Industry structure, industrial districts and employment growth: evidence from semi-parametric geo-additive models*

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Abstract

Using Local Labour Systems (LLSs) data at two-digit sectoral level, we assess how the local productive structure (presence of an industrial district, level of productive specialization, degree of diversification, economic density, level of local competition and average firm size) 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 labour 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

In this paper we analyse the effect of industry structure on local employment growth in Italy. The hypothesis put into empirical test concern the role of many factors characterizing the local productive structure: 1) the presence of an *industrial district*, 2) the level of productive *specialization*; 3) the degree of sectoral *diversification*; 4) the population *density*; 5) the level of *local competition*; and 5) the average *firm size*. In this way we follow the broad literature started by Glaeser et al. (1992) and Henderson et al. (1995).[1]

Previous studies carried out for the case of Italy (Mameli et al., 2008; Paci and Usai, 2008) 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 (corroborating Jacobs theory) on local employment growth. Only Forni and Paba (2002) find a positive impact of both specialization and Jacobs externalities. **As for the other measures of industry structure, Paci and Usai (2008) find 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. Mameli et al. (2008) report evidence of a positive linear effect of population density, while in Paci nd Usai (2008) the effect of population density is positive for the whole sample (including both manufacturing and services) and null for the manufacturing sectors. 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., ...TBC**

In the present paper, we claim that the results of previous studies on the case of Italy may suffer from a number of model mis-specification issues. First, like in Glaeser et al. (1992) and Combes (2000), all of these studies 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

[1] See also, among others, Henderson, 1997; Combes, 2000; Rosenthal and Strange, 2004; de Groot *et al.*, 2007; Melo *et al.*, 2009. For a recent review of the literature, see Beaudry and Schiffauerova (2009).

likely to bolster asymmetric developments and differences in growth rates across local economies, unless some effective insurance mechanisms or "risk sharing" help "protect" the local economic environment against idiosyncratic shocks (Basile and Girardi, 2009). A form of risk sharing mechanism is represented by those socio-economic factors (such as mutual trust and *coopetition*) which contribute to determine the "industrial atmosphere" theorised by Marshall as well as by several Italian economists (e.g. Becattini, 1987; Becattini et al. 2003; Bellandi, 2007). In a nutshell, if we want to empirically 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, previous studies on Italy have disregarded the existence of non-linearities in the relationship between industry structure and employment growth, while the theory suggests a hump-shaped relationship between economic density and growth as well as a hump-shaped relationship between local competition (or scale economies) and growth. 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 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 these studies 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 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), in this paper we contribute to the existing literature a) by assessing the presence of non-linearities in the relationship between industry structure and local-sector employment growth, b) by comparing the relative performance of industrial districts and c) by controlling for 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, longitude and altitude) for each time period which permits us to control for time-varying unobserved spatial heterogeneity.

Controlling for endogeneity with instrumental variables, our empirical evidences confirm that industrial districts have performed better than the other LLSs during the sample period, thus suggesting that Marshallian externalities exerted a positive role on local employment growth. Regression results also highlight a hockey stick-shaped relationship between specialization and local employment growth: a higher specialization reduces the employment dynamics because of a higher exposition 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 organised as follows. Section 2 describes our modelling 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 Modelling regional employment growth

2.1 A log-linear specification

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

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

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; 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*.[2]

The variable *spe* should capture external economies which may occur 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.[3] 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.

[2] A similar specification has been used by Paci and Usai (2008) and Mameli et al. (2008). These authors also extend this model by introducing other explanatory factors (such as human and social capital) into the model framework, but they conclude that the baseline model (1) does not suffer from problems connected to omitted variables. 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.

[3] In MAR-Theory, static externalities refer to cost reductions deriving from the creation of a specialized labour 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.

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). 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 Schiffauerova (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. Finally, 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.[4]

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 favours 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 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. 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 the an increase in economic density involves the accessibility to a broader supply of local public services and a higher

[4]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 the dependent variable, the sign for the MAR coefficient becomes positive.

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. For the case of Italy, Mameli et al. (2008) report evidence of a positive linear effect of population density, while in Paci nd 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 labour, 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 incapabilities. 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

Many empirical studies on local employment growth have used the log-linear model (1), 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 the results of these studies suffer from a number of model mis-specification issues.

First, as mentioned above, all of the previous studies on Italy measure Marshallian externalities, *spe*, with the location quotient (or Balassa index) and in most of the cases they find a negative effect of specialization on employment growth, notwithstanding the strong anecdotal evidence of the economic success of *industrial districts*, the places where Marshallian externalities are magnified. However, 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). Indeed, the Marshall’s theory on external economies, revisited by Becattini (1979) to explain the successful performance of Italian industrial districts, does not only consider the degree of production specialization to describe the characteristics of industrial districts. 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. 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 for the firms and their employees against idiosyncratic 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.

Second, most of the previous studies disregard the existence of non-linearities in the relationship between agglomeration economies and growth. However, non-linearities are very likely to occur in regional 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 an inverted-U 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 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 labour; above a certain threshold, however, a larger plant size can lead to an increase in information and managerial costs.

Third, most of the previous studies 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. 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. However, panel-data studies using area fixed effects to capture any sort of localised advantage (e.g. Henderson, 2003) find that such permanent advantage leave substantial agglomeration effects unexplained.

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:

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

where f_k and h_t are unknown smooth functions of the covariates (see Appendix 2); $ID_{r,s}$ 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; and n, e and a indicate the latitude (*northing*), the longitude (*easting*) and the average *altitude* of the region, respectively.

This model provides a relatively flexible framework for the analysis of regional employment growth. First, the inclusion of smooth terms of the covariates allows us to identify non-linearities in the relationship between growth and industry structure without imposing any parametric polynomial form. Second, the inclusion of a geo-additive component (the smooth interaction between latitude, longitude and altitude) for each time period permits us to control for time-varying spatial unobserved heterogeneity and thus to abstract from heterogeneity of the underlying space.[5] Finally, the inclusion of the dummy variables $ID_{r,s}$ and $ID_{r,s'}$ allows us to identify 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.

[5] Although geo-additive models are widely used in environmental studies and in epidemiology (see, i.a., Kelvyn and Wrigley 1995; Kammann and Wand 2003; Augustin et al. 2009), they are rarely considered for modelling economic data, and, to the best of our knowledge, this paper presents their first application to the analysis of local employment growth.

2.4 The identification of the ID effect

Estimating the *causal* effect of 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).[6] However, 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[7], 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 for the correction of the omitted variable bias.

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 socio-economic conditions (such as mutual trust, family ties, a large number of small enterprises and so on), favourable 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 labour 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

[6] 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.

[7] 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.

bias when estimating the effect of ID on employment growth in our semi-parametric regression framework.

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. 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. Inference on the parameters is carried our through bootstrapping methods.

3 Data and variables

Following Mameli et al. (2008) and Paci and Usai (2008), the geographical units of observation considered in the present analysis are the Local Labour Systems (LLSs), that are territorial aggregations of neighbouring municipalities, identified on the basis of daily labour 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 normative boundaries, since municipalities are the basic unit of observation to survey daily labour 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 constitute 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 employment of the main industry in firms of all sizes; b) the employment

in small firms of the main industry is more than half of the employment of medium-sized firms, if there is only one medium-sized firm (see Sforzi, 2009, for further details).[8] 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 labour 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 (Paci and Usai, 2008), we take into account this process of structural change in employment dynamics. We consider 15 sectors at the 2 digit ATECO91-NACE rev.1 level[9] (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.

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

[8] 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 *scale* more than the effect of Marshallian externalities (industrial atmosphere). However, by including smooth terms for *spe* and *scale* in our model specification allows us to correctly identify the *ID* effect.

[9] 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.

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, t corresponds to the final year of each period (1991, 2001 and 2008), while $t - \tau$ is the initial year of each period (1981, 1991 and 2001). 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 and 1b 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 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 (Glaeser et al., 1992; Combes, 2000; Mameli et al., 2008; Paci and Usai, 2008), 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. This index measures the relative concentration of a sector in a LLS with respect to the average concentration of the same sector in Italy. It can be expressed as follows:

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

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 a de-specialization. According to the traditional view, a positive effect of $spe_{r,s}$ would support the 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. In Model (2) the variable *spe* only captures the vulnerability of the region to idiosyncratic shocks. We also include the dummy $ID_{r,s'}$ to evaluate the impact of industrial district specialized in a given sector s into the employment growth rate of other sectors. However, as discussed above, the identification of the ID effect requires the use of instrumental variables.[10] In the present context, we use as valid instruments two variables: the first one ($man - firms80$) is the number of manufacturing firms active in 1980 in the province to which the LLS belongs; the second instrument ($soc - cap$) is represented by a measure of social capital estimated at the LLS level by Coppola et al. (2007).[11]

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:[12]

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

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 significant 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, den_r, is used to measure the *scale* of urbanization externalities as in Mameli et al. (2008) and Usai and Paci (2008):

[10] Since all other explanatory variables are measured with a sufficiently time lag (about ten years), they can be treated as predetermined. Industrial districts, instead, are identified on the bases of several criteria using census data available in 2001, so that ID cannot be considered as a predetermined dummy variable.

[11] Since there is substantial persistence in the spatial distribution of industrial districts but drivers of high growth today differ from those in the distant past, a good instrument is represented by historical data on the presence of manufacturing firms and on social capital.

[12] 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).

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

where P_r indicates the population in the r-th LLS and A_r indicates the area in km2. A positive effect of den_r implies that positive urbanization economies dominate over negative congestion effects.

Following Combes (2000), O'hUallochain and Satterthwaite (1992) and Mameli et al. (2008), internal economies of scale, $size_{r,s}$, are measured by the average plant size in the s-th sector located in the r-th LLS compared to Italy as a whole:

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

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 labour within the firm dominates over the negative effect of higher information and managerial costs.

Following Illy et al. (2011), Mameli et al. (2008), Paci and Usai (2008) and Combes (2000), we measure local competition, $comp_{r,s}$, using the following normalized Herfindahl index:

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

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 that 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.

Finally, latitude and longitude of the LLS' centroids are included in the model to capture unobserved spatial heterogeneity (e.g. first nature location advantages as defined in Krugman, 1993).

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

Tables 2 and 3 about here

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 be interpreted as elasticities.[13]

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.

Like in Paci and Usai (2008), the effect of population density (*den*) is positive in the case of the whole economy and of services, indicating that that urbanization economies dominate over con-

[13] In order to estimate equation (1), Combes (2000) has used the sample selection regression model (Heckman, 1979) because plants smaller than 20 workers were not in his dataset. In our case this selection bias cannot occur, since our dataset includes local units of all size classes, even those with just 1 worker. Nevertheless, within the group of manufacturing sectors, we had to exclude 2,504 observations (i.e. about 12% of the total number of observations in manufacturing) since 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 (see Table A2 in appendix).

gestion costs, while it is negative and slightly significant in the case of manufacturing. Therefore, according to linear estimation results, in Italy positive urbanization externalities tend to either compensate or over-compensate urbanization dis-economies in service sectors and to under-compensate urbanization dis-economies in manufacturing.

Linear regression models also indicate a negative effect of *size*, 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. 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 by Paci and Usai (2008) and by 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. In conclusion, the diagnostics of the residuals suggest that the log-linear model is mis-specified due to the assumption of homogeneous behaviour. This assumption is relaxed by estimating the semi-parametric model and by letting the variable enter the model smoothly as shown in the next section.

4.2 Evidence from semi-parametric models

In this section we discuss 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, longitude and altitude to control for unobserved spatial heterogeneity. In Table 5 we report the estimation results of Model (2) obtained without controlling for potential endogeneity bias, while in Table 6 we report the IV results obtained when ID is treated as an endogenous dummy variable.

Table 5 about here

In the previous section we have reported a negative effect of *spe* both in manufacturing and in services, a results in line with previous empirical analyses. However, as discussed above, a higher specialization *per se* does not necessarily mean higher Marshallian economies and, thus, higher local economic growth; rather, it is widely recognized that higher specialization levels may lead higher vulnerability to idiosyncratic shocks and, thus, are likely to bolster asymmetric developments and differences in growth rates across local economies, unless some effective insurance mechanisms or "risk sharing" help "protect" the local economic environment against idiosyncratic shocks (Basile and Girardi, 2009). A form of risk sharing mechanism is represented by those socio-economic factors (such as mutual trust and coopetition) which contribute to determine the "industrial atmosphere" theorised by Marshall as well as by many Italian economists (e.g. Becattini, 1987; Bellandi, 2007). Following this line of reasoning, we have included among the parametric terms of Model (2) the dummy variable ID. The coefficients associated to this variable is always positive and significant, indicating that industrial districts (the places where Marshallian externalities are magnified) 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 in 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*). Each univariate smooth term is specified as a cubic regression spline, while the smooth interaction between *latitude*, *longitude* and *altitude* is specified as a tensor product.[14] F-tests indicate that all terms enter the model significantly. 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 for $f_2\left(log(div)\right)$ and $f_3\left(log(den)\right)$ in manufacturing and for $f_2\left(log(div)\right)$ and $f_5\left(log(comp)\right)$ in services. The spatial trend term $\left(h\left(n_r, e_r, a_r\right)\right)$ also is highly significant in all sectors and in all periods, suggesting the presence of an 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. The *log(spe)*-plot (Figure 1 - Panel A) confirms that, *ceteris*

[14] See Appendix 2.

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 and substantially linear in the whole economy and in manufacturing, while it is linearly negative in the service sectors (Figure 2 - Panel A). Thus, in line with previous evidence and corroborating Jacobs' theory, diversification boosts employment growth in manufacturing and reduces it in services.

Figure 2 about here

Allowing for non-linearities, we find a hump-shaped relationship between population density, $log(den)$, and local employment growth for the whole economy and for services (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. In the case of manufacturing sectors the results suggest that negative congestion effect always prevails over the positive externality.

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 labour; 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 services.

Figure 4 about here

The relationship between growth and $log(comp)$ (Figure 5 - Panel A) is monotonically 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 and of the whole economy, however, 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, in line with the MAR theory; after a certain threshold (that is starting from high levels of $log(comp)$), a decrease of market power favours 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

In Table 6 we report the results of the IV estimation of Model (2). Controlling for endogeneity does not change qualitatively the econometric results discussed so far. IV estimates confirm that LLSs belonging to an industrial district have performed better than the other LLSs during the sample period, thus suggesting that Marshallian externalities exerted a positive role on local economic growth. 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, except for $ID_{r,s'}$ in the case of the whole sample.[15] Finally, 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).

[15]The standard error of the coefficient of the dummy variables $ID_{r,s}$ and $ID_{r,s'}$ reported in Table 6 are computed by using bootstrapping methods.

5 Conclusions

In this paper we propose a semi-parametric geo-additive model to analyse the effect of localization and urbanization externalities, local competition and internal scale economies on sector-region employment growth. This specification allows us to simultaneously address some important issues, such as non-linearities in the effect of agglomeration externalities and residual spatial heterogeneity. We apply this model to Italy's Local Labour Systems (LLSs) data collected for three successive periods (1981-1991, 1991-2001 and 2001-2008).

Moreover, we claim that the variable commonly used to capture the effect of specialization externalities, that is the location quotient, is not suitable to effectively capture Marshallian externalities. Higher specialization levels are indeed an indicator of higher 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 the Marshallian externalities depends on a large number of socio-economic factors. In order to bypass this problem, we exploit the availability of a classification of LLSs in Italy as industrial districts and non-industrial districts.

Our empirical evidences (even after controlling for potential endogeneity bias) confirm that industrial districts have performed better than the other LLSs both in manufacturing and service sectors, thus confirming that Marshall externalities exert a positive effect on local employment growth. Moreover, a higher specialization *per se* has a negative (albeit non-linear) impact on employment dynamics. A higher diversification, instead, has a positive effect on employment growth in manufacturing sectors corroborating Jacobs theory and a negative effect in services.

The flexibility of the semi-parametric approach also allows 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 emerges an hump-shaped relationship between average firm size and local employment growth. Non-linearities are also evident for the relationship between the level of local competition and employment growth. Finally, a 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

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 annual average LLS employment growth rates. Total sample

NACE rev.1	1981-1991	1991-2001	2001-2008
Manufacturing			
DA	3.865	3.285	4.261
DB-DC	7.425	7.287	9.517
DD-DE	3.495	3.242	4.585
DF-DG	10.577	9.316	12.276
DH-DI	6.383	5.710	6.944
DJ	4.780	4.242	5.075
DK	8.896	8.454	12.679
DL	10.402	7.859	14.887
DM	10.426	10.928	16.509
DN	9.252	7.570	12.061
Services			
G	1.247	1.445	1.486
H	2.493	2.138	3.292
I	2.169	3.012	3.774
J	2.823	2.541	2.877
K	3.076	2.616	2.946

Table 1c. Mean and standard deviations of annual average LLS 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	4.04(4.04)	3.20(3.20)	3.92(3.92)	3.19(3.19)	3.55(3.55)	5.25(4.04)
DB-DC	7.74(7.74)	7.70(7.70)	10.28(10.28)	5.71(5.71)	5.72(5.72)	6.37(6.37)
DD-DE	3.64(3.64)	3.32(3.32)	4.76(4.76)	2.93(2.93)	2.75(2.75)	3.91(3.91)
DF-DG	10.71(10.71)	9.78(9.78)	12.40(12.40)	10.20(10.20)	7.91(7.91)	11.94(11.94)
DH-DI	6.65(6.65)	6.02(6.02)	7.25(7.25)	5.26(5.26)	4.08(4.08)	5.66(5.66)
DJ	5.07(5.07)	4.44(4.44)	5.35(5.35)	3.51(3.51)	3.30(3.30)	3.91(3.91)
DK	9.58(9.58)	9.39(9.39)	13.81(13.81)	6.45(6.45)	4.77(4.77)	8.03(8.03)
DL	11.10(11.10)	8.24(8.24)	14.68(14.68)	8.15(8.15)	6.41(6.41)	15.34(15.34)
DM	10.65(10.65)	10.96(10.96)	17.33(17.33)	9.65(9.65)	10.80(10.80)	13.88(13.88)
DN	9.58(9.58)	7.90(7.90)	12.30(12.30)	7.44(7.44)	6.35(6.35)	10.70(10.70)
Services		*Non-ID*			*ID*	
G	1.31(1.31)	1.50(1.50)	1.57(1.57)	1.02(1.02)	1.11(1.11)	1.18(1.18)
H	2.59(2.59)	2.21(2.21)	3.34(3.34)	2.15(2.15)	1.75(1.75)	3.12(3.12)
I	2.26(2.26)	3.09(3.09)	4.03(4.03)	1.81(1.81)	2.57(2.57)	2.72(2.72)
J	2.88(2.88)	2.58(2.58)	2.95(2.95)	2.62(2.62)	2.32(2.32)	2.57(2.57)
K	3.22(3.22)	2.70(2.70)	3.05(3.05)	2.55(2.55)	1.20(1.20)	2.55(2.55)

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

Table 4 - Log-linear model

Basic specification

	Whole economy	***Manufacturing***	***Services***
Variables	*Coefficients (s.e. in parentheses)*		
(Intercept)	3.775***	14.787***	-3.874***
	(1.091)	(2.071)	(0.702)
$log(spe)$	-1.305***	-1.333***	-1.474***
	(0.058)	(0.067)	(0.078)
$log(div)$	0.310***	1.000***	-0.200***
	(0.080)	(0.143)	(0.052)
$log(den)$	0.132***	-0.124*	0.311***
	(0.043)	(0.068)	(0.035)
$log(size)$	-0.706***	-0.727***	-0.160*
	(0.077)	(0.086)	(0.094)
$log(comp)$	-0.090**	-0.125**	-0.097***
	(0.042)	(0.058)	(0.035)
No. of obs.	27,949	17,680	10,269
$R^2_{adj.}$	0.076	0.072	0.123
RESET test	24.045	13,804	30.792
	[0.000]	[0.000]	[0.000]

Notes: Dependent variable: Employment growth rate. All estimates includes time fixed effects. Standard deviations (in parenthesis) are computed using robust covariance matrix estimators. RESET test is a test for linearity.

Table 5 - Semi-parametric geo-additive model

	Whole economy	**Manufacturing**	**Services**
Parametric terms		*Coefficients (s.e. in parentheses)*	
(Intercept)	0.465*** (0.040)	0.700*** (0.062)	-0.042 (0.029)
$ID_{r,s}$	1.895*** (0.282)	2.188*** (0.345)	
$ID_{r,s'}$	0.120 (0.094)	0.300** (0.148)	0.224*** (0.068)
Non-parametric terms		*F test and edf (in square brackets)*	
$f_1\,(log(spe))$	233.306*** [3.844]	139.472*** [3.711]	268.512*** [3.909]
$f_2\,(log(div))$	14.676*** [2.302]	35.473*** [1.752]	33.995*** [1.004]
$f_3\,(log(den))$	3.349*** [2.528]	5.978** [1.028]	25.877*** [3.394]
$f_4\,(log(size))$	39.480*** [2.857]	31.640*** [2.904]	16.730*** [2.908]
$f_5\,(log(comp))$	10.416*** [2.512]	7.950*** [2.473]	42.344*** [1.245]
$h_{1981}\,(no, e, a)$	4.646*** [13.997]	4.682*** [11.238]	5.108*** [24.902]
$h_{1991}\,(no, e, a)$	6.500*** [15.003]	4.713*** [14.762]	11.482*** [14.635]
$h_{2001}\,(no, e, a)$	1.528** [21.951]	1.926** [13.882]	5.827*** [30.602]
No. of obs.	27,910	17,656	10,254
$R^2_{adj.}$	0.095	0.093	0.190
$REML$	87,979	58,945	23,801

Table 6 - Semi-parametric geo-additive model - IV method

	Whole economy	**Manufacturing**	**Services**
Parametric terms		*Coefficients (s.e. in parentheses)*	
(Intercept)	0.307*** (0.053)	0.501*** (0.084)	-0.209*** (0.047)
$ID_{r,s}$	1.373** (0.673)	2.671*** (0.842)	
$ID_{r,s'}$	0.880*** (0.182)	1.178*** (0.295)	0.963*** (0.175)
Non-parametric terms		*F test and edf (in square brackets)*	
$f_1\,(log(spe))$	215.007*** [3.852]	116.715*** [3.709]	271.587*** [3.913]
$f_2\,(log(div))$	18.297*** [2.294]	48.203*** [1.589]	34.409*** [1.005]
$f_3\,(log(den))$	3.142** [2.279]	3.931** [1.011]	16.779*** [3.320]
$f_4\,(log(size))$	38.416*** [2.839]	34.454*** [2.910]	17.448*** [2.917]
$f_5\,(log(comp))$	8.689*** [2.471]	5.287** [2.430]	68.515*** [1.061]
$h_{1981}\,(no, e)$	5.566*** [13.641]	4.694*** [12.053]	5.685*** [24.163]
$h_{1991}\,(no, e)$	5.018*** [14.815]	4.884*** [13.050]	5.463*** [15.669]
$h_{2001}\,(no, e)$	1.330 [14.948]	1.879** [12.677]	6.158*** [28.946]
No. of obs.	27,910	17,656	10,254
$R^2_{adj.}$	0.093	0.092	0.190
$REML$	87,989	58,952	23,793

Appendix 1

Table A.1 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.

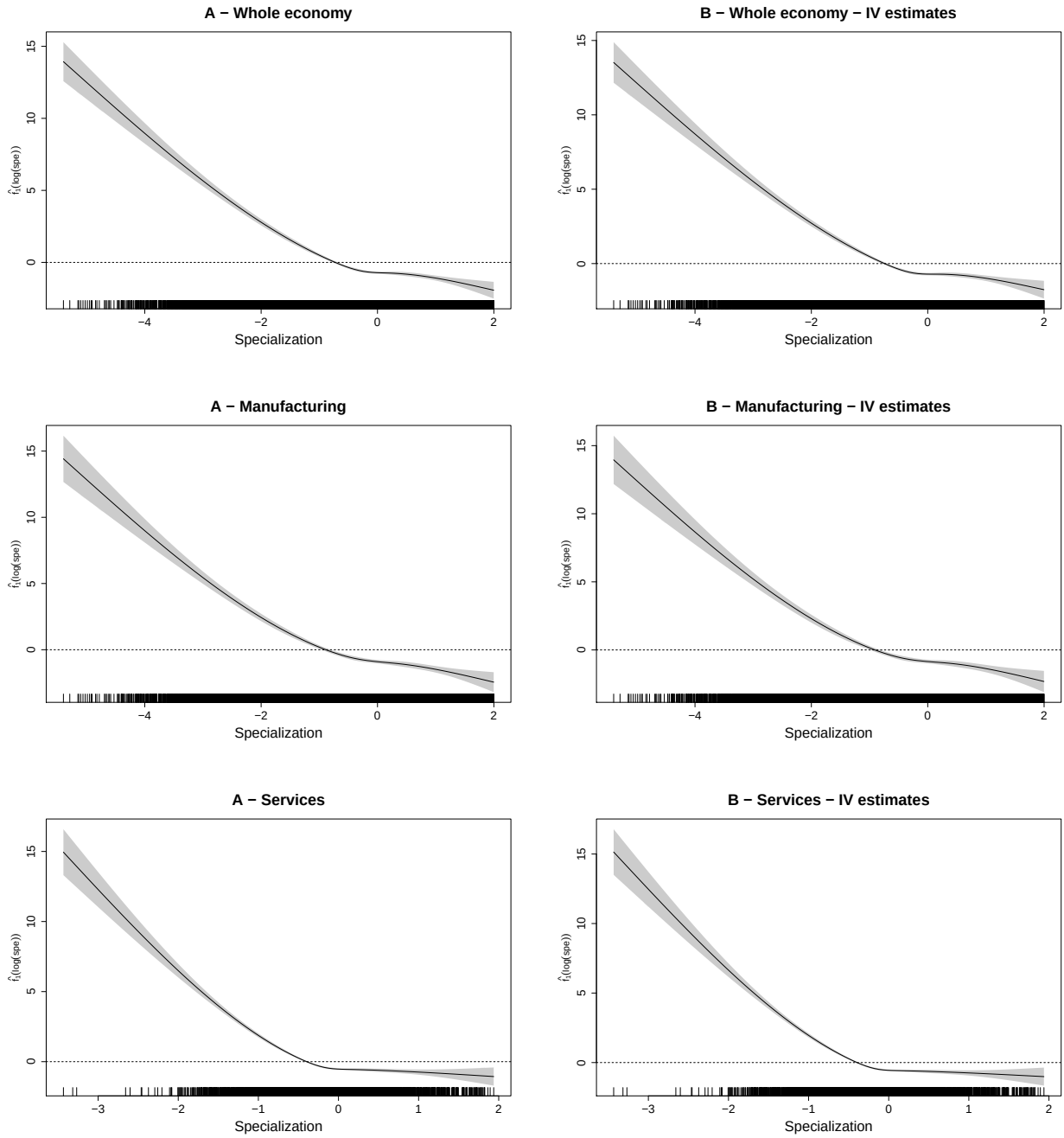

Figure 1: (A) Smooth effect of *spe*. (b) Smooth effect of *spe* with IV estimates.

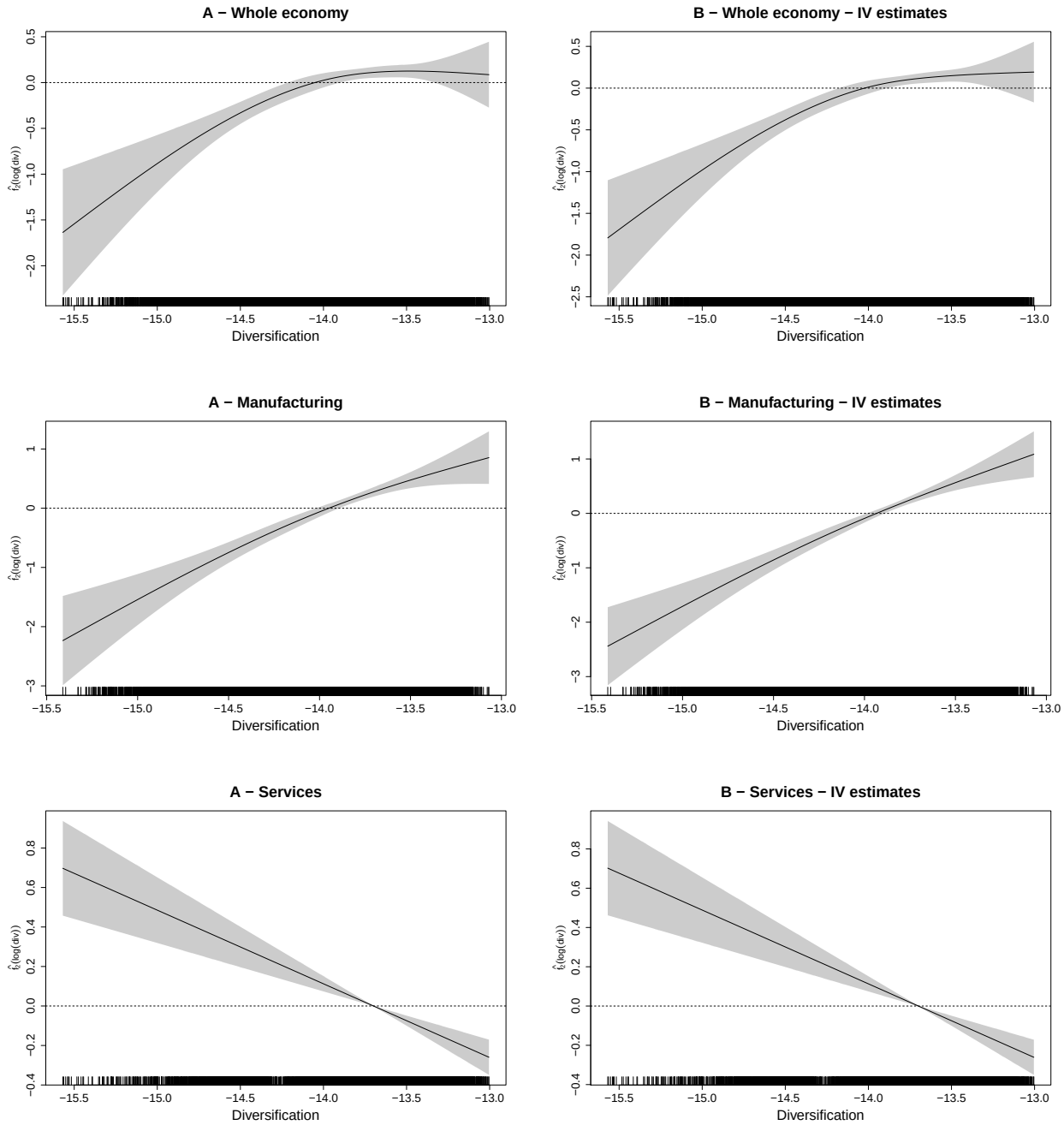

Figure 2: (A) Smooth effect of *div*. (b) Smooth effect of *div* with IV estimates.

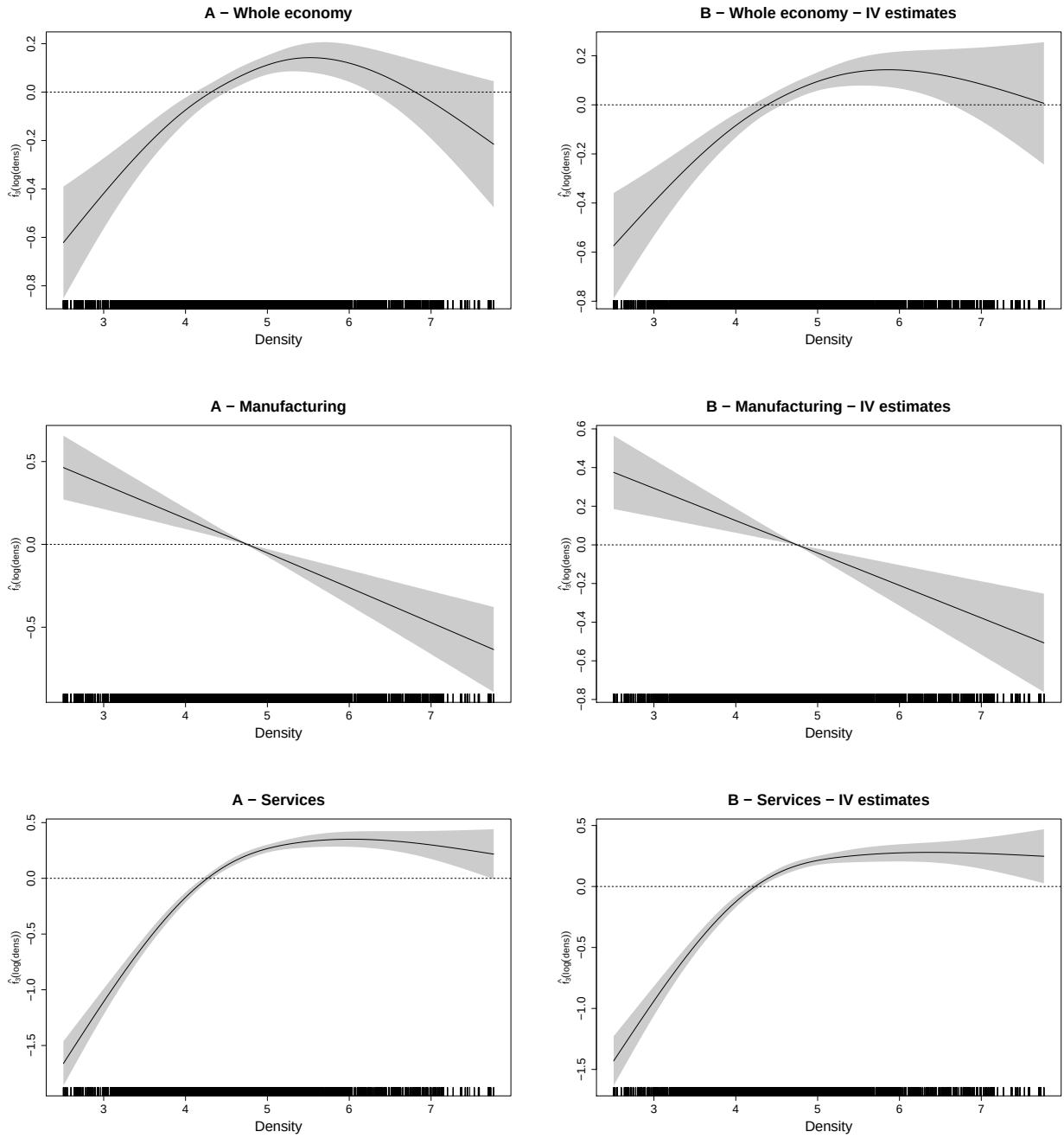

Figure 3: (A) Smooth effect of *den*. (b) Smooth effect of *den* with IV estimates.

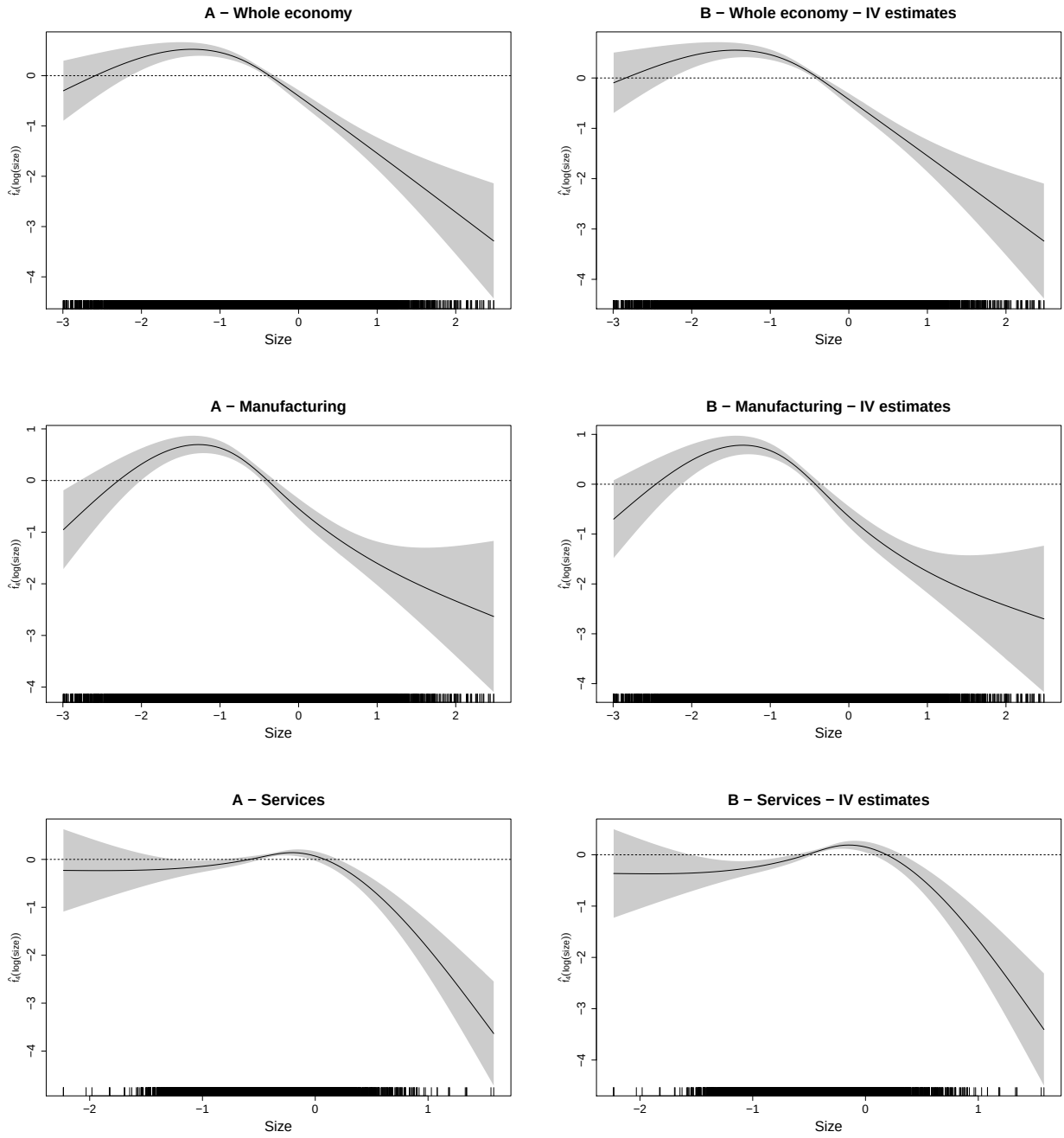

Figure 4: (A) Smooth effect of *size*. (b) Smooth effect of *size* with IV estimates.

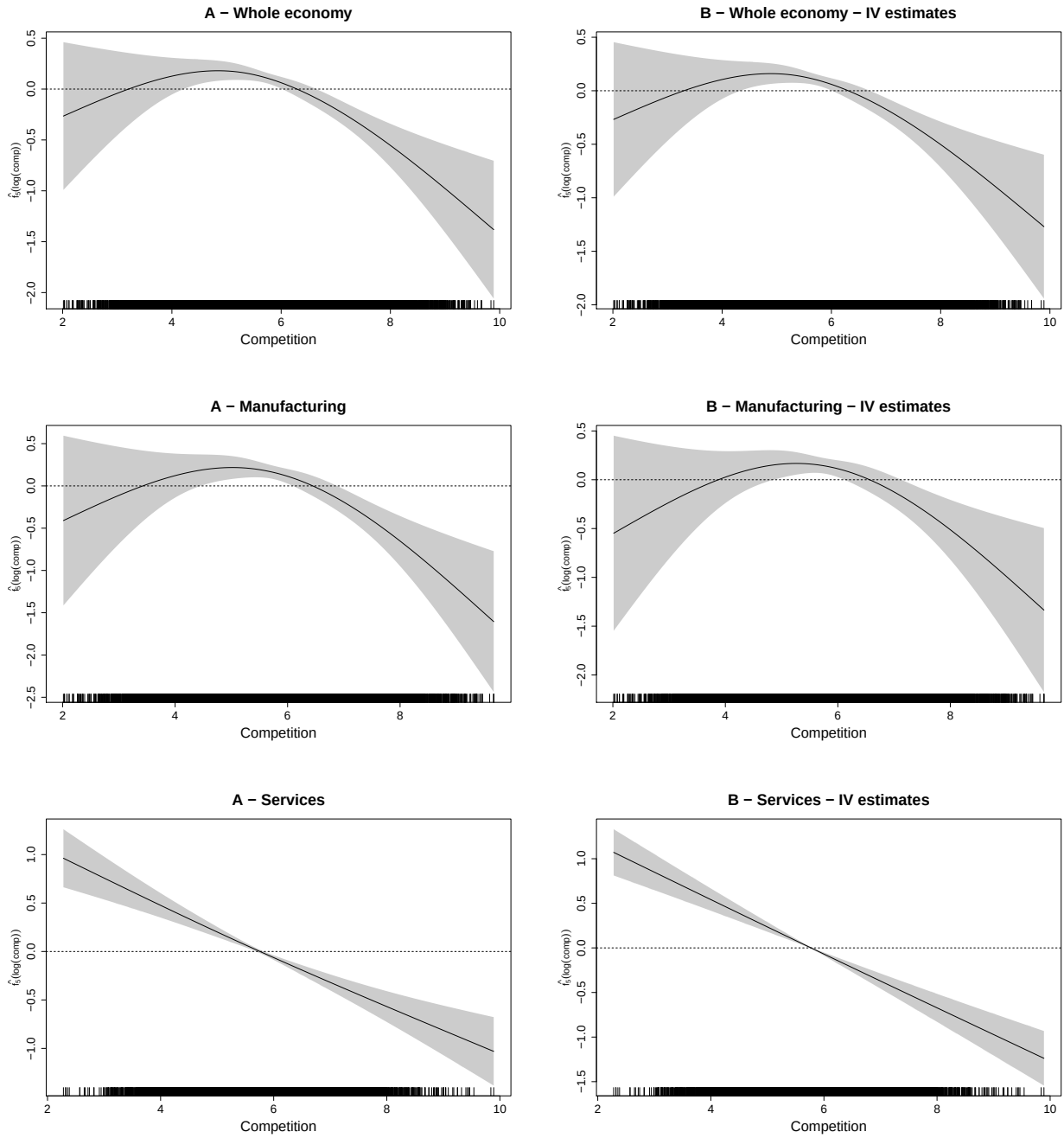

Figure 5: (A) Smooth effect of *comp*. (b) Smooth effect of *comp* with IV estimates.

Appendix 2

Methodology

Each univariate smooth term in equation (2) can be represented as $f_j(x_j) = \sum_{k=1}^{K_j} \beta_{jk} b_{jk}(x_j)$, where the $b_{jk}(x_j)$ are known basis functions, while the β_{jk} are unknown parameters to be estimated. One or more measures of wiggliness $\beta_j^{'} S_j \beta_j$, where S_j are positive semi-definite matrices, is associated with each smooth function. Typically, the wiggliness measure evaluates a function like the univariate spline penalty $\int f_j^{''}(x_j)^2 dx$ or its thin-plate spline generalization (Wood, 2006). The penalized spline base-learners can be extended to two or more dimensions to handle interactions. Specifically, Wood (2006, Section 4.1.5) recommends using thin-plate regression splines for smooth interactions of quantities measured in the same units (such as the spatial coordinates), and tensor products for smooth interactions of quantities measured in different units.

Table A2 - Log-linear model (Sample Selection Model - ML estimation)
Basic specification

	Whole economy		***Manufacturing***	
Variables	*Coefficients (s.e. in parentheses)*			
	Selection	Outcome	Selection	Outcome
(Intercept)	-0.421***	4.018***	-0.879***	15.084***
	(0.061)	(1.188)	(0.068)	(2.028)
Tourism	0.074**		0.072**	
	(0.033)		(0.036)	
Agriculture	-0.016		-0.020	
	(0.057)		(0.063)	
Textile	0.080**		0.092**	
	(0.033)		(0.037)	
Other Made in Italy	0.434***		0.485***	
	(0.033)		(0.037)	
Heavy Manufacturing	0.454***		0.504***	
	(0.050)		(0.054)	
$log(den)$	0.380***	0.091*	0.426***	-0.178**
	(0.014)	(0.048)	(0.015)	(0.074)
$log(spe)$		-1.297***		-1.320***
		(0.047)		(0.061)
$log(div)$		0.311***		0.998***
		(0.086)		(0.141)
$log(size)$		-0.720***		-0.750***
		(0.063)		(0.082)
$log(comp)$		-0.085**		-0.117**
		(0.037)		(0.053)
No. of obs.	30,458		20,184	
Censored obs.	2,509		2,504	
Log-Likelihood	-96,431		-66,158	
Rho	-0.092*		-0.078	
p-value	(0.049)		(0.048)	

Notes: See Table 4. Rho is the estimated correlation coefficient between the error term of the selection equation and the outcome equation.