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# Industry structure and employment growth: evidence from semi-parametric geo-additive models\*

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## Abstract

Using Local Labor Systems (LLSs) data, we assess how the local productive structure affects 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 a semi-parametric geo-additive model, our empirical investigation allows us to identify important non-linearities in the relationship between local industry structure and local employment growth, to assess the relative performance of industrial districts (the places where Marshallian externalities occur) and to control for unobserved spatial heterogeneity.

*Keywords:* Industry structure, Industrial districts, Employment dynamics, Semi-parametric geo-additive models.

*Jel codes:* R11, R12, C14

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# 1 Introduction

Following the broad literature started by Glaeser *et al.* (1992) and Henderson *et al.* (1995)<sup>1</sup>, 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 externalities (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-specification issues. First, all of them measure Marshallian (or specialization) externalities using location quotients disregarding the fact that higher specialization levels may lead higher vulnerability to idiosyncratic shocks (such as a decline faced by the primary industry of the local area) and, thus, are likely to bolster asymmetric developments and differences in growth rates across local economies, unless some effective “risk sharing” mechanisms help “protect” the local economic environment against idiosyncratic shocks (Basile and Girardi, 2009). A form of insurance mechanism is represented by those socio-economic factors (such as mutual trust and *coopetition*) which contribute 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.

Second, most of the previous studies disregard the existence of non-linearities 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 non-linearities (Henderson *et al.*, 2012). Some authors (i.a. De Lucio *et al.*, 2002, Viladecans-Marsal, 2004, and Illy *et al.*, 2011) allow for non-linearities by introducing quadratic terms in their models. Although this is

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<sup>1</sup>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 Schifffauerova (2009).

the easiest way to deal with such a non-linearity in a parametric framework, it is only one of several possible non-linear parameterizations. Indeed, non-linearities can be better accommodated in a semi-parametric framework, 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, disregarding the role of “first nature” characteristics of local areas (Krugman, 1993) in affecting their growth performance.

Using census data for 686 Local Labour 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 non-linearities in the relationship between industry structure and local-sector employment growth, b) assessing the relative performance of industrial districts and c) controlling for 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 semi-parametric model which allows us to identify smooth non-linear 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 dataset, we include in our model a geo-additive component (a smooth interaction between latitude and longitude) for each time period which permits us to control 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 *per se* reduces the employment dynamics due to a higher vulnerability to idiosyncratic shocks, but only up to a certain threshold after which specialization has no effect on growth. In line with

previous evidence and corroborating Jacobs' theory, diversification boosts employment growth in manufacturing and reduces it in services. Allowing for non-linearities and in keeping with theoretical predictions, we find a hump-shaped relationship between population density and local employment growth: 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. This evidence is confirmed even controlling for the endogeneity of the dummy variable  $ID$  only in the case of services, while it becomes monotonically negative in manufacturing when using the IV estimator. 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 due to the first nature features of the LLS.

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:

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

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;  $\beta_0$ - $\beta_5$  are the parameters associated to the intercept and to the explanatory variables expressed in log terms;  $\gamma_s$  is a sector

fixed effect;  $\delta_t$  is a temporal fixed effect; and  $\varepsilon_{r,s,t}$  is an error term assumed to be *iid*.<sup>2</sup>

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 growth.<sup>3</sup> 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 conducive to local economic growth. In line with this interpretation, Duranton and Puga (2000, p. 553) observe

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<sup>2</sup>A similar specification is used by Paci and Usai (2008) and Mameli *et al.* (2008). These authors also extend the model by introducing other explanatory factors (such as human and social capital), but 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.

<sup>3</sup>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.

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). For the case of Italy, Mameli *et al.* (2008) and Paci and Usai (2008) estimate a negative impact of sectoral specialization on local growth. Only Forni and Paba (2002) are able to corroborate the MAR hypothesis. All of the studies on Italy also find a positive impact of the degree of diversification on local employment growth, thus corroborating Jacobs theory. These findings suggest that, if diversification is always better for growth, regional specialization may hinder economic growth. According to Beaudry and Schiffrerova (2009, pp. 320-321) “this may be first related to the lower flexibility of the specialized regions and consequently to their decreased capacity to adjust to exogenous changes, which may prove critical if the main industry in the region declines. In a diversified environment endowed with a wider technological scale, the chances that some new industry will spring out and take the lead is greater. Second, specialized regions may be more vulnerable to lock-in, i.e., closing upon themselves, becoming insular and impermeable, and preventing knowledge and fresh innovative ideas from outside to flow in. The specialized regions tend to become more specialized with time, and thus experience increasingly less external relations than the diversified regions”.

The evidence of a negative effect of specialization can also be interpreted in terms of a product’s life cycle: products first develop in a few places (strong specialization) and then diffuse across space (Combes, 2000), thus places with a higher specialization in a given sector, display lower (or more negative) growth rates. Paci and Usai (2008) observe that from the nineties the manufacturing industry in Italy has undergone a reorganization process which penalized more highly specialized LLSs. Finally, according to Cingano and Schivardi (2004), the evidence of a negative effect of MAR externalities is due to the choice of employment growth as dependent variable. They show that, within the same sample, if one uses total factor productivity growth instead of employment growth as dependent variable, the sign for the MAR coefficient becomes positive.

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 conducive 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 competition. Porters views on competition is most often supported in conjunction with Jacobs theory, which is consistent with the Jacobsian model. 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. Mamelì *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. Mamelì *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. Mamelì

*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, including those on the Italian case (Cainelli and Leoncini, 1999; Mameli *et al.*, 2008; Forni and Paba, 2002; Paci and Usai, 2008). 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 on employment growth contrasts with the strong anecdotal evidence of the economic success of *industrial districts*, the places where Marshallian externalities are magnified (Becattini and Dei Ottati, 2006; Becchetti *et al.*, 2007; Sforzi, 2007). The problem is that the specialization *per se* is not able to capture the role of Marshallian externalities. Marshall (1920) himself recognizes that “a district which is dependent chiefly on one industry is liable to extreme depression, in case of a falling-off in the demand for its produce ...” (p. 273). 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 socio-economic factors which contribute to determine the social capital of the region (Becattini, 1979). These features allow the industrial districts to “exhibit frequent and intensive exchanges of personnel between customers and suppliers and cooperation among competitor firms [coopetition] to share risk, stabilize markets, and share innovation” (Markusen, 1996). 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. In a nutshell, a strong specialization *per se* might be very dangerous for a region since it may lead higher vulnerability to idiosyncratic shocks, unless other factors (those which contribute to determine the industrial atmosphere) are present in the region generating a sort of risk sharing insurance that protect local firms against these kind of shocks. Thus, in order to capture the effect of Marshallian externalities,

a large number of socio-economic 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 identification of industrial districts in Italy.

The second critical issue concerns the possible existence of non-linearities 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 non-linearity in a parametric framework, it is only one of several possible non-linear parameterizations. Indeed, non-linearities can be better accommodated in a semi-parametric 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 non-linearities between growth and industry structure. 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 conducive 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 hetero-

geneity in employment growth rates. Regardless the role of economic factors, there are, indeed, “first nature” characteristics of local areas (Krugman, 1993) 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 scantily devoted to industrial and service activities; some others are plenty of mountains and are sparsely developed.

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 semi-parametric geo-additive model

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

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

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;  $\theta_1$  and  $\theta_2$  are their associated parameters. The inclusion of these dummy variables allows us to assess the relative performance of industrial districts, the places where Marshallian externalities occur. Specifically, the two dummies permits us to distinguish between the within-sector and the between-sector  $ID$  effect. In other words, we suggest that the effect of Marshallian externalities may be simply captured by these dummy variables, while the variable  $spe$  only captures the vulnerability of the region to idiosyncratic shocks.

$f_k$  are unknown smooth functions of the univariate terms. 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 geo-additive component (or smooth spatial trend surface) for each time period permits us to control for time-varying spatial unobserved heterogeneity and thus to abstract from heterogeneity of the underlying space.<sup>4</sup>

## 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).<sup>5</sup> Assuming “*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<sup>6</sup>, 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.<sup>7</sup>

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 instru-

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<sup>4</sup>Although geo-additive 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.

<sup>5</sup>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  $y_1$ ; 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.

<sup>6</sup>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.

<sup>7</sup>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.

ment 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 socio-economic 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.<sup>8</sup>

To implement the IV approach, we run two semi-parametric 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.

### 3 Data and variables

#### 3.1 Data

Following Mameli *et al.* (2008) and Paci and Usai (2008), the geographical units of observation considered in the present analysis are the Local Labor Systems (LLSs), that are territorial aggregations 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

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<sup>8</sup>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.

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).<sup>9</sup> 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.

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

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<sup>9</sup>Since ISTAT identifies industrial districts using threshold values of LQ and firm size, the dummy *ID* could pick up non-linearities 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.

dynamics. We consider 15 sectors (subsections of ATECO91-NACE rev.1 classification)<sup>10</sup> (see Table A1 in the Appendix): 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 sectoral effects. Thus, the dependent variable,  $y_{r,s,t}$ , is the difference between the annual employment growth rate of the  $s$ -th sector ( $s = 1, \dots, 10$ ) in the  $r$ -th LLS ( $r = 1, \dots, 686$ ) 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:

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

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).

#### *Tables 1a-c about here*

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

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<sup>10</sup>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.

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.

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:

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

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  $spe_{r,s}$  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  $spe_{r,s}$  lower than 1 are evidence of de-specialization. According to the traditional view, a positive effect of  $spe_{r,s}$  would support MAR theory.

In a second step of our empirical analysis (i.e. when we estimate the semi-parametric model (2)), we try to capture the effect of MAR externalities by directly including the dummy variable  $ID_{r,s}$ , on the basis of the consideration that Marhsallian economies mainly occur within industrial districts. 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. It is worth noticing again that, once we control for the  $ID$  effect, the variable  $spe$  included in model (2) only captures the vulnerability of the region to idiosyncratic shocks.

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:<sup>11</sup>

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

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 significant share of different sectors (i.e. its production structure is diversified). A low value of  $div_{r,s}$  means

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<sup>11</sup>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).

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):

$$dens_r = \frac{P_r}{A_r} \quad (6)$$

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 O’Huallochain 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:

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

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.

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

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

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.

**Tables 2 and 3 about here**

The five explanatory variables mentioned above cannot capture all the spatial heterogeneity in the LLS’ employment growth rates. As it has been highlighted by Krugman (1993), agglomera-

tion phenomena and local economic performances are primarily conditioned by first-nature location advantages which are often unobservable by the researcher. Thus, it emerges a problem of unobserved spatial heterogeneity that, if it is correlated with the observed characteristics, may generate estimation biases. In our semi-parametric 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 both geography and history 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 historical data consists of information on past dominations. Several authors (see, i.a., Bagnasco, 1977; Trigilia, 1986, 2001; Becattini, 1987) have underlined that the development of agglomerations of small and medium sized firms in Italy over the 1970s can be seen as 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 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.<sup>12</sup>

With respect to geography, following Combes *et al.* (2011), we create a measure of local terrain ruggedness (*Ruggedness*), by taking the difference between the average maximum altitudes across the municipalities belonging to the same LLS minus the average of minimum altitudes. Since the effect of unobserved spatial heterogeneity in employment growth rates is controlled by the smooth nonparametric interaction between latitude and longitude of the LLS centroid, the variable *Ruggedness* should only capture geo-morphological obstacles to industrial agglomerations.

## 4 Econometric results

### 4.1 Evidence from log-linear models

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

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<sup>12</sup>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 relationships are today less important in explaining agglomeration economies than in the past.

be interpreted as elasticities.<sup>13</sup>

*Table 4 about here*

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.<sup>14</sup>

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 or 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

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<sup>13</sup>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 dataset. 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.

<sup>14</sup>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 rule out multicollinearity problems in our analysis.

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 non-linearity (*RESET*) tests raise doubts on 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. 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 geo-additive semi-parametric model (2) as shown in the next section.

## 4.2 Evidence from semi-parametric models

In Table 5 we report the estimation results of the semi-parametric 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 non-linear effects of agglomeration economies and the smooth interaction between latitude and longitude to control for unobserved spatial heterogeneity.

### Table 5 about here

In the previous section we have reported a negative effect of *spe* both in manufacturing and in services, a result in line with previous empirical analyses. However, as discussed above, a higher specialization *per se* does not necessarily mean higher Marshallian economies, while the “industrial district” effect may better identify positive Marshallian externalities. Indeed, 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 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.

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 ( $edf$ ).<sup>15</sup> The results of  $F$ -tests suggest that all univariate smooth terms enter significantly the model. The  $edf$  is a measure of the term's non-linearity: 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 a decline in specialization always appears to be non-linear. In particular, we find a hockey stick-shaped relationship between specialization and local employment growth: a higher specialization reduces the employment dynamics due to a higher vulnerability to idiosyncratic shocks, but only up to a certain threshold, after which the relationship between employment growth and  $\log(spe)$  becomes null or negligible.

**Figure 1 about here**

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.

**Figure 2 about here**

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<sup>15</sup>Each univariate nonparametric term,  $f_k$ , is specified as a linear combination of known basis functions (we have used cubic basis functions) with associated unknown parameters to be estimated. In order to avoid both misspecification 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 between bias and variance of the estimates. To estimate model (2), we have used the method described by Wood (2006) which allows for automatic and integrated smoothing parameters selection. Wood has implemented this approach in the R package *mgcv*.

Allowing for non-linearities, we find a hump-shaped relationship between population density,  $\log(den)$ , and local employment growth (Figure 3 - Panel A): 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. 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. It is worth noticing that in the case of services the positive part of the hump-shaped curve prevails over the negative one; the opposite occurs in the case of manufacturing. This evidence helps explain the difference in the signs of the coefficients associated to  $\log(den)$  for manufacturing and services obtained with the log-linear regression model.

**Figure 3 about here**

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 non-linearities 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.

**Figure 4 about here**

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 accordance with the Porter's theory. In the case of manufacturing, our semi-parametric estimates provide evidence of a non-linear 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.

**Figure 5 about here**

Finally, Figure 6 displays the map of the geographical component in the geo-additive model. It shows that, after controlling for the most relevant variables and allowing for non-linearities, 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).

**Figure 6 about here**

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 semi-parametric 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 affect the coefficients of interest.

**Tables 6 and 7 about here**

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.<sup>16</sup> The results for the smooth non-parametric terms are very similar to those obtained without the IV method (see Figures 1-5 Panel B and Figure 7).

**Table 8 about here**

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<sup>16</sup>Bootstrapping standard errors for the coefficients of  $ID_{r,s}$  and  $ID_{r,s'}$  are reported in Table 8.

## 5 Conclusions

In this paper we have used a semi-parametric geo-additive model to analyze the effect on employment growth of various factors characterizing the local productive structure: localization and urbanization externalities, local competition and internal scale economies. This specification allowed us to simultaneously address some important issues, such as non-linearities in the effect of agglomeration externalities and residual spatial heterogeneity.

Empirical findings, obtained using Italy's Local Labor Systems (LLSs) data collected for the period 1981-2008, have highlighted that the degree of specialization computed by the location quotient is not suitable to effectively capture Marshallian externalities and it is only an indicator of vulnerability to idiosyncratic shocks. In fact, it would be a very hard task to capture Marshallian externalities through a single variable since the essence of this kind of external economies depends on a large number of socio-economic factors. 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 Marshall 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).

The flexibility of the semi-parametric approach has also allowed us to appreciate that some local characteristics have a non-linear 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 an 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 specialization *per se* has a negative (albeit non-linear) impact on employment dynamics, while a higher diversification has a positive effect on employment growth in manufacturing sectors corroborating Jacobs theory and a nonlinear effect in services. Finally, the geo-additive model, which incorporates a smooth spatial trend surface, is able to capture residual spatial heterogeneity.

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**Table 1a. National annual average employment growth rates**

<b>NACE rev.1</b>	1981-1991	1991-2001	2001-2008
<i>Manufacturing</i>			
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
<i>Services</i>			
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**

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

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

**Table 2 - Descriptive statistics**

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

**Table 3 - Correlation matrix**

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

**Table 4 - Log-linear model**

Basic specification

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

Table 5 - Semi-parametric geo-additive model

	Whole economy	Manufacturing	Services
Parametric terms	<i>Coefficients (s.e. in parentheses)</i>		
(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	<i>F test and edf (in square brackets)</i>		
$f_1(\log(spe))$	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
$R_{adj}^2$	0.094	0.091	0.197
REML	85,784	56,815	23,734

Notes: Dependent variable: Employment growth rate. All estimates includes 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.

**Table 6 - First stage: semi-parametric probit model for  $ID_{r,s}$**

	Whole economy	Manufacturing
Parametric terms	<i>Coefficients (s.e. in parentheses)</i>	
(Intercept)	-3.228*** (0.136)	-3.037*** (0.138)
<i>SpecIDsec</i> > 1	0.810*** (0.170)	0.742*** (0.170)
<i>SpecSmallSize</i> > 1	-0.189* (0.101)	-0.159 (0.104)
<i>Interaction</i>	0.561*** (0.180)	0.509*** (0.180)
<i>log(Anjou)</i>	0.194*** (0.041)	0.184*** (0.041)
<i>log(Spain)</i>	0.048** (0.022)	0.044** (0.022)
<i>log(Bourbon)</i>	-0.337*** (0.071)	-0.322*** (0.071)
<i>log(Venice)</i>	0.077*** (0.016)	0.080*** (0.016)
Non-parametric terms	$\chi^2$ test and edf (in square brackets)	
$f_1(\log(spe))$	333.37*** [3.950]	290.07*** [3.934]
$f_2(\log(div))$	10.53*** [2.143]	2.04 [1.001]
$f_3(\log(den))$	39.82*** [3.165]	40.95** [3.096]
$f_4(\log(size))$	86.81*** [2.737]	81.05*** [2.921]
$f_5(\log(comp))$	93.92*** [2.737]	60.99*** [2.680]
$h_{1981}(no, e)$	21.50*** [6.786]	19.44*** [6.828]
$h_{1991}(no, e)$	19.10** [6.738]	23.74*** [6.819]
$h_{2001}(no, e)$	31.23*** [8.075]	30.94*** [7.966]
No. of obs.	27,257	17,006
<i>REML</i>	1,265	1,228

Table 7 - First stage: semi-parametric probit model for  $ID_{r,s'}$

	Whole economy	Manufacturing	Services
Parametric terms	<i>Coefficients (s.e. in parentheses)</i>		
(Intercept)	-1.564*** (0.070)	-1.572*** (0.090)	-1.732*** (0.117)
$\log(\text{Anjou})$	0.152*** (0.016)	0.166*** (0.021)	0.135*** (0.024)
$\log(\text{Spain})$	0.080*** (0.009)	0.088*** (0.011)	0.062*** (0.014)
$\log(\text{Bourbon})$	-0.301*** (0.023)	-0.322*** (0.031)	-0.257*** (0.036)
$\log(\text{Venice})$	0.169*** (0.007)	0.150*** (0.009)	0.169*** (0.011)
$\log(\text{Ruggedness})$	0.052*** (0.009)	0.037*** (0.012)	0.078*** (0.015)
Non-parametric terms	$\chi^2$ test and edf (in square brackets)		
$f_1(\log(\text{spe}))$	351.5*** [3.832]	505.6*** [3.416]	112.7*** [3.679]
$f_2(\log(\text{div}))$	289.3*** [2.969]	453.7*** [2.962]	86.8*** [2.914]
$f_3(\log(\text{den}))$	260.7*** [3.796]	136.7** [3.687]	249.4*** [3.507]
$f_4(\log(\text{size}))$	113.3*** [2.848]	297.8*** [2.880]	201.8*** [2.609]
$f_5(\log(\text{comp}))$	66.9*** [2.690]	2478.5*** [2.474]	134.0*** [2.339]
$h_{1981}(no, e)$	907.9*** [13.224]	415.7*** [12.412]	388.5*** [11.369]
$h_{1991}(no, e)$	757.9*** [13.159]	308.5*** [12.044]	388.2*** [11.120]
$h_{2001}(no, e)$	944.6** [13.083]	435.2*** [11.793]	424.5*** [11.362]
No. of obs.	27,257	17,006	10,251
REML	10,213	6,053	3,788

Table 8 - Semi-parametric geo-additive model - IV method

	Whole economy	Manufacturing	Services
Parametric terms	<i>Coefficients (bootstrap s.e. in parentheses)</i>		
(Intercept)	0.158* (0.083)	0.159 (0.111)	0.091 (0.056)
$ID_{r,s}$	1.743*** (0.473)	2.629*** (0.571)	
$ID_{r,s'}$	0.935*** (0.141)	1.725*** (0.206)	0.084 (0.087)
Non-parametric terms	<i>F test and edf (in square brackets)</i>		
$f_1(\log(spe))$	209.65*** [3.866]	102.605*** [3.739]	227.651*** [3.891]
$f_2(\log(div))$	24.324*** [2.451]	48.892*** [1.866]	12.220*** [2.071]
$f_3(\log(den))$	4.702*** [2.265]	2.601* [1.007]	26.153*** [3.213]
$f_4(\log(size))$	45.147*** [2.860]	36.809*** [2.906]	19.2150*** [2.912]
$f_5(\log(comp))$	8.364*** [2.504]	3.271** [2.335]	37.288*** [1.005]
$h_{1981}(no, e)$	7.582*** [7.582]	9.959*** [6.403]	8.574*** [11.140]
$h_{1991}(no, e)$	12.550*** [5.530]	10.655*** [5.348]	15.435*** [8.246]
$h_{2001}(no, e)$	2.060** [6.618]	2.496** [6.859]	9.018*** [11.314]
No. of obs.	27,257	17,006	10,251
$R_{adj}^2$	0.094	0.091	0.197
REML	85,793	56,818	23,739

## Appendix 1

### Table A.1 Sector disaggregation

NACE rev.1	Sectors
<b>Manufacturing</b>	
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.
<b>Services</b>	
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.

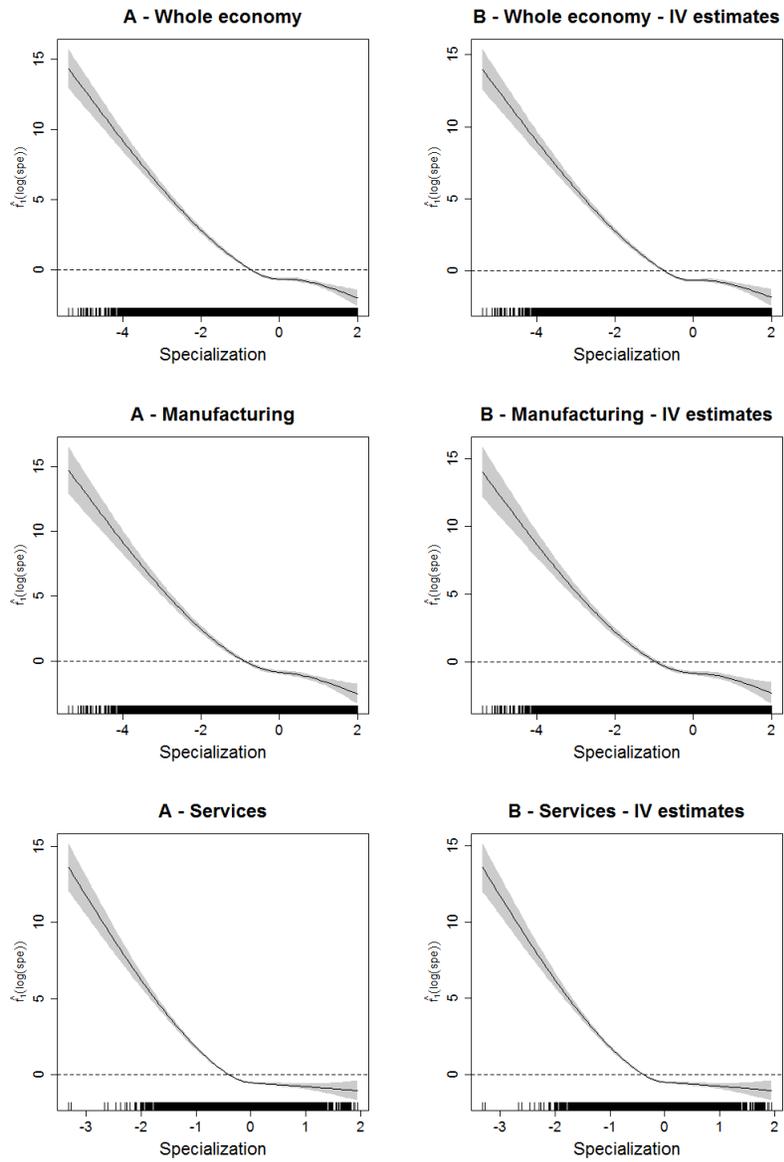


Figure 1: (A) Smooth effect of *spe*. (B) Smooth effect of *spe* with IV estimates.

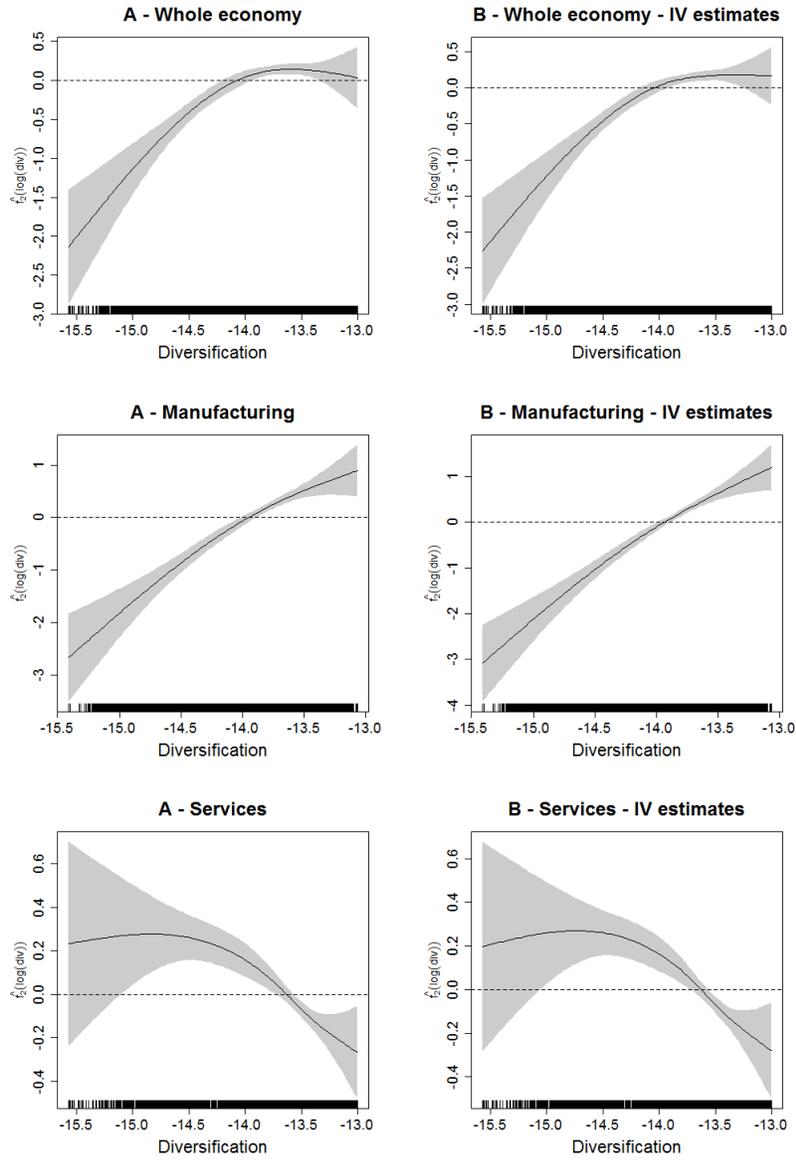


Figure 2: (A) Smooth effect of *div*. (B) Smooth effect of *div* with IV estimates.

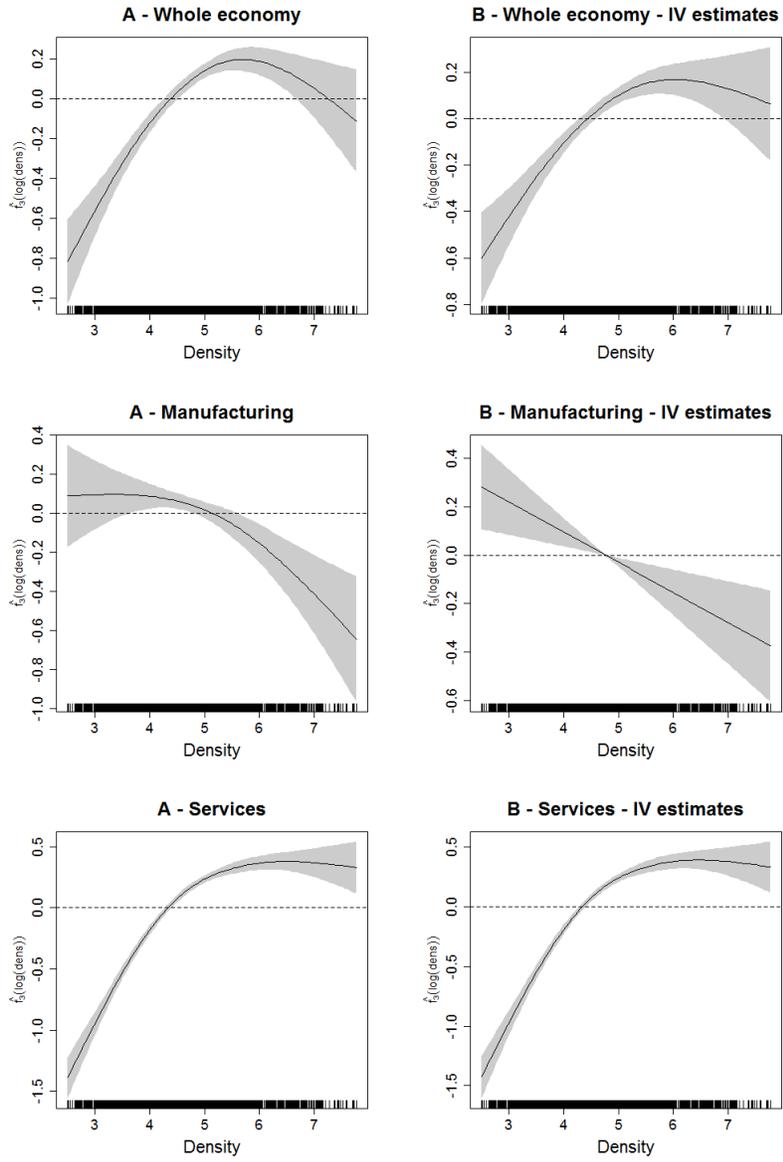


Figure 3: (A) Smooth effect of  $den.$  (B) Smooth effect of  $den$  with IV estimates.

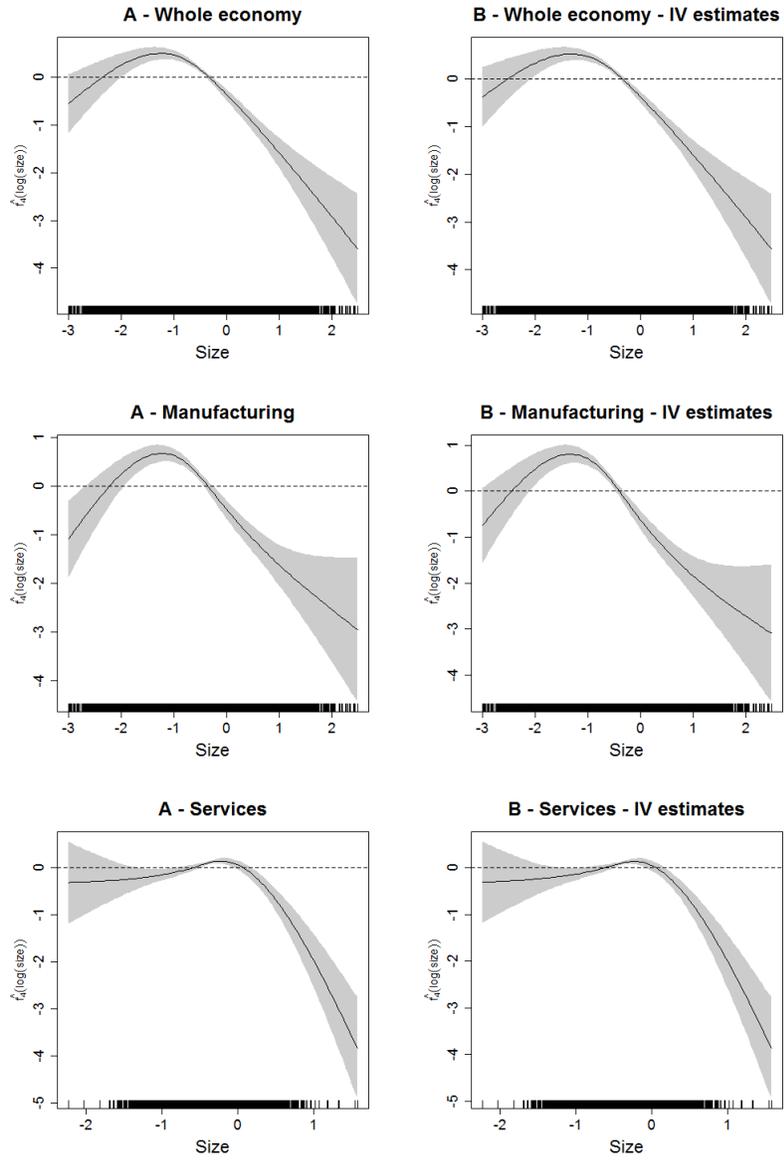


Figure 4: (A) Smooth effect of *size*. (B) Smooth effect of *size* with IV estimates.

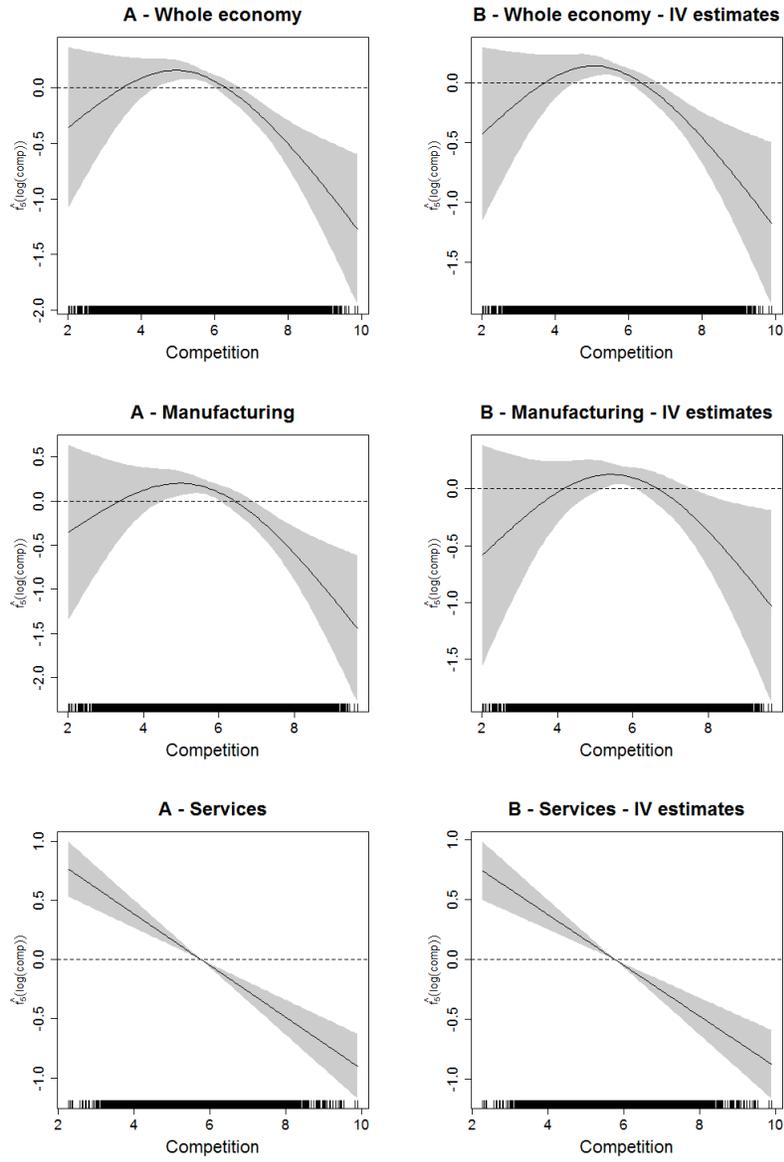


Figure 5: (A) Smooth effect of *comp*. (B) Smooth effect of *comp* with IV estimates.

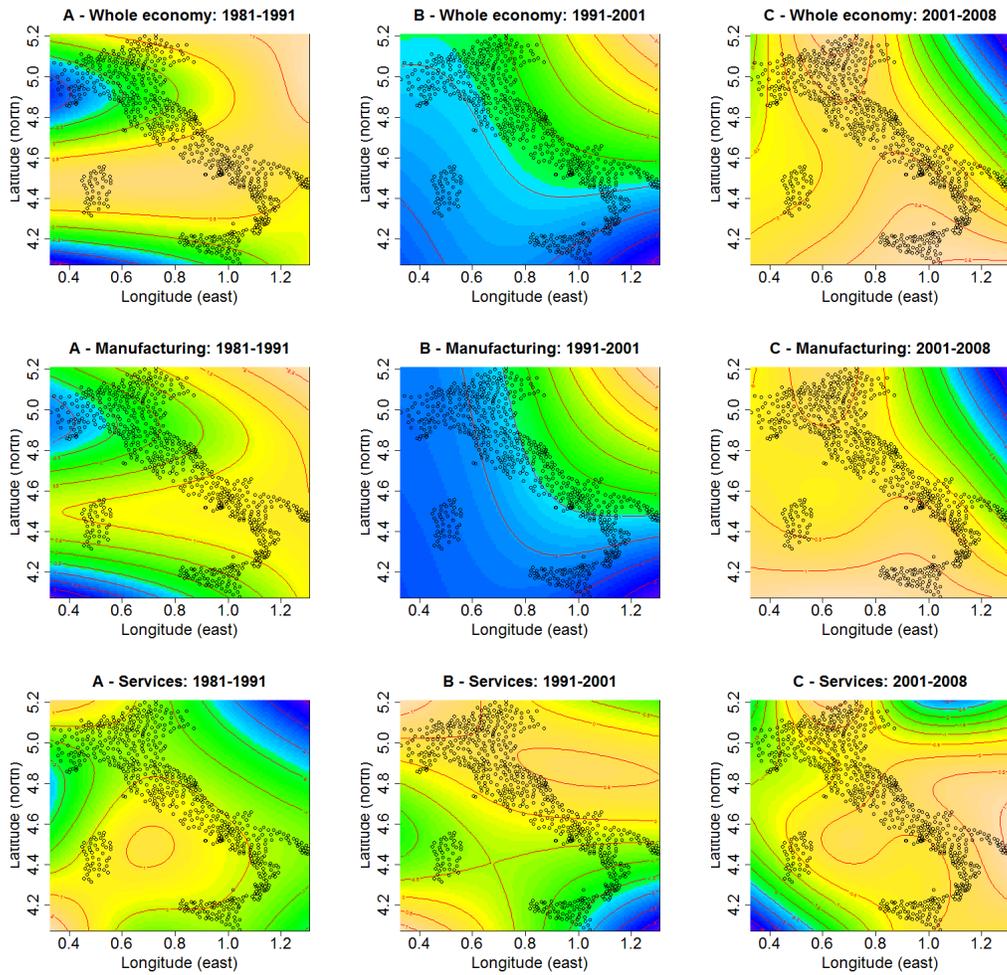


Figure 6: Geographical components of the geo-additive model for each time period. Contour lines for different values of the predicted employment growth rate in each LLS. X- and Y-axes measure degrees of longitude and latitude, respectively.