\varepsilon^2\left(\mathrm{X}'\mathrm{X} + \sum_k \theta_k \mathrm{S}_k\right)^{-1}\right)$$

This latter result can be used directly to calculate credibility intervals for any parameter. Moreover, the credibility intervals derived via Bayesian theory are well behaved also from a frequentist point of view, i.e. their average coverage probability is very close to the nominal level 1−α, where α is the significance level.

ANNEX 1b. The boostrap procedure

Since the second-step regression of both the IV and Control Function approaches contains generated regressors, we use a bootstrap procedure to compute the standard errors and p-values. Indicating with y_1 the response variable (the employment growth rate), with X the *model matrix* (including the dichotomous endogenous variables, $y_2 = ID_{r,s}$ and $y_3 = ID_{r,s'}$) and with Z the set of instrumental variables, this procedure consists of the following steps:

1. Select a bootstrap sample $(\mathrm{y}_{1b}^*, \mathrm{X}_b^*, \mathrm{Z}_b^*)$ drawn with replacement from $(\mathrm{y}_1, \mathrm{X}, \mathrm{Z})$;

2. Run a semiparametric probit first step model for each endogenous variable ($\mathrm{y}_2 = 1[f_2(\mathrm{Z}) + e_2] \geq 0$ and $\mathrm{y}_3 = 1[f_3(\mathrm{Z}) + e_3] \geq 0$) and compute the generalized residuals:

$$\widehat{gr}_2 = \left[\phi\left(\hat{f}_2(\mathbf{Z})\right)/\Phi\left(\hat{f}_2(\mathbf{Z})\right)\right] \times y_2 - \left[\phi\left(\hat{f}_2(\mathbf{Z})\right)/\left(1 - \Phi\left(\hat{f}_2(\mathbf{Z})\right)\right)\right] \times (1 - y_2)$$

$$\widehat{gr}_3 = \left[\phi\left(\hat{f}_3(\mathbf{Z})\right)/\Phi\left(\hat{f}_3(\mathbf{Z})\right)\right] \times y_3 - \left[\phi\left(\hat{f}_3(\mathbf{Z})\right)/\left(1 - \Phi\left(\hat{f}_3(\mathbf{Z})\right)\right)\right] \times (1 - y_3)$$

3. Following the IV procedure, use the estimated probabilities from the first steps ($\Phi\left(\widehat{f_2}(\mathrm{Z})\right)$ and $\Phi\left(\widehat{f_3}(\mathrm{Z})\right)$) as instruments for y_2 and y_3. Alternatively, following the CF procedure, insert the first-step residuals in the original semi-parametric regression;

4. Repeat B=1000 times points (*1*)–(*3*); For each estimated parametric coefficients compute the corresponding equal–tail bootstrap p-value:

$$P^*(\hat{\beta}) = 2 \times min\left(\frac{1}{B}\sum_{b=1}^{B}\#\{\hat{\beta}_b^* \leq 0\}, \frac{1}{B}\sum_{b=1}^{B}\#\{\hat{\beta}_b^* > 0\}\right)$$

5. For each estimated nonparametric coefficients compute the average partial effect at the 95% confidence bands.

ANNEX 2. Sector disaggregation

NACE rev.1	Sectors
	Manufacturing
DA	Manufacture of food products, beverages and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD	Manufacture of wood and wood products
DE	Manufacture of pulp, paper and paper products; publishing and printing
DF	Manufacture of coke, refined petroleum products and nuclear fuel
DG	Manufacture of chemicals, chemical products and man-made fibres
DH	Manufacture of rubber and plastic products
DI	Manufacture of other non-metallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK	Manufacture of machinery and equipment n.e.c.
DL	Manufacture of electrical and optical equipment
DM	Manufacture of transport equipment
DN	Manufacturing n.e.c.
	Services
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
H	Hotels and restaurants
I	Transport, storage and communication
J	Financial intermediation
K	Real estate, renting and business activities

Notes: data for the sectors DB, DC, DD, DE, DF, DG, DH and DI have been merged in pairs. n.e.c. stands for Not Elsewhere Classified.

STRUCTURE INDUSTRIELLE LOCALE ET CROISSANCE DE L'EMPLOI : UNE ANALYSE À PARTIR DE MODÈLES GÉOADDITIFS SEMI-PARAMÉTRIQUES

Résumé - *A partir de données sur les « systèmes locaux de travail » italiens, l'effet de la structure productive locale sur la croissance de l'emploi est étudié durant la période 1981-2008. L'Italie représente un terrain d'étude intéressant à deux titres : en raison, d'une part, du niveau élevé d'hétérogénéité spatiale des performances des marchés du travail locaux et, d'autre part, de la présence de bassins d'emploi fortement spécialisés (districts industriels). Les modèles géo-additifs semi-paramétriques utilisés permettent d'identifier des non-linéarités importantes dans la relation entre la structure industrielle locale et la croissance de l'emploi, d'évaluer les performances relatives des districts industriels et de contrôler l'hétérogénéité spatiale non observée.*

Mots-clés : MODÈLES GÉOADDITIFS SEMI-PARAMÉTRIQUES, DISTRICT INDUSTRIEL, ÉVOLUTION DE L'EMPLOI, STRUCTURE INDUSTRIELLE