# How are the potential gains from economic activity transmitted to the labour factor: more employment or more wages? Evidence from the Portuguese case*

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***JEL classification:*** *R12, O14, C23, L60.*

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# How are the potential gains from economic activity transmitted to the labour factor: more employment or more wages? Evidence from the Portuguese context

**Abstract:**

The paper analyses the role of knowledge externalities in firms' employment and workers' wages. We test whether agglomeration economies and regional knowledge base exert a greater impact on wage growth than on employment growth, using spatial panel econometric techniques to control for unobserved spatial effects. Using a spatial panel for six Portuguese manufacturing industries, we found that regional knowledge spillovers, contrary to the theoretical assumptions, have a greater impact on employment in firms than on workers' wages. This analysis might enhance important policy debates about the effects of regional policies on employment and wages.

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# 1. INTRODUCTION

Agglomeration economies and regional knowledge base, as determinants of employment and wages, due to the concentration of workers and the transmission of knowledge between economic agents, have been receiving growing attention in the regional literature, with empirical support of their effects (Combes and Gobillon 2015). The proximity to sources of knowledge encourages the circulation of ideas and the transmission of knowledge, thanks to face-to-face contacts and social networks, which allow units operating close to those sources to learn and innovate and grow at a faster rate than rival firms located elsewhere (Storper and Venables 2004). Higher wages in regions that are highly specialised in skill-intensive industries are also expected (Combes et al. 2008). Additionally, different streams of literature have provided clear evidence that space matters, acting as a barrier to knowledge transmission (Audretsch and Feldman 2004) and also a barrier to earnings (Verstraten et al. 2019).

While some literature highlights the importance of geography in determining employment and wages, this same literature assumes that there are no spatial interactions between economic agents and sources of knowledge when located in different regions. In this context, the study of the effects of the spatial interactions that may occur between agents located in different regions has aroused little curiosity (Longhi et al. 2006). Even if this assumption is debatable from both theoretical and empirical perspectives, as argued by Nijkamp and Poot (2004), the use of spatial interactions is rarely considered — notable exceptions can be seen in Paci and Usai (2008) for cross-border externality effects on employment growth and in Huang and Chand (2015) for regional wage differences (Anselin 1988; Franzese and Hays 2007; and LeSage and Pace 2009). Consequently, there is still a broad debate on the impacts of agglomeration economies and knowledge spillovers on employment and wage growth. To complement this debate and to have a more detailed and less puzzling picture of their impacts, new studies are needed that must include space (Combes and Gobillon 2015; and de Groot et al. 2016).

The main objective of this paper is to provide new empirical evidence on the impact of agglomeration economies and of regional knowledge on employment and wages, assuming that there are additional spatial effects, that is economic agents of different regions interacting. In particular, we aim to see if firms have increased employment and wages and if the impact is relatively higher on wage growth as a result of agglomeration economies and regional knowledge, as predicted by our hypothesis. This analysis is expected to enhance important policy debates about the effects of regional policies on employment and wages and their implementation.

Considering that firms, employees and regions are not isolated units, as interactions are not limited by administrative boundaries, spatial interactions between them must be considered and should be studied jointly (Quah 1996). To fill in this gap, we use statistical and econometric techniques that consider spatial interactions and their respective effects to quantify spatial spillovers between Portuguese NUTS III regions (28 regions).[1] Supported by theoretical and empirical literature, we consider that employment and wages are determined by agglomeration economies and regional knowledge base, on the one hand, and by spatial interactions at a regional level, on the other. Agglomeration economies may result from (1) specialization or localization economies arising from the regional concentration of employment in an industry; and (2) diversity economies arising from the regional dispersion of employment by different industries. As a regional

[1] Vega and Elhorst (2015) define spatial spillovers "as the impact of changes to explanatory variables in a particular unit r on the dependent variable values in other units j (≠ r)."

knowledge base, we consider the number of employees that have an occupation related to R&D activities.

Using a spatial panel of Portuguese data for six manufacturing industries, we found that the spatial model that fits our models the best is the Spatial Durbin Model. We also found that the coefficients for employment growth regressions are generally higher than the coefficients for wages, an empirical result that is the opposite of the one predicted by our hypothesis derived from an economic model.

## 2. THEORY AND SELECTED EMPIRICAL FINDINGS

### 2.1. Previous empirical literature

In a seminal work, using a panel of US cities-industries from 1956 to 1987, Glaeser et al. (1992) found that diversity economies have a positive impact on employment growth, but localization economies do not. After that, a growing number of studies have attempted to replicate and refine these findings in different countries and industries, but with contradictory results. For example, using another database of US cities-industries, Henderson et al. (1995) do not confirm the results of Glaeser et al. (1992). On the contrary, they found that localization economies have a positive effect and diversity economies have no clear effect. However, Perumal (2017) found that (long-term) employment growth in US metropolitan areas from 1970 to 2011 was driven by diversity economies. Using Italian 1991 data, in turn, Cingano and Schivardi (2004) found that localization economies have a negative impact on local employment growth while the diversity economies have a positive one (see, also, Forni and Paba 2002). Combes (2000) showed that localization and diversity economies in industrial sectors had a negative impact on the 1984-1993 employment growth of 341 French local areas. Blien et al. (2006) use West Germany data from 1980 to 2001 with dynamic panel techniques and conclude that both diversity and specialization economies have had a positive effect on employment growth. Bishop and Gripaios (2010) studied the impact of externalities on employment growth in sub-regions of Great Britain by estimating ordinary least-squares (OLS) and maximum likelihood spatial models at the two-digit level for 8 manufacturing industries. They concluded that the impact on employment growth of specialization economies is mostly negative. The impact of diversity economies is heterogeneous across industries as they "depend critically on the specific technologies, customers, and knowledge relevant to a particular sector" (Bishop and Gripaios 2010: 453). The authors concluded that unrelated diversity, that is firms concentrated in a region that belong to different industries and whose activities are unrelated, has a wider impact (a positive effect, although for only five industries out of eight) than related diversity, which also has a positive effect, although in only one out of eight industries, as a result of the concentration in activities related to the industry. For more results, see Beaudry and Schiffauerova (2009) and Combes and Gobillon (2015) for surveys, and de Groot et al. (2016) for a meta-analysis.

Agglomeration economies can contribute differently to growth in employment across industries. Firms learn differently and have different levels of need for technology, and we can therefore expect that the impacts of agglomeration economies vary across industries (Potter and Watts 2014; and Ellison and Glaeser 1999). However, there are few studies linking agglomeration economies with industry specificities. One of the research lines that is used is the difference in technology intensity. Firstly, they are path dependent, which determines different innovation and technological trajectories (Nelson and Winter

1982). And secondly, the potential learning effects are determined by the technological regimes (Carreira and Teixeira 2011; and Marsili 2002). Consequently, one can admit that externalities due to the learning effects may vary between industries and are relatively the same within the industry (Grimpe and Sofka 2009; Klevorick et al. 1995; and Malerba and Orsenigo 1997). In this context, it is expected that high-tech industries will need more access to R&D knowledge than low-tech industries, while on the other hand, low-tech industries will depend more on localization economies.[2] Hervas-Oliver et al. (2018) examined the effect of localization externalities on innovation, using firm-level Spanish data for the period between 2004 and 2006. The authors concluded that all firms gain from localization economies, but less advanced or average firms in terms of knowledge stock and innovation capacity gain the most. Liang and Goetz (2018) studied the impacts of agglomeration economies focusing also on technological intensity. The authors, using employment data covering all 3-digit NAICS industries of U.S. counties, from 2003 to 2013, empirically confirm that high technology-intensive industries benefit more from diversity economies, measured by related variety. On the contrary, industries with low technology intensities benefit from localization economies. Cieślik and Ghodsi (2015), using data on high-tech industries in 285 regions of the European Economic Area from 1995 to 2007, found that localization and urbanization economies do not seem to affect employment growth.

Other approaches used wages to analyse the scope and influence of agglomeration economies (e.g. Fingleton and Longhi 2011; and Fafchamps and Hamine 2017). This approach rests on the assumption that the local wage rate equates the value of the marginal

[2] In this sense, Combes (2000) and Henderson et al. (2001), using aggregated data, and Ehrl (2013) and Carreira and Lopes (2018), using firm-level data, for studying the effects of agglomeration economies on productivity showed that there are good reasons to believe that the effects of the agglomeration economies are not homogeneous across industries.

product for profit maximization.[3] Following Combes et al. (2008), within this approach, the concentration of economic activities, either of specialization or diversification, will enhance productivity growth that will increase wages on average, i.e. the urban wage premium that is attributed to selection. This wage premium can also be explained by the matching efficiency and learning (Duranton and Puga 2004; see also Glaeser and Maré 2001). In other words, wages are higher in large urban areas. These authors found that the spatial differences can also be explained by the large differences in the skill composition of workers. As industries are not equally distributed across space, and as they have different technological requirements, higher wages are expected to exist where there is more specialized labour. The authors, using French data for the period 1976-1998, confirm empirically this idea. However, in the urban economics literature, there is also no consensus about the urban wage premium, as the different results obtained in studies on the impacts on wages of agglomeration economies show (D'Costa & Overman, 2014), first that the agglomeration economies explain this difference, and second that the migration and sorting of the highly specialized labour in the urban areas can explain the urban wage premium. The authors provided empirical evidence, using a panel of British workers for the period of 1998 to 2008, of a city size premium on wage growth in the first year, but that is not reflected in continuous growth.

The empirical literature has focused on the difference between wages in the most and least densely populated regions (in particular, cities). Combes et al. (2020) using 2005 data from China, concluded that location matters and there are urban gains being unequally distributed. As a result of internal migration, it is high-skilled natives who earn the most. However, as already referred, these studies have also produced ambiguous

[3] We will discuss this hypothesis in detail in the next section.

results (Beaudry and Schiffauerova 2009). Fafchamps and Hamine (2017) showed that firms pay lower wages when there is a high concentration of workers in the respective industry. However, conditional on this result, they also found that wages are relatively higher in regions where there is more diversity of manufacturing industries. Andersson et al. (2014), using data for Sweden from 2002 to 2008, concluded that there are spatial wage disparities between workers with non-routine and routine skills. The authors found that, for non-routine workers, agglomeration economies are significant, while for workers with routine skills, agglomeration economies appear to be non-existent. Tavares et al. (2015) studied the Portuguese case, using the same source data as us, but limited to the period between 2000 and 2005. They concluded that the wage premium for regional migration under the same employer is around 3 percentage points. For a different employer, the wage premium is around zero. The authors consider internal migration when a worker migrates from one district to another as long as they don't have a common border.[4]

The importance of the knowledge base, which is a source of localized knowledge and technology spillovers for innovative activity, has also been highlighted in several studies, such as Fritsch and Slavtchev (2007) and Cassia et al. (2009), with an expected positive effect. The differences in proximity to a knowledge-transfer environment play a key role in explaining employment differentials between firms located in different geographic areas.

Consequently, the discussion on the relative impact of agglomeration economies and of regional knowledge base on employment and wages is still very much alive. This

[4] Being the Portuguese territory divided in 18 districts, in the Mainland, plus the islands of Madeira and Azores, the regional level used by Tavares et al. (2015) is more aggregated than the one that we have used.

paper is a further step in this research path: it uses spatial econometric techniques to control for unobserved spatial effects, a drawback identified in previous empirical studies.

As we are studying the effects of agglomeration on both employment and wages at the industry level, in the next section we introduce the main hypothesis of our study.

### 2.2. Theoretical model

The main hypothesis under examination may be summarized in a simple economic model that will serve as a guide in the econometric analysis. Let us consider a firm operating in a given industry and region that produces a homogeneous product under constant returns to scale.[5] Suppose also that the production can be modelled by a Cobb-Douglas function:

$$Y_{irt} = A_{irt}(L_{irt})^{a}(K_{irt})^{1-a}, \tag{1}$$

where subscripts *i*, *r* and *t* denote industry, region and year respectively; $a$ is a constant such that $0 < a < 1$; $Y_{irt}$ is the real gross output and $L_{irt}$ and $K_{irt}$ are labour and capital inputs, respectively; and $A_{irt}$ represents the technology (i.e. the total factor productivity, TFP), which is assumed to depend on local milieu:

$$A_{irt} = f(SPE_{irt}, DIV_{irt}, RD_{irt}), \tag{2}$$

where $SPE_{irt}$, $DIV_{irt}$ and $RD_{irt}$ are measures of localization, diversity and regional knowledge-base economies, respectively.

In a competitive equilibrium, the first-order condition for profit maximization equates the value of marginal product to the local wage rate:[6]

$$w_{irt} = p_{it} a A_{irt}\left(\frac{K_{irt}}{L_{irt}}\right)^{1-a}, \tag{3}$$

[5] The constant returns to scale are the prevalent regime in estimates made by Carreira and Teixeira (2016) for Portugal.
[6] Combes et al. (2004) used a similar model to discuss imperfect competition, as well as other hypotheses for the demand elasticity. However, their conclusions are almost the same.

where $w_{irt}$ is the wage rate in the local labour market and $p_{it}$ is the output price. Labour markets are therefore assumed to be local and labour mobility imperfect, which explains why the wage is region specific. By contrast, output markets are supposed to be perfectly integrated, which seems quite natural in a well-integrated economy such as the Portuguese economy. Inserting the first-order condition for profit maximization with respect to the capital in equation (3) yields:

$$w_{irt} = a(1-\alpha)^{\frac{1-a}{a}} \left[\frac{p_{it}}{(r_{it})^{1-a}} A_{irt}\right]^{\frac{1}{a}}, \tag{4}$$

where $r_{it}$ is the price of capital. Capital markets are also supposed to be perfectly integrated.

Equation (4) can be written in terms of growth rates as:

$$\frac{dw_{irt}}{w_{irt}} = \frac{1}{a}\frac{dp_{it}}{p_{it}} - \frac{1-a}{a}\frac{dr_{it}}{r_{it}} + \frac{1}{a}\frac{dA_{irt}}{A_{irt}}. \tag{5}$$

Let us now focus our attention on the impact of the local milieu. According to the previous assumptions regarding space mobility, output and capital price growth do not vary across regions. Therefore, wage growth can be explained by local productivity shocks, that is:

$$\frac{dw_{irt}}{w_{irt}} = \frac{1}{a}\frac{dA_{irt}}{A_{irt}}. \tag{6}$$

An increase in wage rate is expected to have a positive effect on the supply of labour. Note that, under the previous assumptions of both perfect competition and constant returns to scale, the demand elasticity of output and inputs are supposed to be infinite. Let $\sigma$ denote the supply elasticity of labour, $\sigma = \frac{dL_{irt}}{L_{irt}} \Big/ \frac{dw_{irt}}{w_{irt}}$, which is assumed to be a finite positive constant. Inserting the labour supply elasticity in equation (6) yields:

$$\frac{dL_{irt}}{L_{irt}} = \frac{\sigma}{a}\frac{dA_{irt}}{A_{irt}}. \tag{7}$$

Comparing equations (6) and (7), the effect of local externalities on employment growth is visibly larger than the effect on wage growth, only if the labour supply elasticity is greater than 1.[7] However, empirical estimates seem to suggest that its value is generally less than 1 (e.g. Evers et al. 2008; and Bargain et al. 2014). Therefore, according to our model, it will be expected that:

> *Hypothesis: Agglomeration economies have a larger impact on wage growth than on employment growth.*

## 3. EMPIRICAL METHODOLOGY

### 3.1. The spatial panel data

To conduct our analysis, we used a panel of manufacturing employment data covering the period 1985-2012 for mainland Portugal. The raw data is drawn from the Matched employer–employee data (*Quadros de Pessoal*) compiled by the GEP - Office of Strategy and Planning of the Ministry of Labour and Social Solidarity. This data is collected on an annual basis through a mandatory inquiry for each firm with employees. Due to its nature, it has detailed information on the establishment, on the firm and on each of its workers (it does not cover workers from the public administration and domestic servants). For our purpose, we have collected data on the employees and wages that was afterwards aggregated, by industry and by region, which allowed us to obtain the data, for six manufacturing industries (see Table 1), on the number of employees, on the total wage paid by industry and by NUTS III regions (definition of 2002). This data also allowed us

[7] Combes et al. (2004) used a similar model to discuss other hypotheses for the demand elasticity, as well as imperfect competition. However, their conclusion is comparable.

to calculate the average employee wage by industry and by NUTS III regions. The wages were all deflated with the Consumer Price Index. We also have collected data on the regional R&D employment, the regional knowledge base, from the same source.

[Tables 1 and 2 around here]

Following the standard procedures, we have excluded from the raw data all employees that did not receive a wage and the outlier employees with an average wage positioned in the 1st percentile and in the 99th percentile. After all the adjustments were made, we obtained, for each industry and for all the variables, a balanced spatial panel of 28 regions and 28 years, with a total of 784 observations.[8]

### 3.2. The construction of the local milieu variables

As we have assumed in section 2.1, we consider that employment growth and wage gains may have three sources of externalities: (i) localization economies that derive from the intra-industry specialization; (ii) diversity economies that are related to inter-industry variety; and (iii) the regional knowledge base.

[8] As the data for 1990, 1995, 2001 and 2006 is not available, we have estimated the missing observations by an autoregressive process of lag one, with five iterations, at the industry and regional level.

First, localization economies will be measured by a location quotient, which retains the relative importance of the share of employment in the industry and in the region relative to the national levels (used, namely by Hervas-Oliver at al. 2018; Liang and Goetz 2018; and Mukkala 2004). In our study we use localization economies (SPE), based on employment, for the industry *i* in region *r*, for each period *t*, that is defined as:

$$SPE_{irt} = \frac{\frac{L_{irt}}{\sum_r L_{irt}}}{\frac{\sum_i L_{irt}}{\sum_i \sum_r L_{irt}}}, \tag{8}$$

A second source of externalities are the diversity economies, commonly proxied by the inverse of the Herfindahl-Hirschman index of industry concentration based on the employment share of the different industries, excluding the respective industry (used by Fafchamps and Hamine 2017; Carreira and Lopes 2015; and Martin et al. 2011). The diversity economies (DIV), based on employment, for the industry *i* in region *r* with respect to the rest of the economy (*i'*≠*i*), are thus calculated as:

$$DIV_{irt} = \frac{1}{\sum_{\substack{i'=1 \\ i' \neq i}} \left( \frac{L_{i'rt}}{L_{rt} - L_{irt}} \right)^2} \tag{9}$$

Finally, to capture the regional knowledge base of a region, we consider regional R&D employment (*RD*), calculated as the number of employees that have, in each region, an occupation related to R&D (see Table 2 for the details of the occupations that we have considered).

### 3.3. The spatial panel model estimation strategy

We use the following empirical models in the log forms and in first differences to estimate the potential determinants of employment growth, *l*:

$$l_{irt} = \alpha_l + \beta_{l,spe} spe_{irt} + \beta_{l,div} div_{irt} + \beta_{l,rd} rd_{rt} + v_{irt} \tag{10}$$

and of wage growth, $w$:

$$w_{irt} = \alpha_w + \beta_{w,spe} spe_{irt} + \beta_{w,div} div_{irt} + \beta_{w,rd} rd_{rt} + \mu_{irt} \tag{11}$$

where α are the constant terms, β the parameters to be estimated, and $v$ and μ the error terms.

To consider the possibility of some cross-regional dependence arising from the presence of spatial effects or from omitted explanatory variables related to the spatial features of the data, we adopted an estimation approach for the employment and wage equations of each industry, which includes spatial interaction effects.

Following Elhorst (2014), there are three different types of spatial interaction effects. Firstly, endogenous interactions among the dependent variable; secondly, exogenous interactions among the explanatory variables; and thirdly, interactions among the error terms. The model that incorporates all three types of spatial interaction effects, generally known as General Nested Spatial Model (GNS), takes the form:

$$Y = \delta WY + \alpha \iota_N + X\beta + WX\theta + u \tag{12}$$

$$u = \lambda Wu + \varepsilon \tag{12'}$$

where $W$ is a non-negative weight matrix describing the spatial configuration of the regions, $WY$ denotes the endogenous spatial interaction effects among the dependent variable, $WX$ the exogenous spatial interactions among the explanatory variables, $Wu$ the spatial interactions among the error term, $\alpha$ is the constant term and $\mu$ and $\varepsilon$ are the error terms. In this model, $\delta$ is known as the spatial autoregressive coefficient, $\lambda$ as the spatial autocorrelation coefficient, $\theta$ and $\beta$ are the parameter vectors to be estimated. Starting with this general model, and according to Elhorst (2014), we can consider the following specifications that have been widely used in spatial econometric studies (see O'Connor et al. 2018; Gutiérrez Posada et al. 2018; and Huang and Chand 2015):

i) the *Spatial Durbin Model* (SDM) with spatially lagged dependent and independent variables ($\lambda$=0),

ii) the *Spatial Autoregressive Model* (SAR) with spatially lagged dependent variables ($\theta$=$\lambda$=0),

iii) the *Spatial Error Model* (SEM) with spatially lagged error term ($\delta$=$\theta$=0).

One major point that must be stressed is the one related to the global or local nature of the spillovers that are estimated in each spatial model. Following the distinction made by LeSage and Pace (2011), spillovers are global when a spatial model considers endogenous spatial interaction effects among the dependent variable that will, consequently, feed back into the own region. In this case, a change in one independent variable in a region *r* will have effects on the dependent variable, not only of the own region *r* that is called the *direct effect*, but of all other regions, the *indirect or spatial spillover effect,* which will finally loop back to affect again the dependent variable of the region *r*, where the change was originated. Spillovers are local when a change in an independent variable of a region *r* has an indirect impact on the dependent variable of another region that will not feed back into the region *r,* since there are no endogenous interaction effects (LeSage 2014; Vega and Elhorst 2015; and Elhorst 2014). The *total effect* measures the total impact of a change in the independent variable of a region *r* on the dependent variable of all the regions, region *r* also considered, being the sum of the *direct* and *indirect effects*. Therefore, in both SDM and SAR models, global spillover effects are present, whereas the SEM model only considers the direct effect of an independent variable.

First, it is necessary to choose, for each spatial model, between random and fixed effects. The next step is to choose the spatial model that best represents the underlying reality with several specifications for the spatial effect. The most suitable spatial model must be chosen according to the empirical data. There are various strategies for their selection, the goal being to use the spatial model that best fits the data, with the highest number of significant variables (Kopczewska et al. 2017). We will therefore apply some tests to choose the appropriate spatial panel model for each industry.

For that purpose, it is necessary first to check whether the data has some spatial pattern, with the use of a distance weight matrix, a necessary condition for applying the referred techniques. Empirical studies show that spillovers are different across industries (Carreira and Lopes 2018), so we might expect the transmission of knowledge through space to also be different across industries. As entries for the distance weight matrix, W, that define the spatial transmission of knowledge, we have tested the three most common solutions: the squared inverse distance matrix, the inverse distance matrix and the contiguity matrix, which were all normalized.[9] The squared inverse matrix is commonly used in empirical studies, as it assumes that the higher the distance between spatial units, the lower the relative weights of the distant ones and the lower the interaction between them. It is also assumed that there is a non-linear relationship between spatial units that declines more rapidly as the distance increases and that all the regions have spatial interactions with each other. The inverse matrix shares one of the advantages of the squared inverse distance, as it also considers the spatial dependency between all region pairs. However, in this case, the relationship between spatial units is linear, decreasing proportionally with distance. Due to its nature, the contiguity matrix considers only

[9] This analytical standard procedure, common in studies that use spatial econometrics, is the base for the criticism made by Corrado and Fingleton (2012), who consider that the choice of spatial matrices based on this type of procedures lacks strong theoretical arguments that are fundamental to support their choice. These authors discuss in detail the conditions needed for the knowledge of the network dependence and spatial externalities and argue that failing to acknowledge them might lead “to an incorrect understanding of true causal processes”.

spatial effects between two contiguous regions, as the links between the units end there (Kopczewska et al. 2017).

In order to test whether spatial pattern is present in the data, the Moran test is commonly used (Moran 1950). The test is performed after fitting an OLS model, without the spatially lagged variables, among the residuals obtained for each employment and wage function for each year and each distance weight matrix. If the Moran test is statistically significant, we can reject the hypothesis that the errors are i.i.d. and therefore the data presents spatial autocorrelation. If spatial autocorrelation is detected for at least one year, spatial dependence should be considered (Levratto 2014).

# 4. EMPIRICAL RESULTS

## 4.1. Spatial panel econometrics

The econometric results without spatial effects are presented in Table 3, using fixed effects (the results with random effects are presented in Table A1 of the Appendix). The results are not all conclusive. The localization economies are statistically significant in all regressions, except for the Textile industry in the case of the wage model. In the employment regressions, the diversity-economy estimated coefficients are all statistically significant, while in the wage regressions they are not. Overall, the estimated coefficients for the localization economies are always higher in the employment regressions than in the wage regressions. A similar finding is found for the regional knowledge coefficients. Moreover, the effect of regional knowledge on wages is even negative in all industries.

Thus, empirical evidence seems to support the idea that agglomeration economies have had a greater impact on employment growth than on wage growth, contrary to what our theoretical hypothesis predicted.

[Table 3 around here]

The results of Table 3 do not fully account for the spatial effects on employment and wages. To consider the cross-regional dependence, we first tested the spatial correlation among the residuals, for each year *t*, for both employment and wage models.[10] The spatial correlation was tested for every three normalized distance weight matrices: the squared inverse distance matrix, the inverse distance matrix and the contiguity matrix.[11]

We have concluded that for both employment and wage models, data shows a spatial pattern due to the estimated statistical significance of the Moran test. According to the number of years with a statistically significant Moran test and its range, we might consider that the data presents a spatial pattern which is characterized by a contiguity matrix for the two models and for all industries.[12]

The likelihood-ratio test (LR test) was used to test for fixed versus random effects, also available in Table 4. We had to reject the null hypothesis according to which

**10** To test the spatial correlation among the residuals the Stata command, *estat moran* was used.

11 In Table A2 of the Appendix we present for each industry and for each distance weight matrix the number of years in which the test has statistical significance in the indicated range.

12 Some doubts may arise in the Textile and Paper industries, for which we can consider that the most adequate distance matrix is that of the inverse squared distance, respectively for the wage and employment growth (see Table A3 of the Appendix). However, the overall results do not change with the use of this matrix in the referred industries (see Tables A6 and A7 of the appendix).

differences in coefficients are not systematic and, consequently, as expected, the fixed effects should be used in all estimations.

After choosing the spatial matrix, the spatial model for each function must be selected. The tests displayed in Table 4 are used to select the spatial model that is best suited to both the data and the spatial weight matrix, using fixed effects (random effects tests are displayed in Table A3 of the Appendix).

To choose the best spatial model that fits each one of our models, we follow the strategy described in LeSage and Pace (2009), Elhorst (2010) and also Belotti et al. (2016).[13] The SDM is assumed to be the starting point as both SAR and SEM are nested in SDM, and therefore they are tested against SDM. In the SAR vs. SDM model, the hypothesis of being a SAR model is tested against not being SAR, but SDM. In the model SEM vs SDM, the hypothesis of being a SEM model is tested against not being SEM, but SDM (the Wald test was used). If neither SAR nor SEM are rejected, against SDM and being non-nested, a solution for choosing the most appropriate model is to use the Akaike's and Schwarz's Bayesian information criterion, knowing that the spatial model with the smallest value for this criterion fits the data and the spatial distance matrix best.[14]

To test the validity of the models that are nested in SDM we have used the Wald test that is available in Table 4. We concluded that the SDM is the spatial model that best fits our regressions in all industries.

[Table 4 around here]

[13] The same methodology is used in, for example, O'Connor et al. (2018) for the estimation of the effects of the economic diversity on employment growth.
[14] The tests used to choose the most appropriate spatial panel model for each industry were the Wald test and AIC and BIC criteria (as Kopczewska et al. 2017 and Belotti et al. 2016 referred, for example). Estimations were performed using the Stata command, *spxtregress*.

Table 5 reports the results for the employment and wage spatial panel regressions by industry, using fixed effects (the results with the random effects are available in Table A4 of the Appendix). We can conclude that the effects of agglomeration variables that are not spatially lagged are higher on employment than on wage growth. Therefore, our empirical results contradict our hypothesis, which was driven by the theory, at least for the levels of regional and industrial aggregation used. A possible explanation might be the regional level if it is considered that it is not sufficiently disaggregated. In this case, it is admitted that the wage spillovers are mainly local being the employment spillovers more spread in space which could explain the higher effect over the employment than over the wages. However, Huang and Chand (2015) investigates the effects of spatial interactions on local wages based on a panel data between 2001 and 2010 from 31 Chinese provinces, a much more aggregated regional level. They conclude that, even for the level of aggregation used, the wage spillover across provinces is important in the determination of local wages. Consequently, we cannot exclude the hypothesis of our conclusion being valid, even for the regional level of aggregation used on our study.

In our study, the coefficients are all positive, except for the wage growth in what concerns diversification economies for the Textile, Paper and Non-metal industries (and for Food, Wood and Metal industries they are statistically non-significant). We can find two main explanations for the empirical results obtained, which contradict our hypothesis. The first one is possibly the misallocation of resources, a characteristic of the Portuguese economy that was highlighted by Dias et al. (2016). The authors, using Portuguese firm-level data between 1996 and 2011, concluded that the misallocation of resources contributed to the poor economic performance, as the resources were allocated mostly to the least productive industries and also deteriorated in the referred period. According to Simões and Pereira (2019), textile and leather product manufacture was the industry with the lower productivity (on average between 2006 and 2016), but the industry with highest allocated share of labour. In all cases, the coefficient of the localization economies is higher than that of the diversification economies. This is possibly explained by the level of technological intensity, as already referred by Liang and Goetz (2018). As employment growth benefited especially from localization economies, we might assume that the technological level of our selected industries is closer to low technology intensities than to high, the Food industry being the one with the lowest level of technology intensity. As the highest estimated coefficient for the diversity economies was obtained for the Metal industry, we might assume that this is one of the industries with the highest technology intensity. The second one is related with the observed mismatch between educational level and occupation in the Portuguese economy. Pimenta and Pereira (2019) studied for Portugal the evolution of the adequacy of educational level for occupation over the last two decades. The authors concluded that the low level of education which characterizes the Portuguese labour force, when compared to the majority of the European countries, has improved in the recent years, while overeducation remained contained. This mismatch between level of education and occupation might explain the relatively low effects of agglomeration economies and regional knowledge-base on the wage growth. We have mentioned that the estimated diversity economies in the wage growth function, with statistical significance, are negative (for the Textile, Paper and Non-metal industries). According to the literature this might be explained by the negative externalities of agglomeration. Another plausible explanation is related to labour skills. Assuming that the industries that we have considered have relatively low technological intensity, it is also plausible that labour needs are mainly directed at non-specialized labour for routine jobs. That might explain the negative coefficients of the wage growth for the diversity economies, for both the non-lagged and lagged independent variable.

In what concerns regional R&D employment for the wage growth function, an unexpected result was obtained in the Metal industry, i.e. a negative sign, whereas for the other industries the estimated coefficients were not significant. Harrison, Jaumandreuc, Mairesse, and Peters (2014) studied the impact of innovations introduced by firms in employment using data from France, Germany, Spain and the UK for 1998–2000. They concluded that innovation increases productivity and reduces employment requirements. However, the growth of employment because of the increase in production of new products tends to compensate the referred reduction. Probably this aspect was not observed in this industry, which has led to a decrease in average wage. In relation to our hypothesis, it is not possible to draw any conclusion, as we did not obtain statistically significant coefficients for the same industry for both employment and wage regression.

[Table 5 around here]

Spatial interactions should also be considered. A conclusion that can be derived from the estimated coefficients of the spatially lagged variables and their statistical significance. In all of the estimations there are coefficients for the spatially lagged variables that are statistically significant, which is a sign of confirmation of the importance of the spatial effects (Kopczewska et al. 2017).

It is possible to conclude that there are significant global spatial spillovers, in all cases the spatially lagged dependent variable being positive. (The only statistically insignificant result was obtained for the employment growth function in the Wood industry). If we wish extrapolate our hypothesis, we can thus conclude that it is also not seen here, except for Textile. In all of the industries the employment growth coefficient for the spatially lagged dependent variable is higher than the wage growth coefficient, except for the Textile industry. In the aforementioned industry, a 1% increase in wage in a given region will induce response in all other regions, which will feed back a response in the first region of 0.710% wage growth (LeSage and Pace 2011; and LeSage 2014). This feedback effect is higher on wage than on employment growth, the latter having a growth feedback of 0.643%. Furthermore, it should be noted that the feedback response for both employment and wage growth is positive in every case.

In relation to the spatial exogenous interactions effects as a result of the spatially lagged independent variables, the localization economies and the diversity economies have always negative impacts on employment and wage growth, in absolute terms being lower on the wage growth. If our hypothesis can also be extended to these spatially lagged independent variables, we can then conclude that, in this case, it is confirmed. For the Wood industry, 1% increase in the spatially lagged localization economies variable will decrease wages by 0.121% and decrease employment by 0.799%**.** One possible explanation for the estimated negative signs is that the region's growth is obtained not through a different mix in the industrial composition of the region, but through resources from other regions. When we consider one region, the employment growth of other regions, independently of being concentrated in a single industry or in several industries, is obtained with the resources of the regions under consideration. Firms and consequently employment will migrate to the growing regions, reducing the employment and wage growth in the first region. Wage growth is negative because labour demand also decreases once the firm migrates. We have also found a positive spatial effect in the spatially lagged knowledge base for employment and wage growth in the Metal industry, which is higher in the wage response (0.053%) when compared with employment growth (0.023%). We might also conclude that our hypothesis is confirmed.

[Table 6 around here]

Table 6 displays the direct, indirect, total and feedback effects using fixed effects (the results with the random effects are available in Table A5 of the Appendix). Through spatial models and using the estimated coefficients it is also possible to estimate the feedback effect that a change in the independent variable in a region has on the dependent variable of its own region, i.e. the impact a change in the independent variable of a given region has on the dependent variable of other regions that will feed back into the dependent variable of the own region.[15] In the Food industry, 1% change in localization economies has a 1.249% direct impact change (i.e., an aspatial change) in the employment growth of its own region, the total impact on all regions being 1.332%. Concerning wage growth, the estimated direct, indirect and total effects of localization economies are not statistically significant. We can also see that the direct effect of localization economies on employment growth is always higher than 1% in all industries, and for wage growth it is estimated to be 0.066% in the Paper industry and 0.091% in the Metal industry. The estimated spatial spillover effects for the localization economies are positive just for the Wood (0.462%) and the Metal (0.272%) industries, in what concerns employment growth. In terms of the feedback effects, localization economies have a positive feedback

[15] The analytical methodology for calculating the feedback effect is described in the note of Table 6.

effect on employment growth and a negative effect on wage growth of the Metal industry. The opposite situation is observed for the Paper industry. In the case of the Metal industry, a 1% growth of localization economies in a certain region induces a feedback of 0.020% growth in the employment in the same region, after impacting employment growth in the other regions. Overall, the total effect on the growth in employment observed is positive and higher than 1% in all industries but one, the Paper industry (which is 0.701%). In terms of the total effect, we have estimated a negative total effect for wage growth in the Wood and Non-Metal industries, -0.379% and -0.524% respectively.

The picture is somewhat different when we look at the diversity economies. The direct effect is always negative for wage growth and positive for employment growth, albeit lower than 1%. The same is observed for the indirect effect: negative for wage growth and positive for employment growth, although lower than 1%. Consequently, the feedback effects are negative for wage growth and positive for employment growth, except for the Metal industry as far as employment is concerned (-0.001%). Overall, the total effect for employment growth is positive and it is negative for wage growth. Last but not least, in every industry, the total effects for knowledge-base economies are positive for employment growth (but lower than 1%) and negative for wage growth. This is the result of positive direct and indirect effects for the employment growth, although the direct effect is always lower than the indirect effect. The direct and indirect effects for wage growth are always negative, which necessarily leads to a negative total effect.[16]

The general pattern that we observed in the estimated coefficients is also observed in the estimated direct, indirect and total effect coefficients. In what concerns the

[16] Again, for more robustness of our conclusions, we have also estimated the employment and wage functions for each industry with the use of the inverse distance matrix and the contiguity matrix. We concluded that overall results do not change.

employment function, the estimated coefficients for the localization economies are generally higher than for diversification economies, except for the indirect effect on the paper industry. Here the indirect effect of the localization economies is negative and of the diversification economies is positive. This possibly reinforces our view that, on average, the industries addressed by our data are using relatively low levels of technology intensity.

Our results therefore support the idea that agglomeration effects vary and depend on the industry, as previously stated. They also show that knowledge spillovers play an important role in explaining both employment and wage growth and that spatial interactions should be considered. Finally, they show that the impact of agglomeration economies is greater on employment growth than on wage growth, the opposite of what was expected according to our hypothesis.

## 5. CONCLUSION

This study focuses on the extent to which the externalities arising from agglomeration effects and knowledge base contribute positively to employment and wage growth. It also questions whether it is worth adding spatial interactions to the traditional models to properly estimate those effects. For that purpose, we have used a balanced spatial panel of six manufacturing industries in NUTS III regions on mainland Portugal, during the period from 1985 to 2012. To address the spatial interactions that might occur in these kinds of models, firstly, we used exploratory spatial data analysis to test the presence of a spatial pattern and, secondly, spatial panel data econometric techniques to estimate the functions. We have observed that evidence of a spatial dependence pattern does exist, which allows us to conclude that spatial interactions should be considered to estimate employment and wage growth.

We have concluded the following: first, contrary to the hypothesis, agglomeration economies have a greater impact on employment growth than on wage growth; and second, knowledge spillover is different according to the industry.

This study contributes to a better understanding of how regional knowledge spillovers that arise from the agglomeration economies and regional knowledge work, and how they affect employment and wages at industry-regional level. The knowledge of these mechanisms and their functioning is essential for the setting up of more assertive regional policies that foster employment and wage growth.

Knowledge does not spread in the same way across all industries, due to its innovation and technological trajectories, and regions have different characteristics concerning the location of economic activities. Therefore, not all regions benefit in the same way from the same type of policies, which means that for employment and wage growth, industry and region-specific general policies must be outlined. Those policies should take into account the economic structure and the endowments of the region and the agglomeration effects that predominate. This is the recommendation that is generally found in the literature studying the effects of agglomeration on employment and also on wages (e.g. Liang and Goetz 2018; Bishop and Gripaios 2010; and Blien et al. 2006).

Since, in general, the effects of agglomeration economies on wages are relatively small and, when compared with the effects on employment, they are lower than the predicted theory, we cannot expect the labour market and the agglomeration of economic activities to solve the problems highlighted by our findings. Therefore, while the agglomeration of economic activities has overall positive effects on employment, the effects on wages should be increased. First by allocating resources differently. As studies for the Portuguese economy have shown, labour is specially allocated to industries with relatively low productivity levels and, as wages are directly related to productivity, these occupations are also linked to low wages. And second, by improving the educational levels and technical skills of workers to address the problem of the visible mismatch between education level and occupation that was also identified in the Portuguese economy. Much has been done in recent years, but policies must continue to improve the technical skills through education policies and vocational and technical training policies that can exogenously increase wages. The goal is to trigger a process of endogenous wage growth that could reverse the current situation and, finally, strike a balance where the agglomeration economies might impact wages more than employment. Thirdly, as Bishop and Gripaios (2010) suggested for the Great Britain context, it is necessary to create the conditions and to develop the opportunities for spillovers to occur in the regions.

In terms of policies directed towards employment growth, they should consider the industrial structure of each region. The direct effects derived from the localization economies are generally higher than that which is derived from the diversity economies. Therefore, in regions where a great variety of industries is observed, policies should target new investors of similar industries. However, since spatial spillovers on employment were seen to derive from the diversity economies in two industries (Textile and Paper) in the regions where these exist, for a more equal territory one can opt for policies of greater diversity. In relation to the Wood and Metal industries, spatial spillovers on the localization economies have been estimated, and therefore in the regions where these are in place, one can adopt economic policies that lead to higher specialisation.

It is worth noting that this analysis has some major limitations. Primarily, due to the nature of the data, aggregated at industrial and regional levels, it was not possible to study the effects at the level of the firm, namely firm entry, growth and exit, which might lead to more specialized or diversified economic activity. As discussed by van Oort et al. (2012), when studying the effects of agglomeration economies on employment and wages using aggregated data, this does not mean that the same results are obtained with firm level data (see also Duranton and Puga 2004). Beaudry and Schiffauerova (2009) surveys the literature that have used the different approaches to study the specialization and diversity effects on the economic performance of the regions. They conclude that, according to the industry aggregation and to the region aggregation the estimated effects are different. The estimated results that we have obtained can contribute to the debate about the choice and measurement issues. As a result, this study should be extended and data at the level of the firm should be used to better understand the agglomeration effects (see Audretsch and Feldman 2004; Döring and Schnellenbach 2006; or Combes and Gobillon 2015, for surveys; and Melo et al. 2009; or de Groot et al. 2016, for meta-analyses). Furthermore, it was not possible to investigate whether there is an optimal regional density of economic activity of the different sources of agglomeration economies that could maximize employment and wage growth. Although some work has been done, namely by Carreira and Lopes (2018), on Portuguese productivity at the level of firms, plenty of research is carried out on whether such non-linearities do exist across industries, much remains to be done. In particular, the use of spatial econometric techniques to study the existence of the referred non-linearities. Adding to this, Mameli et al. (2014), Beaudry and Schiffauerova (2009) and Araújo et al. (2019) also sustained that the level of industry aggregation influences the empirical outcomes even for the same spatial units. Therefore, future studies should consider a more detailed industrial aggregation level but also more detailed regional aggregation. Secondly, as previously mentioned, the standard procedure that we have used to choose the spatial matrices is strongly analytical, as referred by Corrado and Fingleton (2012). The authors consider that the choice of spatial matrices should be based on strong theoretical economic arguments that address the conditions needed for the knowledge of the network dependence and spatial externalities. This study should therefore be extended to incorporate distance matrices derived from economic theory that can be drawn after a complete study of the input-output relations of the sectors, which should also consider regional infrastructures. Finally, as it is known, Portugal was subject to an adjustment programme, which formally ended in 2014, leading to substantial changes in the Portuguese economy. Consequently, more recent years should be incorporated in future studies that take into account these changes.

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[Tables A1 to A7, of the appendix, around here]

**References**


Andersson M, Klaesson J, Larsson J (2014) The sources of the urban wage premium by worker skills. *Papers in Regional Science* 93(4): 727-747.

Anselin L (1988) *Spatial econometrics: Methods and models*. Kluwer Academic, Boston.

Araújo IF, Gonçalves E, Almeida E (2019) Effects of dynamic and spatial externalities on local growth: Evidence from Brazil. *Papers in Regional Science* 98(2): 1239–1259.

Audretsch DB, Feldman MP (2004) Knowledge spillovers and the geography of innovation. In: Henderson JV, Thisse JF (eds) *Handbook of urban and regional economics* (Vol. 4). Elsevier, Amsterdam: 2713–2739.

Bargain O, Orsini K, Peichl A (2014) Comparing labor supply elasticities in Europe and the United States: New results. *Journal of Human Resources* 49(3): 723-838.

Beaudry C, Schiffauerova A (2009) Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy* 38: 318–337.

Belotti F, Hughes G, Mortaria AP (2016) Spatial-panel data models using Stata. *The Stata Journal* 17(1): 139-180.

Bishop P, Gripaios P (2010) Spatial externalities, relatedness and sector employment growth in Great Britain. *Regional Studies* 44 (4): 443-454.

Blien U, Suedekum J, Wolf K (2006) Local employment growth in West Germany: A dynamic panel approach. *Labour Economics* 16: 445-458.

Carreira C, Lopes L (2015) Are small firms more dependent on the local environment than larger firms? Evidence from Portuguese manufacturing firms. In Leitão JC, Baptista R (eds) *Entrepreneurship, human capital, and regional development*, Springer, Cham: 263–280.

Carreira C, Lopes L (2018) Regional knowledge spillovers: A firm-based analysis of non-linear effects. *Regional Studies* 52(7): 948–958.

Carreira C, Teixeira P (2011) Entry and exit as a source of aggregate productivity growth in two alternative technological regimes. *Structural Change and Economic Dynamics* 22(2): 135–150.

Carreira C, Teixeira P (2016) Entry and exit in severe recessions: Lessons from the 2008-2013 Portuguese economic crisis. *Small Business Economics* 46(4): 591-617.

Cassia L, Colombelli A, Paleari S (2009) Firms' growth: Does the innovations system matter? *Structural Change and Economic Dynamics* 20: 211–220.

Cieślik A, Ghodsi M (2015) Agglomeration externalities, market structure and employment growth in high-tech industries. *Miscellanea Geographica: Regional Studies on Development* 19 (3): 76-81.

Cingano F, Schivardi F (2004) Identifying the sources of local productivity growth. *Journal of the European Economic Association* 2: 720–742.

Combes PP (2000) Economic structure and local growth: France, 1984–1993. *Journal of Urban Economics* 47: 329–355.

Combes PP, Démurger S, Li S, Wang J (2020) Unequal migration and urbanisation gains in China. *Journal of Development Economics* 142: 1-17.

Combes PP, Gobillon L (2015) The empirics of agglomeration economies. In: Duranton G, Henderson JV, Strange WC (eds) *Handbook of urban and regional economics* (Vol. 5). Elsevier, Amsterdam: 247–348.

Combes PP, Magnac T, Robin JM (2004) The dynamics of local employment in France. *Journal of Urban Economics* 56: 217–243.

Combes PP, Duranton G, Gobillon L (2008) Spatial wage disparities: Sorting matters! *Journal of Urban Economics* 63:723–742.

Corrado L, Fingleton B (2012) Where is the economics in spatial econometrics. *Journal of Regional Science* 52(2): 210–239.

D'Costa S, Overman HG (2014) The urban wage growth premium: Sorting or learning? *Regional Science and Urban Economics* 48: 168–179.

de Groot HLF, Poot J, Smit MJ (2016) Which agglomeration externalities matter most and why? *Journal of Economic Surveys* 30: 756–782.

Dias D, Marques C, Richmond C (2016) Misallocation and productivity in the lead up to the Eurozone crisis. *Journal of Macroeconomics* 49: 46–70.

Döring T, Schnellenbach J (2006) What do we know about geographical knowledge spillovers and economic growth? A survey of the literature. *Regional Studies* 40: 375–395.

Duranton G, Puga D (2004) Micro-foundations of urban agglomeration economies. In: Henderson JV, Thisse JF (eds) *Handbook of urban and regional economics* (Vol. 4), Elsevier, Amsterdam: 2063–2117.

Ehrl P (2013) Agglomeration economies with consistent productivity estimates. *Regional Science and Urban Economics* 43: 751-763.

Elhorst JP (2010) Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis* 5(1): 9-28.

Elhorst JP (2014) *Spatial econometrics. From cross-sectional data to spatial panels.* Springer, Heidelberg.

Ellison G, Glaeser E (1999) The geographic concentration of industry: does natural advantage explain agglomeration? *American Economic Review* 89(2): 311–316.

Evers M, de Mooij R, van Vuuren D (2008) The wage elasticity of labour supply: A synthesis of empirical estimates. *De Economist* 156(1): 25–43.

Fafchamps M, Hamine SE (2017) Firm productivity, wages, and agglomeration externalities. *Research in Economics* 71: 291–305.

Fingleton B, Longhi S (2011) The effects of agglomeration on wages: Evidence from the micro-level. *Journal of Regional Science* 53(3): 443-463.

Forni M, Paba S (2002) Spillovers and the growth of local industries. *Journal of Industrial Economics* 50, 151–171.

Franzese RJ, Hays JC (2007) Spatial econometric models of cross-sectional interdependence in political science panel and time-series-cross-section data. *Political Analysis* 15(2): 140–164.

Fritsch M, Slavtchev V (2007) Universities and innovation in space. *Industry and Innovation* 14: 201–218.

Glaeser E, Kallal H, Sheikman J, Shleifer A (1992) Growth in cities. *Journal of Political Economy* 100(6): 1126–1152.

Glaeser E, Maré D (2001) Cities and skills. *Journal of Labor Economics* 19(2): 316–342.

Grimpe C, Sofka W (2009) Search patterns and absorptive capacity: Low- and high-technology sectors in European countries. *Research Policy* 38: 495–506.

Gutiérrez Posada D, Rubiera Morollón F, Viñuela A. (2018) The determinants of local employment growth in Spain. *Applied Spatial Analysis and Policy* 11(3): 511–533.

Harrison R, Jaumandreuc J, Mairesse J, Peters B (2014) Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization* 35: 29–43.

Henderson JV, Kuncoro A, Turner M (1995) Industrial development in cities. *Journal of Political Economy* 103(5): 1067–1090.

Henderson V, Lee T, Lee, YJ (2001) Scale externalities in Korea. *Journal of Urban Economics* 49: 479–504.

Hervas-Oliver JL, Sempere-Ripoll F, Alvarado RR, Estelles-Miguel S (2018) Agglomerations and firm performance: Who benefits and how much? *Regional Studies* 52(3): 238-349.

Huang Q, Chand S (2015) Spatial spillovers of regional wages: Evidence from Chinese provinces. *China Economic Review* 32: 97–109.

Klevorick A, Levin R, Nelson R, Winter S (1995) On the sources and significance of interindustry differences in technological opportunities. *Research Policy* 24: 185–205.

Kopczewska K, Kudła J, Walczyk K (2017) Strategy of spatial panel estimation: Spatial spillovers between taxation and economic growth. *Applied Spatial Analysis and Policy* 10(1): 77–102.

LeSage JP (2014) What regional scientists need to know about spatial econometrics. *The Review of Regional Studies* 44: 13–32.

LeSage JP, Pace RK (2009) *Introduction to spatial econometrics*. CRC Press, Boca Raton.

LeSage JP, Pace RK (2011) Pitfalls in higher order model extensions of basic spatial regression methodology. *The Review of Regional Studies* 41: 13-26.

Levratto N (2014) Does firm creation depend on local context? A focus on the neighbouring effects. *Working Papers* Research Network on Innovation, nº 40, Dunkerque.

Liang J, Goetz SJ (2018) Technology intensity and agglomeration economies. *Research Policy* 47: 1990-1995.

Longhi S, Nijkamp P, Poot J (2006) Spatial heterogeneity and the wage curve revisited. *Journal of Regional Science* 46(4): 707–731.

Malerba F, Orsenigo L (1997) Technological regimes and sectoral patterns of innovative activities. *Industrial and Corporate Change* 6: 83–118.

Mameli F, Faggian A, Mccann P (2014) Estimation of local employment growth. Do sectoral aggregation and industry definition matter? *Regional Studies* 48(11): 1813-1828.

Marsili O (2002) Technological regimes and sources of entrepreneurship. *Small Business Economics* 19: 217–231.

Martin P, Mayer T, Mayneris F (2011) Spatial concentration and plant-level productivity in France. *Journal of Urban Economics* 69: 182–195.

Melo PC, Graham DJ, Noland RB (2009) A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics* 39: 332–342.

Moran PAP (1950) Notes on continuous stochastic phenomena. *Biometrika* 37: 17–23.

Mukkala K (2004) Agglomeration economies in the Finnish manufacturing sector. *Applied Economics* 36: 2419–2427.

Nelson RR, Winter SG (1982) *An evolutionary theory of economic change*. Belknap/Harvard University Press, Cambridge, MA.

Nijkamp P, Poot J (2004) Meta-analysis of the effect of fiscal policies on long-run growth. *European Journal of Political Economy* 20: 91–124.

O'Connor S, Doyle E, Doran J (2018) Diversity, employment growth and spatial spillovers amongst Irish regions. *Regional Science and Urban Economics* 68: 260-267.

Paci P, Usai S (2008) Agglomeration economies, spatial dependence and local industry growth. *Revue d'Économie Industrielle* 3(123): 87-109.

Perumal A (2017) 42 Years of urban growth and industry composition. *Atlantic Economic Journal* 45(2): 133–147.

Pimenta AC, Pereira MC (2019) Aggregate educational mismatches in the Portuguese labour market. *Working paper* Bank of Portugal.

Potter A, Watts HD (2014) Revisiting Marshall’s agglomeration economies: Technological relatedness and the evolution of the Sheffield metals cluster. *Regional Studies* 48(4): 603–623.

Quah DT (1996) Empirics for economic growth and convergence. *European Economic Review* 40(6): 1353-1375.

Simões M, Pereira JA (2019) Productivity and resource allocation of Portuguese firms. *Boletim Mensal de Economia Portuguesa* Gabinete de Estratégia e Estudos, Ministério da Economia, BMEP nº 08: 59-89.

Storper M, Venables AJ (2004) Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography* 4: 351–370.

Tavares M, Carneiro A, Varejão J (2015) The spatial dimension of internal labor markets. *Journal of Regional Science* 58:181–203.

van Oort FG, Burger MJ, Knoben J, Raspe O (2012) Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys* 26: 468–491.

Vega SH, Elhorst JP (2015) The SLX model. *Journal of Regional Science* 55(3): 339–363.

Verstraten P, Verweij G, Zwaneveld PJ (2019) Complexities in the spatial scope of agglomeration economies. *Journal of Regional Science* 59: 29–55.

## Tables

**Table 1.** Industry classification.

| Industry | Shortcut | Statistical Classification of Economic Activities codes NACE | NACE Rev.1.1 | NACE Rev. 2 | Observations (28 regions * 28 years) |
|---|---|---|---|---|---|
| Food products and beverages | Food | 311, 312, 313 | 15 | 10, 11 | 784 |
| Textiles and wearing apparel | Textile | 321, 322 | 17, 18 | 13, 14 | 784 |
| Wood and wood products | Wood | 331 | 20 | 16 | 784 |
| Pulp, paper and paper products | Paper | 341, 342 | 21, 22 | 17, 18 | 784 |
| Other non-metallic mineral products | Non-metal | 361, 362, 369 | 26 | 23 | 784 |
| Basic metals and metallic products | Metal | 371, 372, 381 | 27, 28 | 24, 25 | 784 |

**Note:** Codes at the 3-digit level of the Statistical Classification of Economic Activities (by version) considered in each industry.

**Table 2.** R&D employment occupations.

| National Classification of Occupations (CNP) | Period | CNP Code | Occupation |
|---|---|---|---|
| CNP 85 | 1985-1994 | 0, 1 | Scientific, technical, artistic and similar professions |
| CNP 94 | 1995-2012 | 2 | Intellectual and scientific professions |

**Note:** Occupations of the two National Classification of Occupations (codes by CNP version) considered as R&D employment activities.

**Table 3.** Regression results using fixed effects by industry.

| | Food | | Textile | | Wood | | Paper | | Non-metal | | Metal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Employment | Wage | Employment | Wage | Employment | Wage | Employment | Wage | Employment | Wage | Employment | Wage |
| $spe_{irt}$ | 1.071*** | 0.122* | 1.026*** | 0.005 | 1.158*** | -0.058* | 0.944*** | 0.078*** | 1.112*** | -0.063* | 1.127*** | 0.063** |
| | (0.044) | (0.045) | (0.014) | (0.017) | (0.019) | (0.031) | (0.023) | (0.030) | (0.021) | (0.034) | (0.021) | (0.031) |
| $div_{irt}$ | 0.440*** | 0.003 | 0.414*** | -0.019 | 0.472*** | 0.005 | 0.450*** | -0.012 | 0.474*** | -0.002 | 0.429*** | -0.004 |
| | (0.013) | (0.013) | (0.012) | (0.015) | (0.009) | (0.015) | (0.015) | (0.020) | (0.010) | (0.016) | (0.011) | (0.016) |
| $rd_{rt}$ | 0.372*** | -0.184*** | 0.313*** | -0.168*** | 0.187*** | -0.152*** | 0.363*** | -0.183*** | 0.175*** | -0.181*** | 0.349*** | -0.183*** |
| | (0.017) | (0.017) | (0.017) | (0.021) | (0.012) | (0.020) | (0.019) | (0.025) | (0.013) | (0.021) | (0.013) | (0.020) |
| Observations | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 |
| Wald test | 1089*** | 55*** | 2548*** | 34*** | 3197*** | 31*** | 1179*** | 29*** | 2546*** | 41*** | 2715*** | 38*** |

**Note:** $spe_{irt}$, $div_{irt}$ and $rd_{rt}$ denote localization economies, diversity economies and R&D employment, respectively. All the variables are in the log forms and in first differences. Standard errors are given in parentheses. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table 4.** Model specification by industry.

| | | Food | | Textile | | Wood | | Paper | | Non-metal | | Metal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| **Test to choose between random effects and fixed effects** | | | | | | | | | | | | | |
| | LR test | 95.76*** | 109.02*** | 46.05*** | 17.82*** | 111.94*** | 38.26*** | 64.71*** | 30.30*** | 89.44*** | 16.84*** | 104.68*** | 40.50*** |
| | | FE | FE | FE | FE | FE | FE | FE | FE | FE | FE | FE | FE |
| **Tests to choose the most appropriate spatial panel model** | | | | | | | | | | | | | |
| SAR vs. SDM | Wald test | 3749*** | 15.87*** | 514*** | 18.49*** | 1479*** | 32.24*** | 14873*** | 7.61* | 7363*** | 27.92*** | 8684*** | 27.21*** |
| SEM vs. SDM | Wald test | 2612*** | 15.97*** | 329*** | 17.36*** | 903*** | 33.47*** | 9707*** | 7.86** | 4354*** | 27.85*** | 5163*** | 27.82*** |
| SAR | AIC | -1721 | -2188 | -1156 | -1229 | -2067 | -1622 | -1290 | -613 | -1883 | -1160 | -1875 | -1363 |
| | BIC | -1697 | -2165 | -1133 | -1206 | -2044 | -1599 | -1267 | -590 | -1860 | -1137 | -1852 | -1340 |
| SEM | AIC | -2759 | -2176 | -1430 | -1213 | -2645 | -1622 | -3066 | -600 | -3244 | -1143 | -3524 | -1367 |
| | BIC | -2735 | -2153 | -1407 | -1190 | -2622 | -1599 | -3043 | -576 | -3220 | -1120 | -3301 | -1344 |
| SDM | AIC | -2800 | -2198 | -1496 | -1240 | -2707 | -1649 | -3174 | -615 | -3263 | -1181 | -3382 | -1384 |
| | BIC | -2763 | -2161 | -1459 | -1203 | -2670 | -1612 | -3135 | -578 | -3226 | -1144 | -3345 | -1347 |
| Most appropriate model | | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM |

**Note:** In the SAR vs. SDM model, it is tested the null of being SAR, with the Wald test. In the SEM vs. SDM model, it is tested the null of being SEM, with the Wald test. If both SAR and SEM are not rejected, against SDM and being non-nested, a solution for choosing the most appropriate model is to use the Akaike's and Schwarz's Bayesian information criterion, knowing that the spatial model with the smaller value for this criterion fits the data and the spatial matrix better. It was used the contiguity matrix as distance weight matrix. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table 5.** Regression results using spatial panel specification and fixed effects by industry.

| | **Food** | | **Textile** | | **Wood** | | **Paper** | | **Non-metal** | | **Metal** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| $spe_{irt}$ | 1.242*** | 0.056*** | 1.027*** | 0.0002 | 1.076*** | 0.038** | 1.021*** | 0.058** | 1.053*** | 0.028 | 1.087*** | 0.107*** |
| | (0.011) | (0.017) | (0.009) | (0.011) | (0.008) | (0.038) | (0.004) | (0.025) | (0.005) | (0.024) | (0.004) | (0.018) |
| $div_{irt}$ | 0.492*** | -0.008 | 0.442*** | -0.031*** | 0.493*** | 0.007 | 0.494*** | -0.040** | 0.495*** | -0.022* | 0.497*** | 0.005 |
| | (0.004) | (0.006) | (0.009) | (0.011) | (0.004) | (0.007) | (0.003) | (0.019) | (0.003) | (0.012) | (0.002) | (0.010) |
| $rd_{rt}$ | 0.016** | -0.010 | 0.072*** | 0.026 | 0.017* | -0.014 | -0.0005 | -0.021 | 0.011** | -0.003 | 0.005 | -0.085*** |
| | (0.008) | (0.012) | (0.021) | (0.024) | (0.009) | (0.014) | (0.006) | (0.040) | (0.005) | (0.026) | (0.005) | (0.022) |
| spatially lagged $l_{irt}$ or $w_{irt}$ | 0.916*** | 0.868*** | 0.643*** | 0.710*** | 0.825 | 0.782*** | 0.949*** | 0.513*** | 0.927*** | 0.652*** | 0.928*** | 0.729*** |
| | (0.009) | (0.013) | (0.025) | (0.023) | (0.015) | (0.018) | (0.006) | (0.034) | (0.008) | (0.026) | (0.008) | (0.022) |
| spatially lagged $spe_{irt}$ | -1.130*** | -0.106*** | -0.666*** | 0.008 | -0.799*** | -0.121*** | -0.985*** | 0.024 | -0.968*** | -0.211*** | -0.988*** | -0.127*** |
| | (0.023) | (0.033) | (0.032) | (0.020) | (0.026) | (0.032) | (0.008) | (0.048) | (0.014) | (0.048) | (0.012) | (0.036) |
| spatially lagged $div_{irt}$ | -0.445*** | -0.018* | -0.236*** | -0.026 | -0.399*** | -0.048*** | -0.459*** | -0.044 | -0.455*** | -0.005 | -0.463*** | -0.072*** |
| | (0.008) | (0.010) | (0.021) | (0.019) | (0.011) | (0.015) | (0.006) | (0.033) | (0.006) | (0.022) | (0.006) | (0.019) |
| spatially lagged $rd_{rt}$ | 0.019** | -0.014 | 0.041* | -0.071*** | 0.007 | -0.004 | 0.018*** | -0.059 | 0.002 | -0.040 | 0.023*** | 0.053*** |
| | (0.009) | (0.014 | (0.024) | (0.028) | (0.010) | (0.021) | (0.007) | (0.045) | (0.006) | (0.030) | (0.006) | (0.024) |
| Observations | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 |
| Wald test | 70459*** | 6641*** | 19333*** | 1408*** | 69138*** | 2661*** | 185406*** | 407*** | 160148*** | 1037 | 225222*** | 1691*** |
| Wald test of spatial terms | 14267*** | 5428*** | 980*** | 1146*** | 4484*** | 2292*** | 37424*** | 281*** | 16453*** | 775*** | 21096*** | 1367*** |

**Notes**: See notes to Table 3. $l_{irt}$ and $w_{irt}$ denote labour and employment growth, respectively. The spatial model used was the SDM model with the contiguity matrix. Standard errors are given in parentheses. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table 6.** Direct, spatial spillover and feedback effects using spatial panel specification and fixed effects by industry.

| | **Food** | | **Textile** | | **Wood** | | **Paper** | | **Non-metal** | | **Metal** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| *Coefficient* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.242*** | 0.056*** | 1.027*** | 0.0002 | 1.076*** | 0.038** | 1.021*** | 0.058** | 1.053*** | 0.028 | 1.087*** | 0.107*** |
| $div_{irt}$ | 0.492*** | -0.008 | 0.442*** | -0.031*** | 0.493*** | 0.007 | 0.494*** | -0.040** | 0.495*** | -0.022* | 0.497*** | 0.005 |
| $rd_{rt}$ | 0.016** | -0.010 | 0.072*** | 0.026 | 0.017* | -0.014 | -0.0005 | -0.021 | 0.011*** | -0.003 | 0.005 | -0.085*** |
| *Direct effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.249*** | 0.021 | 1.026*** | 0.003 | 1.119*** | 0.001 | 1.001*** | 0.066** | 1.060*** | -0.021 | 1.107*** | 0.091*** |
| $div_{irt}$ | 0.497*** | -0.024** | 0.454*** | -0.046*** | 0.497*** | -0.010 | 0.506*** | -0.050** | 0.498*** | -0.026* | 0.496*** | -0.017 |
| $rd_{rt}$ | 0.045*** | -0.024* | 0.094*** | 0.010 | 0.027*** | -0.020 | 0.021*** | -0.032 | 0.024*** | -0.014 | 0.032*** | -0.088*** |
| *Indirect or spatial spillover effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.084 | -0.399 | -0.013 | 0.024 | 0.462*** | -0.380*** | -0.300** | 0.102 | 0.105 | -0.503*** | 0.272** | -0.163 |
| $div_{irt}$ | 0.063 | -0.174** | 0.123*** | -0.151*** | 0.039 | -0.176*** | 0.180* | -0.121* | 0.048 | -0.051 | -0.013 | -0.227*** |
| $rd_{rt}$ | 0.373*** | -0.156*** | 0.223*** | -0.166*** | 0.110*** | -0.063 | 0.318*** | -0.131** | 0.168*** | -0.111** | 0.358*** | -0.030 |
| *Total effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.332*** | -0.377 | 1.013*** | 0.027 | 1.581*** | -0.379** | 0.701*** | 0.167 | 1.165*** | -0.524*** | 1.379*** | -0.072 |
| $div_{irt}$ | 0.560*** | -0.198** | 0.577*** | -0.197*** | 0.535*** | -0.186** | 0.686*** | -0.171** | 0.546*** | -0.077 | 0.483*** | -0.244*** |
| $rd_{rt}$ | 0.418*** | -0.180*** | 0.317*** | -0.156*** | 0.137*** | -0.083 | 0.338*** | -0.164*** | 0.192*** | -0.125** | 0.390*** | -0.118** |
| *Feedback effect in the own region* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.007 | | -0.001 | | 0.043 | | -0.020 | 0.008 | 0.007 | | 0.020 | -0.016 |
| $div_{irt}$ | 0.005 | | 0.012 | -0.015 | 0.004 | | 0.012 | -0.010 | 0.003 | -0.004 | -0.001 | |
| $rd_{rt}$ | 0.029 | | 0.022 | | 0.010 | | | | 0.013 | | | -0.003 |
| *Feedback effect as a percentage of the coefficient* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.6% | | -0.1% | | 4.0% | | -2.0% | 13.8% | 0.7% | | 1.8% | -15.0% |
| $div_{irt}$ | 1.0% | | 2.7% | 48.4% | 0.8% | | 2.4% | 25.0% | 0.6% | 18.2% | -0.2% | |
| $rd_{rt}$ | 181.3% | | 30.6% | | 58.8% | | | | 118.2% | | | 3.5% |

No**tes:** See notes to Table 3. The spatial model used was the SDM model with the contiguity matrix. The feedback effect in the own region is calculated as the difference between the estimated direct effect and the estimated coefficient. The feedback effect as a percentage of the coefficient is calculated as the ratio between the feedback effect in the own region and the estimated coefficient. With respect to the feedback effect, we only present the effect in which the estimated direct effect and the estimated coefficient are both statistically significant. Standard errors are not presented due shortage of space, but they are available upon request. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table A1.** Regression results using random effects by industry.

| | Food | | Textile | | Wood | | Paper | | Non-metal | | Metal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| $spe_{irt}$ | 1.072*** | 0.119*** | 1.025*** | 0.007 | 1.158*** | -0.057* | 0.945*** | 0.074** | 1.111*** | 0.057 | 1.127*** | 0.064** |
| | (0.043) | (0.044) | (0.014) | (0.017) | (0.019) | (0.030) | (0.022) | (0.029) | (0.021) | (0.034) | (0.020) | (0.030) |
| $div_{irt}$ | 0.440*** | 0.004 | 0.413*** | -0.019 | 0.471*** | 0.006* | 0.449*** | -0.008 | 0.474*** | 0.001 | 0.429*** | -0.001 |
| | (0.013) | (0.013) | (0.012) | (0.015) | (0.009) | (0.015) | (0.015) | (0.020) | (0.010) | (0.016) | (0.010) | (0.015) |
| $rd_{rt}$ | 0.371*** | -0.184*** | 0.312*** | -0.167*** | 0.187*** | -0.151*** | 0.362*** | -0.182*** | 0.175*** | -0.182*** | 0.349*** | -0.182*** |
| | (0.017) | (0.170) | (0.017) | (0.021) | (0.012) | (0.020) | (0.019) | (0.025) | (0.019) | (0.021) | (0.013) | (0.020) |
| Observations | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 |
| Wald test | 3397*** | 169*** | 7907*** | 101*** | 9926*** | 93*** | 3664*** | 85*** | 7922*** | 119*** | 8472*** | 118*** |

**Notes**: See notes to Table 3. Standard errors are given in parentheses. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table A2.** Statistical significance of the Moran test for spatial dependence by range and industry

| Industries | Range | Inverse distance | | Inverse squared distance | | Contiguity | |
|---|---|---|---|---|---|---|---|
| | | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| Food | 0-5 | | | | | 1 | 1 |
| | 5-10 | | | 1 | 3 | 2 | 1 |
| | 10-15 | 1 | 2 | 1 | | 2 | 1 |
| | 15-20 | 1 | 1 | 2 | | | 1 |
| Textile | 0-5 | | | | 1 | | |
| | 5-10 | | | | 1 | 2 | 2 |
| | 10-15 | | | | 3 | | 1 |
| | 15-20 | | 2 | 3 | 1 | 1 | 3 |
| Wood | 0-5 | | 1 | | | | 2 |
| | 5-10 | | | | 1 | 1 | 2 |
| | 10-15 | | | 1 | 1 | 1 | |
| | 15-20 | 1 | 2 | 1 | | 3 | 1 |
| Paper | 0-5 | | | 2 | | | 1 |
| | 5-10 | 1 | | | | 1 | |
| | 10-15 | 1 | | 1 | 3 | | |
| | 15-20 | | | 1 | 1 | 1 | 1 |
| Non-metal | 0-5 | | | | 2 | | 2 |
| | 5-10 | | 1 | | 1 | | 3 |
| | 10-15 | | | 1 | | 4 | |
| | 15-20 | 2 | 1 | | 3 | 1 | 1 |
| Metal | 0-5 | | | | | | 1 |
| | 5-10 | | | | | | |
| | 10-15 | | | 1 | | 1 | 1 |
| | 15-20 | 1 | | 2 | 2 | | |

**Note:** Number of years in which the Moran test for spatial dependence has statistical significance in the indicated range.

**Table A3.** Spatial specification by industry using random effects.

| | | Food | | Textile | | Wood | | Paper | | Non-metal | | Metal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| **Tests to choose the spatial model** | | | | | | | | | | | | | |
| SDM vs SAR | Wald test | 3712*** | 16.34*** | 508*** | 16.87*** | 1490*** | 33.69*** | 14718*** | 9.28*** | 7299*** | 29.44*** | 8597*** | 28.97*** |
| SDM vs SEM | Wald test | 2581*** | 16.45*** | 329*** | 19.06*** | 911*** | 35.02*** | 9605*** | 9.59*** | 4315*** | 30.52*** | 5110*** | 29.67*** |
| SAR | AIC | -1801 | -2292 | -1201 | -1250 | -2161 | -1655 | -1357 | -638 | -2254 | -1278 | -1964 | -1398 |
| | BIC | -1769 | -2260 | -1169 | -1218 | -2129 | -1623 | -1325 | -605 | -2222 | -1244 | -1932 | -1365 |
| SEM | AIC | -2853 | -2280 | -1473 | -1240 | -2750 | -1660 | -3138 | -624 | -3562 | -1270 | -3430 | -1404 |
| | BIC | -2820 | -2247 | -1441 | 1208 | -2718 | -1628 | -3105 | -592 | -3530 | -1237 | -3398 | -1372 |
| SDM | AIC | -2892 | -2303 | -1358 | -1263 | -2815 | -1883 | -3234 | -641 | -3582 | -1288 | -3482 | -1421 |
| | BIC | -2845 | -2256 | -1491 | -1217 | -2769 | -1637 | -3188 | -595 | -3536 | -1241 | -3436 | -1374 |
| Most appropriate model | | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM | SDM |

**Note**: See notes to Table 4. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table A4.** Regression results using spatial panel specification and random effects by industry.

| | Food | | Textile | | Wood | | Paper | | Non-metal | | Metal | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| $spe_{irt}$ | 1.237*** | 0.056*** | 1.027*** | 0.0007 | 1.077*** | 0.037** | 1.020**** | 0.053** | 1.053*** | 0.031 | 1.087*** | 0.108*** |
| | (0.011) | (0.017) | (0.009) | (0.011) | (0.008) | (0.016) | (0.004) | (0.025) | (0.005) | (0.024) | (0.004) | (0.018) |
| $div_{irt}$ | 0.491*** | -0.008 | 0.441*** | -0.032*** | 0.493*** | 0.007 | 0.494*** | -0.038** | 0.495*** | -0.021* | 0.497*** | 0.006 |
| | (0.004) | (0.006) | (0.009) | (0.011) | (0.003) | (0.008) | (0.003) | (0.018) | (0.003) | (0.012) | (0.002) | (0.010) |
| $rd_{rt}$ | 0.018** | -0.010 | 0.074*** | 0.028 | 0.015* | -0.013 | -0.001 | -0.014 | 0.011** | -0.002 | 0.006 | -0.082*** |
| | (0.008) | (0.012) | (0.021) | (0.024) | (0.009) | (0.018) | (0.006) | (0.039) | (0.005) | (0.026) | (0.005) | (0.022) |
| spatially lagged $l_{irt}$ or $w_{irt}$ | 0.914*** | 0.867*** | 0.637*** | 0.702*** | 0.822*** | 0.776*** | 0.948*** | 0.505*** | 0.925*** | 0.642*** | 0.926*** | 0.723*** |
| | (0.009) | (0.012) | (0.025) | (0.023) | (0.015) | (0.018) | (0.006) | (0.034) | (0.008) | (0.026) | (0.008) | (0.022) |
| spatially lagged $spe_{irt}$ | -1.125*** | -0.103*** | -0.660*** | 0.008 | -0.795*** | -0.122*** | -0.983*** | 0.022 | -0.966*** | -0.219*** | -0.985*** | -0.131*** |
| | (0.022) | (0.031) | (0.032) | (0.020) | (0.026) | (0.032) | (0.008) | (0.047) | (0.014) | (0.048) | (0.012) | (0.035) |
| spatially lagged $div_{irt}$ | -0.443*** | -0.018* | -0.232*** | -0.027 | -0.398*** | -0.049*** | -0.458*** | -0.046 | -0.454*** | -0.007 | -0.462*** | -0.073*** |
| | (0.008) | (0.010) | (0.021) | (0.019) | (0.011) | (0.015) | (0.006) | (0.033) | (0.006) | (0.022) | (0.006) | (0.019) |
| spatially lagged $rd_{rt}$ | 0.018** | -0.014 | 0.041* | -0.075*** | 0.010 | -0.006 | 0.018*** | -0.067 | 0.003 | -0.042 | 0.023*** | 0.049*** |
| | (0.009) | (0.013) | (0.025) | (0.028) | (0.010) | (0.018) | (0.007) | (0.034) | (0.006) | (0.030) | (0.006) | (0.025) |
| Observations | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 | 756 |
| Wald test | 70017*** | 6848*** | 19478*** | 1376*** | 69812*** | 2616*** | 184344*** | 402*** | 159720*** | 1013*** | 224706*** | 1666*** |
| Wald test of spatial terms | 14034*** | 5602*** | 965*** | 1120*** | 4508*** | 2251*** | 37051*** | 281*** | 16272*** | 757*** | 20851*** | 1351*** |

**Notes**: See notes to Table 5. Standard errors are given in parentheses. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table A5.** Direct, spatial spillover and feedback effects using spatial panel specification and random effects by industry.

| | **Food** | | **Textile** | | **Wood** | | **Paper** | | **Non-metal** | | **Metal** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** | **Employment** | **Wage** |
| *Coefficient* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.237*** | 0.056*** | 1.027*** | 0.0007 | 1.077*** | 0.037** | 1.020**** | 0.053** | 1.053*** | 0.031 | 1.087*** | 0.108*** |
| $div_{irt}$ | 0.491*** | -0.008 | 0.441*** | -0.032*** | 0.493*** | 0.007 | 0.494*** | -0.038** | 0.495*** | -0.021* | 0.497*** | 0.006 |
| $rd_{rt}$ | 0.018** | -0.010 | 0.074*** | 0.028 | 0.015* | -0.013 | -0.001 | -0.014 | 0.011** | -0.002 | 0.006 | -0.082*** |
| *Direct effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.241*** | 0.024 | 1.026*** | 0.003 | 1.120*** | 0.0004 | 1.000*** | 0.061** | 1.060*** | -0.019 | 1.107*** | 0.090*** |
| $div_{irt}$ | 0.496*** | -0.023** | 0.453*** | -0.046*** | 0.497*** | -0.010 | 0.506*** | -0.049** | 0.498*** | -0.026* | 0.496*** | -0.016 |
| $rd_{rt}$ | 0.047*** | -0.024* | 0.096*** | 0.012 | 0.026*** | -0.019 | 0.021*** | -0.026 | 0.024*** | -0.013 | 0.032*** | -0.085*** |
| *Indirect or spatial spillover effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.054 | -0.373 | -0.014 | 0.026 | 0.457*** | -0.378*** | -0.291** | 0.092 | 0.100 | -0.509*** | 0.271** | -0.175 |
| $div_{irt}$ | 0.064 | -0.171** | 0.123*** | -0.151*** | 0.038 | -0.176*** | 0.181** | -0.122** | 0.049 | -0.052 | -0.014 | -0.224*** |
| $rd_{rt}$ | 0.369*** | -0.156*** | 0.221*** | -0.168*** | 0.112*** | -0.064 | 0.318*** | -0.138** | 0.168*** | -0.111** | 0.358*** | -0.033 |
| *Total effect* | | | | | | | | | | | | |
| $spe_{irt}$ | 1.295*** | -0.350 | 1.012*** | 0.030 | 1.577*** | -0.377** | 0.709*** | 0.153 | 1.160*** | -0.527*** | 1.378*** | -0.084 |
| $div_{irt}$ | 0.561*** | -0.195** | 0.576*** | -0.197*** | 0.535*** | -0.186*** | 0.687*** | -0.171** | 0.547*** | -0.077 | 0.482*** | -0.240*** |
| $rd_{rt}$ | 0.416*** | -0.180*** | 0.317*** | -0.156*** | 0.138*** | -0.083 | 0.339*** | -0.164*** | 0.192*** | -0.124** | 0.390*** | -0.118** |
| *Feedback effect in the own region* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.004 | | -0.001 | | 0.043 | | -0.020 | 0.008 | 0.007 | | 0.02 | -0.018 |
| $div_{irt}$ | 0.005 | | 0.012 | -0.014 | 0.004 | | 0.012 | -0.011 | 0.003 | -0.005 | -0.001 | |
| $rd_{rt}$ | 0.029 | | 0.022 | | 0.011 | | | | 0.013 | | | -0.003 |
| *Feedback effect as a percentage of the coefficient* | | | | | | | | | | | | |
| $spe_{irt}$ | 0.3% | | -0.1% | | 4.0% | | -2.0% | 15.1% | 0.7% | | 1.8% | -16.7% |
| $div_{irt}$ | 1.0% | | 2.7% | 43.8% | 0.8% | | 2.4% | -28.9% | 0.6% | 23.8% | -0.2% | |
| $rd_{rt}$ | 161.1% | | 29.7% | | 73.3% | | | | 118.2% | | | 3.7% |

**Notes:** See notes to Table 6. ***. ** and * Statistical significance at the 0.01. 0.05 and 0.10 levels respectively. Standard errors are not presented due shortage of space, but they are available upon request.

**Table A6.** Regression results using spatial panel specification and fixed effects by industry.

| | Textile | | Paper | |
|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** |
| $spe_{irt}$ | 1.021*** | 0.004 | 1.022*** | 0.052** |
| | (0.008) | (0.010) | (0.003) | (0.024) |
| $div_{irt}$ | 0.437*** | -0.027*** | 0.495*** | -0.040** |
| | (0.008) | (0.010) | (0.003) | (0.018) |
| $rd_{rt}$ | 0.077*** | 0.014 | -0.004 | -0.002 |
| | (0.020) | (0.024) | (0.006) | (0.040) |
| spatially lagged $l_{irt}$ or $w_{irt}$ | 0.753*** | 0.800*** | 0.959*** | 0.652*** |
| | (0.025) | (0.022) | (0.005) | (0.035) |
| spatially lagged $spe_{irt}$ | -0.771*** | 0.022 | -0.995*** | -0.010 |
| | (0.035) | (0.027) | (0.010) | (0.067) |
| spatially lagged $div_{irt}$ | -0.210*** | -0.053** | -0.454*** | -0.097* |
| | (0.027) | (0.26) | (0.009) | (0.052) |
| spatially lagged $rd_{rt}$ | -0.019 | -0.034 | 0.017** | -0.037 |
| | (0.023) | (0.028) | (0.007) | (0.046) |
| | | | | |
| Observations | 756 | 756 | 756 | 756 |
| Wald test | 24488*** | 1870*** | 215700*** | 576*** |
| Wald test of spatial terms | 1525*** | 1574*** | 56086*** | 436*** |

**Notes**: The spatial model used was the SDM model with the inverse distance squared matrix. Standard errors are given in parentheses. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

**Table A7.** Direct, spatial spillover and feedback effects using spatial panel specification and fixed effects by industry.

| | Textile | | Paper | |
|---|---|---|---|---|
| | **Employment** | **Wage** | **Employment** | **Wage** |
| *Coefficient* | | | | |
| $spe_{irt}$ | 1.021*** | 0.004 | 1.022*** | 0.052** |
| $div_{irt}$ | 0.437*** | -0.027*** | 0.495*** | -0.040** |
| $rd_{rt}$ | 0.077*** | 0.014 | -0.004 | -0.002 |
| *Direct effect* | | | | |
| $spe_{irt}$ | 1.020*** | 0.010 | 1.007*** | 0.056** |
| $div_{irt}$ | 0.460*** | -0.045*** | 0.516*** | -0.056*** |
| $rd_{rt}$ | 0.085*** | 0.008 | 0.008 | -0.007 |
| *Indirect or spatial spillover effect* | | | | |
| $spe_{irt}$ | -0.009 | 0.122 | -0.347 | 0.067 |
| $div_{irt}$ | 0.458*** | -0.356*** | 0.502*** | -0.337** |
| $rd_{rt}$ | 0.150*** | -0.110 | 0.295*** | -0.105* |
| *Total effect* | | | | |
| $spe_{irt}$ | 1.011*** | 0.132 | 0.659*** | 0.123 |
| $div_{irt}$ | 0.918*** | -0.401*** | 1.018*** | -0.393*** |
| $rd_{rt}$ | 0.235*** | -0.101 | 0.302*** | -0.112* |
| *Feedback effect in the own region* | | | | |
| $spe_{irt}$ | -0,001 | | -0,015 | 0,004 |
| $div_{irt}$ | 0,023 | -0,018 | 0,021 | -0,016 |
| $rd_{rt}$ | 0,008 | | | |
| *Feedback effect as a percentage of the coefficient* | | | | |
| $spe_{irt}$ | -0,1% | | -1,5% | 7,7% |
| $div_{irt}$ | 5,3% | 66,7% | 4,2% | 40,0% |
| $rd_{rt}$ | 10,4% | | | |

**Notes:** The spatial model used was the SDM model with the inverse distance squared matrix. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels respectively. Standard errors are not presented due shortage of space but they are available upon request.