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GEOGRAPHICALLY VARIABLE HUMAN CAPITAL: TRIGGER FOR JOB CREATION

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RESUMEN: Esta investigación mide cuánto contribuye el capital humano a la creación de empleo a nivel regional. Su objetivo es medir el desarrollo económico a través de variables asociadas al capital humano, que pueden generar retornos como la difusión de conocimientos o la explotación de reservas de mano de obra calificada. Los datos permiten observar y medir el empleo durante un período de contracción económica significativa. Sostenemos que la creación de empleo no es uniforme en todo el territorio, sino que hay excepciones focalizadas debido a la composición única de trabajadores, recursos y otros elementos que tienen las regiones y las fuerzas económicas que implican. Se utilizó la regresión ponderada geográficamente (GWR) para capturar la heterogeneidad regional, y se encontraron retornos crecientes del capital humano de diferentes magnitudes y desviaciones de las tendencias globales en lugares específicos del territorio.

Palabras Clave: Empleo; Capital humano; Econometría; Regresión ponderada geográficamente; Geografía económica.

ABSTRACT: This research measures how much human capital contributes to job creation at the regional level. It aims to measure economic development through variables associated with human capital, which can generate returns such as the spillover of knowledge or the exploitation of pools of skilled labour. The data allow for the observation and measurement of employment during a period of significant economic contraction. We argue that job creation is not uniform across the territory, but that there are focused exceptions due to the unique composition of workers, resources and other elements that regions have and the economic forces that they entail. Geographically weighted regression (GWR) was used to capture regional heterogeneity, and increasing returns on human capital were found of different magnitudes and deviations from global trends in specific places in the territory.

Keywords: Employment; Human Capital; Econometrics; Geographically weighted regression; Economic geography.

1 Introduction

This article contributes to the current knowledge on regional variation in employment and the regional factors that influence it by studying the influence that local human capital has on job creation. According to Faggian (2019), the aggregate stock of human capital is positively associated with the level of economic growth and development. In the same vein, Mellander & Florida (2021) highlight that the key factor for regional growth and development is the geographic concentration of skills. Mellander & Florida (2021) observe that such skill concentration is increasingly important for innovation, productivity, and regional economic expansion.

Moreover, Wang & Li (2022) found a significant positive relationship between human capital and regional resilience in their study. This suggests that investments in education can enhance human resources and boost productivity, which may help explain the differences between regions during both growth periods and times of crisis (Rodríguez-Pose & Garcilazo, 2015).

Zhang & Wang (2021), for their part, estimated the regional composition of human capital using the Jorgenson-Fraumeni (J-F) lifetime income approach (Jorgenson & Fraumeni, 1992a, 1992b). This method begins by estimating individuals' expected lifetime earnings and then aggregates them at time t across the population, taking into account gender, age, educational attainment, and location. Using this J-F index — which captures the regional heterogeneity of individuals— Zhang & Wang (2021) found a strong positive effect of human capital on growth, which they considered consistent with human capital theory and the empirical evidence reported in the literature.

Previous studies on the subject (Hansen and Winther, 2015; Holl, 2018; Simon, 1998) have not taken into account the effect of differing regional characteristics. Nor have they assessed the heterogeneous regional effects of the 2008 financial crisis, despite some regions having been more severely affected than others (Sutton & Arku, 2022). The crisis exposed the vulnerabilities of regional economies within the current global economic landscape (Martin and Sunley, 2020). This raises two key questions: how did the Great Recession affect regions differently? And how do regional characteristics influence employment?

To address these questions, two population censuses were used as sources of information (the 2001 and 2011 Population and Housing Censuses), which span the period of the 2008 crisis. This approach offers three advantages for the research: first, it ensures that the findings are based on a nationally representative dataset; second, it allows for an analysis of employment variation from a spatial heterogeneity perspective—an aspect that has been underexplored in the country; and third, it provides a unique opportunity to observe regional employment behaviour under conditions of economic stress.

From the perspective on how the human capital impacts employment growth Samara et al. (2020) recommends conducting economic studies to identify regional characteristics, as the effectiveness of local policies relies on a sound understanding of scientific and technological potential, industrial structures, distribution systems, local demand features, and local knowledge diffusion channels, among other features.

Meanwhile Huggins & Williams (2011) propose a link between entrepreneurship and enterprise development as a tool for improving regional competitiveness and regional policy in less competitive regions. Technological policies aimed at promoting private R&D are important for firms not only for the direct beneficial effects it has on their innovation activity, but also because it improves their capability of assimilating external knowledge (Nonnis et al., 2023). Recent evidence suggests that national policies and business environments play a crucial role in fostering firm growth (Andrews et al., 2014; Bravo-Biosca et al., 2016). Moreover, Samara et al. (2020) advocates for promoting an entrepreneurial culture not only among students but also among researchers and mentions that during the last decade all the researchers and students in lagging regions have followed entrepreneurship related training programs, an initiative driven by central government policies. This has enhanced the level of awareness of the importance of spin-offs, entrepreneurial activities and new venture creation related needs.

Dettori et al., (2012) highlight the geographical implications of technological, human, and social capital on growth. Similarly, Borensztein et al., (1998) concludes that the effect of FDI on economic growth depends on the level of human capital available in the host economy—there is a strong positive interaction between FDI and educational attainment. Here, regional authorities hold an important role for innovation policies to prioritize the knowledge flows (Samara et al., 2020).

From this perspective human capital development strategies that adopt a lifelong learning approach are essential to the economic success of both nations and institutions (Jacobs, 2013). In addition to contributing to increase the absorptive capacity of firms, making their investment important not only per se, but also in order to enhance the capability to absorb knowledge produced elsewhere (Nonnis et al., 2023) . Aghion et al., (2009) summarise the channels through which education may affect growth. The direct effect includes the private return on individuals' increased human capital, but there are also various externalities (Kamar et al., 2019). In highly developed countries, the most frequently discussed externality is that investments in education foster technological innovation, which enhances the productivity of both capital and labour, thus generating income growth. In developing countries, the mechanisms linking education to growth are more often related to basic social institutions, fertility, or agricultural adaptation (Kamar et al., 2019).

Kasarda & Rondinelli (1998) also emphasise that increased global competition means that industry and government must work together to ensure that manufacturers have support networks of transportation, telecommunications, services, and knowledge centers. However, it is well understood that quality infrastructure alone is not sufficient to make a territory attractive.

In the same vein, Anos Casero & Udomsaph (2009) summarises five microeconomic foundations—quality infrastructure, financial development, governance, labour market flexibility, and workforce quality—that are closely linked to business growth. Nonnis et al. (2023) add measures that create a favorable regional environment for local economic actors: the promotion of human capital universities and training, as they allow translating R&D investment into new products and processes, besides attracting and absorbing more external knowledge in a sort of knowledge loop. In practice, firms are not able to exploit the full potential of their R&D investment if, for example, their employees are not provided with adequate training, the company does not have the appropriate IT equipment and infrastructure or the organizational capabilities to translate R&D outcomes into innovation. This could form part of a regional strategy aimed at supporting businesses.

To address the problem of quantifying regional human capital a dataset based on the characteristics of the inhabitants of each municipality has been used within this research framework, and a geographically weighted regression model is employed to account for the influence of local conditions on employment at the regional level. We start from the hypothesis that resources are focused on the areas or regions where the best yields are obtained. Hence, several authors (Bass et al., 1968; Cui and Liu, 2000; Govind et al., 2014; Mulhern, 1994; Sarabia-Sánchez et al., 2012) have worked on identifying these areas of opportunity in studies that segment by regions (Cui and Liu, 2000), groups of people (Bass et al., 1968; Mulhern, 1994; Sarabia-Sánchez et al., 2012) or even weather conditions (Govind et al., 2014) to identify the mutually exclusive groups from an accumulation of apparently identical elements.

Once this classification has been made, the authors focus on the group or groups of interest, which implies accepting the fact that different segments have different responses to the same stimulus; applied in geographical economics, this implies that the same stimuli can have different effects in different regions. It should be stressed that recognising this phenomenon can help identify the regional factors that trigger employment growth (Partridge et al., 2008) and suggests the existence of spatial heterogeneity. This arises because regions vary in their structure, social context and history (Lloyd and Shuttleworth, 2005), among other characteristics that are particular to each labour market and impossible to replicate in other regions.

It should also be mentioned that the estimation of spatial heterogeneity may become a hypothesis to be evaluated (Partridge et al., 2008). In this context, Govind et al. (2014) stated that, in San Francisco, the regional variation in *per capita* alcohol consumption rates could be due to the variation in the presence of homeless people in each region. For their part, Acemoglu and Angrist (2000) concluded that the evident positive relationship between average education and wages is more prominent in some regions.

The evidence thus highlights the need to delve into the nature of local relationships, processes and dynamics, because the successful development of economic strategies at the local level depends on it (Partridge *et al.*, 2008). For this purpose, the methodology must recognise the heterogeneity of each community through *ad hoc* statistical modelling that considers the non-stationarity of space. Standard approaches such as ordinary least squares (OLS) or other traditional econometric models, by providing only a "global" measure for the entire space, tend to compromise spatial heterogeneity in favour of average estimates, because the marginal responses of the explanatory variables are generally presupposed to be fixed in space. Although a global average is a useful reference point for making general statements about responses to a variable, it clearly cannot reflect the actual response for many regions.

The GWR model has been applied to processes that vary spatially (Brunsdon et al., 1998). The theoretical basis of GWR argues that the closer two regions are geographically, the greater the probability that they are similar in terms of their response to a given stimulus. This is because they face similar socioeconomic and regional factors that influence the relationship between dependent and independent factors. GWR thus facilitates the interpretation of information, as it produces a surface of parameters across the study region. This replaces the traditional global forms of regression models and adds spatial heterogeneity to the analysis.

2 Literature Review

Once the fact that economic agents are subject to forces that exert different pressures in different geographical regions was recognised, this hypothesis was evaluated with methodologies that analysed the information contained in variables generated by the processes of phenomena influenced by the location of economic and social agents (Atkinson-Palombo and Kuby, 2011; Boermans et al., 2011; Carey, 1966; Plane and Heins, 2003). These studies assumed that there are factors that act at a local level and influence the economic and social environment that develops around them. This suggests the usefulness of considering the unique characteristics of each region, because its structure (e.g., economic, social, political, historical or legal) determines productive and consumption activities. Hawkins et al. (1981) considered as possible influences both the physical landscape (topography, climate, natural resources) and the psychological landscape (historic, economic, religious, legal and population structure), while Kahle (1986) suggested climate and shared resources as cohesive forces or elements at the regional level, pushing the vicinity to be together. Meanwhile, Cui and Liu (2000) proposed geographical diversity and economic disparity as factors that produce differences between neighbourhoods, which implies that a single strategy, across all constituencies, is not advisable (Govind et al., 2014).

In addition to topographic, climatic and economic differences, (Hawkins et al., 1981) suggested considering the predominant cultural differences at the local level, which (Sarabia-Sanchez et al., 2012) exemplified by recognising the existence of a significant cultural group of consumers that considers the ecological commitments of each business. According to (Sarabia-Sanchez et al., 2012), this group is characterised by its particular awareness of campaigns concerned with the environment, as well as with ecological production processes, use of materials, store accessories and environmentally friendly experimental aspects. They also stressed that it is possible to influence this group by highlighting the company's ecological attitudes. Among the authors who highlighted cultural aspects, (Cui & Liu, 2000) allude to cultural heritage as a condition that makes each market unique. (Roy Chaudhuri & Haldar, 2005) showed that residents in areas with more cultural attachment to traditional values are less likely to make acquisition a life objective, which affects the degree of consumption and therefore the level of production at a regional level. Policymakers and planners should thus consider geographic subcultures as a potentially useful variable when developing marketing (Hawkins et al., 1981) or production strategies.

Under the same assumption, (Beane & Ennis, 1987) explained that this type of segmentation implies recognising that people and their needs vary geographically and that the term "geographically" can take several meanings (e.g., country, population density or climate). (Hawkins et al., 1981) justified this approach by arguing that there are subcultures in each region and that members of these subcultures must share patterns (climate, legislation, religion, etc.) to belong to that subculture. This eventually affects the consumption process and therefore production, which is why influences at the regional level became an element of interest in the economic environment.

This panorama thus leads to the idea that each region is composed of a set of agents and resources (e.g., companies, human capital, natural resources, public spending policies) that, when conglomerated, produce a unique combination which cannot be replicated anywhere else. These actors have an economic influence at the regional level through job creation, development and investment in the surrounding area. This generates statistically significant differences between regions (Roy Chowdhury and Haldar, 2005), as well as differences in purchasing power, attitudes, lifestyles, use of electronic media (Cui and Liu, 2000) and purchasing behaviour (Mulhern, 1994).

Considering the financial and economic crisis of 2008, which led to widespread job destruction in the country, Holl (2018) found that human capital was key to local resilience during the recession and explained local economic resilience, particularly in cities. Accordingly, Simon (1998) provided evidence of a positive relationship between human capital and employment growth in metropolitan areas, as well as "contagion" effects between cities near metropolitan areas. It should also be note that Shapiro (2006) pointed out that the effect of employment growth (by university graduates) operates through changes in productivity.

Hansen and Winther (2015) were more specific in finding that human capital is not only the stock of school years or a percentage of people with a higher degree, but an analytical category by itself that, when disaggregated, can indicate the competencies and skills that contribute most to economic growth and could explain uneven geographic economic growth. In this same sense Eriksson and Forslund (2014) reported that university regions (which have high concentrations of human capital) that contain workers with an engineering knowledge base show higher growth rates. In other words, the influence of universities is greater in regions with high concentrations of skills capable of applying the knowledge created in them, thus enhancing the indirect effects on the social environment. Finally, Poelhekke (2013) found that the effect of the share of university graduates on employment growth is positive (0.5% growth for a 10% increase in human capital). Positive effects were also found for high school graduates with vocational training, especially if the concentration of technical professionals is high, thus attracting the "right" mix of skills is related to the success of the region.

Adler & Florida (2021) highlight that large, globally connected cities have advantages as hubs for urban technology development, as they tend to possess higher levels of human capital, which has been linked to business innovation (Adler et al., 2019; Kerr, 2010). In the same vein, Sun (2020) notes that human capital plays a key role in fostering innovation, concluding that a higher level of human capital in the workforce leads to a greater number of patents and a higher likelihood of innovation. Similarly, Zhang & Wang (2021) emphasises that highly skilled human capital becomes increasingly important as an economy advances, with technological progress and innovation becoming the primary engines of growth. Therefore, in building resilient cities, it is crucial to reduce income inequality while also increasing innovation, the concentration of human capital, and financial development to ensure long-term economic sustainability (Wang & Li, 2022).

Ehrl & Monasterio (2021) demonstrate that the spatial concentration of analytical skills produces positive wage externalities for all workers within the local labour market. Likewise, Yang (2023) emphasises that, alongside social, economic and spatial externalities, human capital increasingly and endogenously shapes spatial development. This has been illustrated in knowledge economies, across a wide range of industries, and in the attraction effects between regions and sectors (Liu, 2014; Morris et al., 2020).

In terms of focused exceptions, Yang (2023) points out that the geography of high-tech urban industries is primarily determined by the scale of existing high-tech activity and the size and extent of metropolitan areas (Adler & Florida, 2021). In other words, the level of human capital and the presence of multiple actors at city or regional level (regional heterogeneity) are decisive. In this regard, Martini (2020) argues that what clearly emerges from their analysis is that the capacity of a region's structure—in terms of industrial, technological, labour force, and institutional configurations—to adapt to changes (driven by competitive, technological and global markets) is key to long-term regional economic success. Human capital, among other factors, supports this adaptability by enhancing the absorption of foreign investment and facilitating outward investment (Yang et al., 2022).

Further studies also examine the regional composition of human capital. In the case of China, for example, Yang (2023) shows that human capital enables regions to evolve from merely receiving external resources to becoming active contributors in the global market (Yang et al., 2022). In Italy, Martini (2020) concludes that long-term regional success also depends on region-specific factors such as labour productivity and the quality of institutions. Similarly, in Spain, Martínez (2019) finds that regions oriented towards industry and with higher levels of human and public capital tend to be more resilient during periods of crisis, whereas regions focused on market services are more resilient during recovery periods. This highlights the fact that regions with differing compositions of human capital exhibit distinct economic behaviours.

A key reference in this field is the work, Osiobe, (2019) who provides a comprehensive review of the literature on human capital, summarising articles in terms of: (i) the theoretical framework of economic growth theory, (ii) the neoclassical growth model, (iii) the Solow growth production function, (iv) the new endogenous growth theory, and (v) empirical evidence on the relationship and causal link between human capital and economic growth.

2.1 Regional heterogeneity

To analyse how the composition of human capital at the municipal level influences regional employment growth in a differentiated manner, this study compares employment levels before and after the 2008 economic crisis. It begins from the recognition that regional characteristics are not homogeneous and that human capital —in terms of education, skills, and spatial distribution— interacts unevenly with the processes of job creation across different parts of the territory.

Recent studies, such as those by Adler et al. (2019) and Sun (2020), highlight that human capital not only promotes general economic growth but also serves as a key driver of innovation in regions with advanced productive structures. Zhang & Wang (2021) further notes that as economies mature, highly skilled human capital becomes increasingly crucial in sustaining knowledge- and technology-driven growth.

However, it is essential to acknowledge that regions exhibit substantial differences which directly affect how human capital contributes to employment creation. These differences are not merely geographical but also structural and functional. Firstly, regions vary significantly in their economic and industrial structure: while some urban or metropolitan areas have diversified economies based on advanced services, innovation, and specialised manufacturing, others —such as many coastal or rural areas— rely almost exclusively on traditional sectors such as tourism or agriculture, which typically require lower skill levels and offer more precarious, seasonal jobs. Moreover, there is an unequal distribution of physical and technological infrastructure —such as transport networks, digital connectivity, and access to higher education— which influences the ability of regions to attract and retain human capital (Calderon & Serven, 2010; Luo, 2022). Additionally, local institutions and the quality of governance are also key differentiators: regions with strong institutional frameworks and well-developed administrative capacities tend to manage their human and financial resources more effectively, thereby making better use of the available human capital (Mohanty & Bhanumurthy, 2018; Cooke et al., 2004).

These conditions are in turn shaped by unique economic, social, and political trajectories in each territory. Factors such as the degree of administrative decentralisation, regional innovation policies, local business networks, and internal labour mobility all contribute to creating diverse regional contexts. For example, the presence of innovation ecosystems or dynamic university networks can enhance the value of human capital in a given region, whereas their absence may significantly limit its impact, regardless of the population's education level (Tödtling & Trippl, 2005).

Regional variations or exceptional behaviours are observed at the local level, as well as their influence at the econometric level, when working with georeferenced variables. Tödtling and Wanzenböck (2003) thus suggested the need for a markedly differentiated policy when they found regional variations in terms of both the intensity and structural quality of business creation. Guastella and Van Oort (2015), meanwhile, pointed out that regional heterogeneity can help explain innovation clusters based on localised knowledge transfer. In such cases, the spatial partnership is econometrically related to the transfer of research, which indicates the importance of the analysis of regional heterogeneity to explain the differences captured by variables such as cultural values differentiated by region (Roy Chaudhuri and Haldar, 2005).

Regarding the regional heterogeneity in the endowment of human capital, the evidence indicates that this component is especially significant in the case of the capacity for labour insertion if educational level is considered. For this reason, at the regional level, human capital can drive employment growth in an area (Hansen and Winther, 2015), as well as influencing wage differentials by region and the profits made from this capital (López-Bazo and Motellón, 2012). In this context, it should be noted that while the public sector contributes to the reduction of the unequal spatial distribution of human capital, the private sector increases it (Hansen and Winther, 2015). That is, they located regions where there are focused exceptions or deviations from global trends (Grose et al., 2008).

In summary, academic studies or policy design in a regional context requires explicit recognition of spatial heterogeneity in the characteristics of a community and how it affects the target variables (Ali et al., 2007). Recognising this spatial variation implies applying a statistical modelling that takes this consideration into account in some way. The GWR technique represents one approach to address this issue (Brunsdon et al., 1998; Fotheringham et al., 2002). GWR estimates a locally variable sample for each potential observation point or for other desired locations, which then produces a separate set of regression parameters for each observation point. These parameters reflect the heterogeneity of the sample by estimating different marginal responses of an explanatory variable across space. GWR thus allows the modelling of processes that vary in space.

Eckey et al. (2007) used GWR to analyse convergence processes in Germany and estimated an individual convergence velocity for each region based on local coefficients. They obtained different convergence velocities for each region; likewise, they found that the speed of convergence is substantially lower in the production sector than in the services sector. This approach provided evidence that southern regions, with high labour productivity and low unemployment, would be the most prosperous regions. They found that southern regions have a long half-life, while northern regions have a short half-life. On this basis of economic development, they concluded that, in the long run, there would be a gap between north and south.

It should also be noted that substantially different coefficients indicate that a global convergence model, estimated by other researchers (Funke and Niebuhr, 2005; Kosfeld et al., 2006; Kosfeld and Lauridsen, 2012), could be improved through a GWR approach. Thus, in using a geographically and temporally weighted regression (GTWR) model, both spatial and temporal non-stationarity in real estate market data are addressed. Huang et al. (2010), for example, studied the case of housing sales from 2002 to 2004; they found that there were substantial benefits in simultaneously modelling spatial and temporal non-stationarity. On the other hand, Lo (2008) applied GWR to estimate the population and found that it could help improve the accuracy of the estimate by 28% compared to the global model.

3 Data and Methodology

The data sample in this study is based on the responses of the people interviewed by the National Institute of Statistics (*Instituto Nacional de Estadística,* INE) during the population and housing censuses in 2001 and 2011, based on the fact that the 2008 crisis falls between these two timepoints and makes them suitable samples to capture a generalised contraction of employment throughout the country. In addition to its availability, this source was chosen for the rigor of application, the methodological validity, the nature of national surveys and the need for georeferenced data to conduct GWR.

These censuses summarise the characteristics of people and their homes throughout the peninsular and non-peninsular territory (Ceuta, Melilla, the Balearic and Canary Islands). For reasons of anonymity, the 2001 and 2011 censuses only reported information on municipalities with more than 20,000 inhabitants; in 2001, there were 317, and in 2011, there were 394. The municipalities from 2011 that were not reported in 2001 were discarded to allow comparison. With the information on the inhabitants in each municipality, it is possible to express their characteristics in terms of the structure of human capital corresponding to 2001 (Table 1).

The sample used here is spatially heterogeneous because the municipalities and their surroundings vary in terms of their business structure, political, economic, social, historical and legal context, among other characteristics. These differences between regions cannot be captured through traditional global regression, because spatial heterogeneity can cause misleading global estimates as they are not interpreted in local terms. For example, incorrect findings regarding the role of key variables may be accepted, which may be the result of global estimates that significantly mask local variation, including in the direction of influence. For example, global estimates may suggest that there are no marginal effects when, in fact, the factor stimulates growth in some areas while in others it reduces it, thus resulting in an average effect of approximately zero.

The analysis of the relationships between variables with the GWR technique showed that it can support regional analysis, because it indicates places of focused exception where the variable under investigation has distinctive behaviours.

Table 1. Descriptive statistics of the variables used in the sample (317 municipalities)

VARIABLE KEY	VARIABLE DESCRIPTION	MEAN	SD	NO. DATA
$\Delta EMP_{i,2001-2011}$	Percentage variation in employment in municipality i between 2011 and 2001	-0.44	0.18	317
$\%PROF_{i,2001}$	Proportion of administrators, professionals and technicians living in municipality i in 2001	0.11	0.04	317
$\%MANNC_{i,2001}$	Proportion of unskilled manual workers living in municipality i in 2001	0.09	0.03	317
$\%DIFPEAP_{i,2001}$	Difference between two ratios: (a) professional men to the economically active population (EAP) and (b) professional women to the EAP (both ratios in municipality i and in 2001)	0.04	0.03	317
$\%SUPNM_{i,2001}$	Proportion of non-manual supervisors resident in municipality i in 2001	0.10	0.03	317
$\%MANC_{i,2001}$	Proportion of qualified manual workers living in municipality i in 2001	0.07	0.02	317
$\%MAFAC_{i,2001}$	Proportion of workers in the manufacturing sector living in municipality i in 2001	0.07	0.04	317
$\%PESC_{i,2001}$	Proportion of workers in the fishing sector living in municipality i in 2001	0.02	0.03	317
$\%EDU3_{i,2001}$	Proportion of people with tertiary education (diploma, bachelor's and doctorate) living in municipality i in 2001	0.10	0.05	317
$\%DIFOCUP_{i,2001}$	Distance between two ratios: (a) employed men to the EAP and (b) employed women to the EAP (both ratios in municipality i and in 2001)	-0.01	0.02	317
$\%CONST_{i,2001}$	Proportion of workers in the construction sector living in municipality i in 2001	0.05	0.02	317

Source: Population and Housing Census 2001, 2011 (INE). National Directory of Activities (CNAE) and National Directory of Occupations (CNO).

The population and housing census is carried out every 10 years by the INE, so it is possible to quantify the evolution of the information and verify the impact on the variables of interest. Here, the percentage variation in the number of jobs between 2001 and 2011 in the 317 municipalities of the sample was determined. The variation in the number of jobs according to the human capital structure in each municipality was then proposed using a multiple linear regression model (Table 2). Variables whose coefficient β is not significant at a level of $\alpha = 0.10$ were eliminated from the model.

Table 2. Multiple linear model (MCO)

Residuals:

MY.	**1Q**	**MEDIAN**	**3Q**	**MAX.**
-0.18659	-0.03748	0.00053	0.03849	0.14406

Coefficients:

VARIABLE KEY	**ESTIMATE**	**STD. ERROR**	**t VALUE**	**PR(>|t|)**
(Intercept)	0.83915	0.07274	11.537	< 2e-16 ***
$\%PROF_{i,2001}$	0.15735	0.05626	2.797	0.00549 **
$\%MANNC_{i,2001}$	0.83941	0.13613	6.166	2.22e-09 ***
$\%DIFPEAP_{i,2001}$	-0.47106	0.19348	-2.435	0.01548 *
$\%SUPNM_{i,2001}$	0.20051	0.03758	5.335	1.87e-07 ***
$\%MANC_{i,2001}$	0.75231	0.1718	4.379	1.64e-05 ***
$\%MAFAC_{i,2001}$	0.15423	0.05488	2.81	0.00527 **
$\%PESC_{i,2001}$	0.92278	0.50842	1.815	0.07051
$\%EDU3_{i,2001}$	0.96057	0.16739	5.738	2.31e-08 ***
$\%DIFOCUP_{i,2001}$	-0.56167	0.18332	-3.064	0.00238 **
$\%CONST_{i,2001}$	-1.11094	0.36309	-3.06	0.00241 **

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.06035 on 304 degrees of freedom
Multiple R-squared: 0.6024
F-statistic: 46 on 10 and 304 DF, p-value: <2.2e-16
Adjusted R-squared: 0.5894
Source: Own elaboration

The variables eliminated because they were not significant were the difference between the unemployment rate of men and women, population density, people with employment activity related to services, proportion of employed people with activity related to agriculture, the dependency rate and the proportion of the total population belonging to the economically active population (EAP). The final model proposed is expressed in Eq. (1):

$$\begin{aligned}\Delta EMP_{i,2001-2011} &= \beta_{0i} + \beta_{1i}\%PROF_{i,2001} + \beta_{2i}\%MANNC_{i,2001} + \beta_{3i}\%EDU3_{i,2001} \\ &+ \beta_{4i}\%SUPNM_{i,2001} + \beta_{5i}\%MANC_{i,2001} + \beta_{6i}\%MFAC_{i,2001} + \beta_{7i}\%PESC_{i,2001} \\ &+ \beta_{8i}\%DIFPEAP_{i,2001} + \beta_{9i}\%DIFOCUP_{i,2001} + \beta_{10i}\%CONST_{i,2001} + \varepsilon_i\end{aligned} \tag{1}$$

All parameter estimates in the model were significant ($p<0.05$), except for the parameter of the variable that summarises the percentage of employment dedicated to fishing ($\%PESC_{i,2001}$), which has a level of $p<0.10$. This is possibly due to the fact that this parameter is only relevant in municipalities near the coast of the country and particularly to those on the north coast. It should be noted that the model is significant and explains 58% of the behaviour of the dependent variable, with a coefficient of determination $r^2 = 0.5894$; this means that the model manages to capture a good part of the behaviour of the variable studied, although around 40% is still not explained.

A high degree of variation in the growth rate (decrease) of employment is observable throughout the 317 municipalities in the sample (Table 3), which takes values ranging from a maximum employment growth of 58.05% in the municipality of Barabate, Cadiz, province of Andalusia, to a minimum employment decrease rate of −75.44% in the municipality of Arraste/Mondragón, Guipúzcoa, in the Basque Country. For the 317 municipalities in the sample, the mean change in employment growth is −43.94%, with a standard deviation of 17.64%. This implies that there is a general indication of spatial variation in the sample and suggests the use of GWR as a technique to describe variations in employment growth at the local level, because the methodology makes it possible to describe spatial variations in the relationships among the variables in the model.

Table 3 Statistics on the percentage change in employment 2001–2011 (ΔEMPi, 2001–2011) in the 317 municipalities

MAX.	STAND. DEV.(S)	MEAN ($\bar{x}$)	MIN.	N
58.05 %	17.64 %	-43.94 %	-75.44 %	317

Note: Data extracted from the censuses (2001 and 2011) of the INE

The data were processed using GWR, and cross-validation was used to determine the bandwidth (350 km); it was considered a Gaussian kernel. GWR weights depend on the linear distance between observations and represent adjacency effects for neighbouring locations within the specified bandwidth (Brunsdon et al., 1998). It is thus a diagonal weighting matrix that selects the observations intervening in the estimation of the local coefficients at the point $W_i\widehat{\beta_i}\ i$

$$W_i = \begin{bmatrix} \alpha_{i1} & 0 & 0 & \dots & 0 \\ 0 & \alpha_{i2} & 0 & \dots & 0 \\ 0 & 0 & \alpha_{i3} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & \alpha_{ij} \end{bmatrix}$$

Following the assumption that the closest locations are more similar, the weights should decrease with distance. Many weighting schemes could be used to meet this requirement, including the dichotomous, bisquare or trisquare decay function, W_i(Gutiérrez-Posada et al., 2017), but as Fotheringham et al. (2002) point out (pp. 44): "GWR results are relatively insensitive to the choice of the weighting function". When choosing a Gaussian core, the weighting function is specified as in Eq. (2):

$$\alpha_{ij} = e^{-(1/2)\left(d_{ij}/h\right)^2} \tag{2}$$

where d_{ij} is the distance between observations i and j, and h is the overall distance bandwidth adopted, while the weight decreases rapidly with distance from the geographical observation in question.

4 Results

The degree of impact on employment growth (decrease) ($\Delta EMP_{i,2001-2011}$) of the human capital accumulated by the residents in each municipality *i* of the sample was analysed. Diversity in local responses across space is to be expected – that is, explanatory variables were expected to have differential effects on employment growth across space.

Table 4. Statistics of employment change parameter based on geographically weighted regression

	Min.	1st Qu.	Media	3rd Qu.	Max.	Global
X. Intercept	0.7548	0.7892	0.8142	0.8504	0.9364	0.8392
$\%PROF_{i,2001}$	-0.0247	0.08845	0.1326	0.1792	0.2555	0.1573
$\%MANNC_{i,2001}$	0.3677	0.7435	0.8026	0.8905	1.1337	0.8394
$\%DIFPEAP_{i,2001}$	-0.6976	-0.5124	-0.4493	-0.3724	-0.2335	-0.4711
$\%SUPNM_{i,2001}$	0.1672	0.1833	0.1903	0.2099	0.2443	0.2005
$\%MANC_{i,2001}$	0.2744	0.5103	0.6466	0.8335	1.21	0.7523
$\%MFAC_{i,2001}$	-0.0124	0.0948	0.1225	0.144	0.1736	0.1542
$\%PESC_{i,2001}$	-1.9245	0.4299	0.7187	1.102	3.223	0.9228
$\%EDU3_{i,2001}$	0.7691	0.9215	0.9757	1.011	1.093	0.9606
$\%DIFOCUP_{i,2001}$	-0.7548	-0.5336	-0.4167	-0.2855	-0.05618	-0.5617
$\%CONST_{i,2001}$	-1.871	-1.365	-0.8787	-0.7379	-0.4368	-1.1109

All the estimated parameters are significant at p<.01, for>.95 of the municipalities. All the parameters estimated at a p>.05, for >.98 of the municipalities.
Function Kernel: gwr.Gauss
Adaptive Quantile: 0.1872818 (approximately 59 of the 317 data points)
Summary of estimated coefficients at data points
Source: Own elaboration

4.1 Maps of local gradients (β_i) in municipality i

It is expected that academic preparation and work experience, as well as the regional spillovers associated with these factors, would have a positive influence on the growth of the economy and therefore increase the number of available jobs both globally and regionally. However, the GWR makes it possible to detect whether the influences of the explanatory variables used are uniform throughout all municipalities or if, on the contrary, there are differentiated impacts on the response variable ($\Delta EMP_{i,2001-2011}$) at the regional level. These differentiated impacts could be due to the distinctive characteristics of each municipality and their influence as the geographical distance increases (decreases). The GWR technique postulates that the closer two municipalities are geographically, the greater the mutual influence exerted and vice versa. This influence is quantified with the weighting (Gaussian kernel) assigned to each point in space, which varies according to geographical distance and is subsequently summarised in the regional gradients produced by the geographically weighted model. The most representative regional gradients are shown in the maps below. The period used for this analysis (2001–2011) is very particular, because there were economic and labour adjustments of great magnitude in the country due to the economic slowdown that affected most of the world in 2008.

4.1.1 Determination of employment growth by variable ($\%DIFPEAP_{i,2001}$)

The global parameter (β=−.4711) of the variable $\%DIFPEAP_{i,2001}$ shows an inversely proportional relationship to employment growth ($\Delta EMP_{i,2001-2011}$). In other words, these two covariants behave inversely at the global level and indicate that the smaller the difference between the proportion of professional men and women, the greater the impact on employment growth at the global level.

At the local level, other behaviours focused on this parameter are apparent. It is noteworthy that a differentiated gradient behaviour is observed between the south and the centre of the country (Figure 1), with the southern gradients being greater. This regional gradient of greater magnitude implies that, in these regions, the impact on employment growth is greater than in the north when there is a change in the variable $\%DIFPEAP_{i,2001}$. Figure 1 shows the region in question (South-Central Spain), in which the spatial variation of the estimated local β_s coefficients between the $\Delta EMP_{i,2001-2011}$ and $\%DIFPEAP_{i,2001}$

covariants can be observed. As can be seen, the relationship between the two variables has the highest level of impact in the South-Central region of the country.

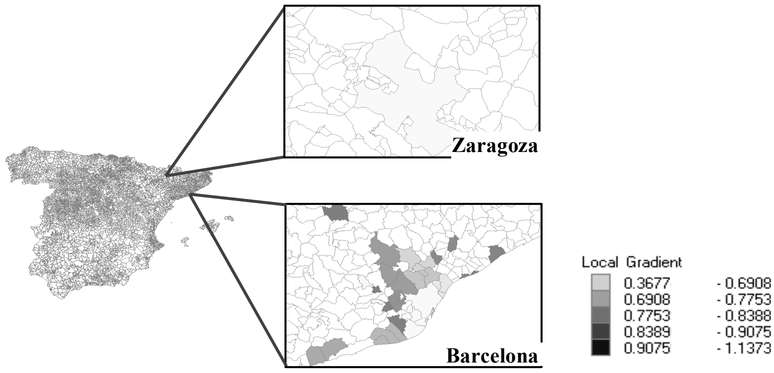
Figure 1. Influence of distance between professional men and women ($\%\mathrm{DIFPEAP}_{i,2001}$) on employment (Detail: Andalucia)

4.1.2 Unskilled manual workers ($\%MANNC_{i,2001}$) as a factor in employment growth

The coefficient (β=0.8394) of the global model (Table 2) that quantifies the impact suffered by the employment growth variable ($\Delta EMP_{i,2001-2011}$) when the proportion of unskilled manual workers ($\%MANNC_{i,2001}$) varies shows that their relationship is directly proportional. This positively quantifies the contribution of these workers in the creation of jobs at a global level throughout the territory. They are thus a factor in employment growth: the higher the proportion of unskilled manual workers, the greater the positive influence on the variation in the number of jobs between 2001 and 2011 in the 317 municipalities of the sample.

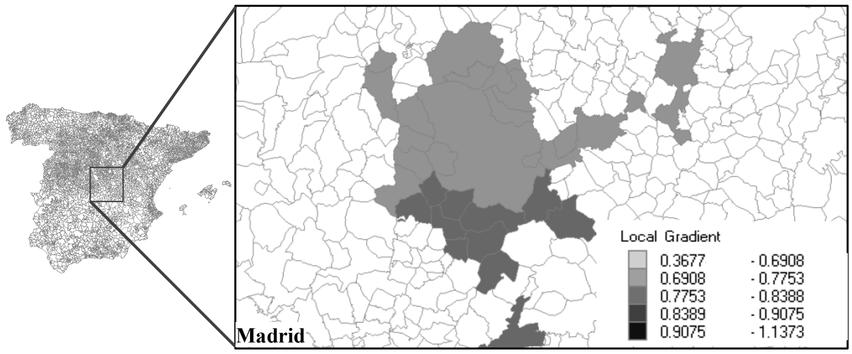
This positive impact varies at the local level ($0.3677 \leq \beta_i \leq 1.137$) throughout the 317 municipalities, and its impact is of greater magnitude in some regions (Figure 2) than in others. In this context, the cases of the metropolitan areas of Barcelona and Zaragoza (Figure 2) stand out, as the gradients take very small values; this behaviour is interpreted as meaning that, in these two cities and in the nearby municipalities, the dependent variable (variation of employment, $\Delta EMP_{i,2001-2011}$) does not have particularly significant variations in response to changes in the variable $\%MANNC_{i,2001}$. It is possibly because, in larger metropolitan areas, job creation is based on knowledge and the service sector rather than on manual activities. This exception from global trends may suggest that attention is needed to education and training policies for blue-collar workers in larger metropolitan areas.

Figure 2. Influence of people in unskilled manual activities ($\%\mathbf{MANNC}_{i,2001}$) on employment (Detail: Barcelona and Zaragoza).



The case of the metropolitan area of Madrid (Figure 3) is notable, because as the proportion of unskilled manual workers increases, the employment variation changes more significantly in the municipalities to the south of it (i.e., Getafe, Pinto, Fuenlabrada, Móstoles Alcorcón, Rivas-Vaciamadrid), where a large percentage of territory is dedicated to industry and manufacturing. This testifies to the greater impact of such workers in areas less focused on knowledge-driven employment like the municipalities around Madrid.

Figure 3. Influence of people in unskilled manual activities (%$\mathbf{MANNC_{i,2001}}$) on employment (Detail: Madrid)



4.1.3 Non-manual supervisors (%$SUPNM_{i,2001}$) as a determinant of employment growth

The degree of the impact on employment ($\Delta EMP_{i,2001-2011}$) of the human capital possessed by non-manual supervisors possess (%$SUPNM_{i,2001}$), can be seen in the global model (Table 2) where the coefficient (β=0.2005) shows a direct global relationship in the 317 municipalities (Table 4) – that is, the greater the proportion of non-manual supervisors who live in a municipality, the greater the growth of employment in that place. The variations of the local coefficients (Figure 4) take values ranging from a minimum β_i = 0.1672 to a maximum β_i = 0.2443 (Table 4). Figure 4 shows that these become smaller as the municipalities approach the coast, except in the Balearic Islands and in the suburban municipalities of Barcelona (Figure 5). This implies focused exceptions to global trends, perhaps due to the fact that the spillovers of knowledge or added value generated by non-manual supervisors, measured in terms of variation in employment, have a more noticeable impact in areas far from the country's coasts. It is possible that the skills of non-manual supervisors generate more of an impact in municipalities where economic activity is diversified. It is also possible that, on the coast, the economic activities of the municipalities depend largely on the tourism, hospitality and fishing industries. This situation is not reflected in the cases of the Balearic Islands and the metropolitan area of Barcelona (Figure 5), which, despite being coastal areas, feature diversified economic activity.

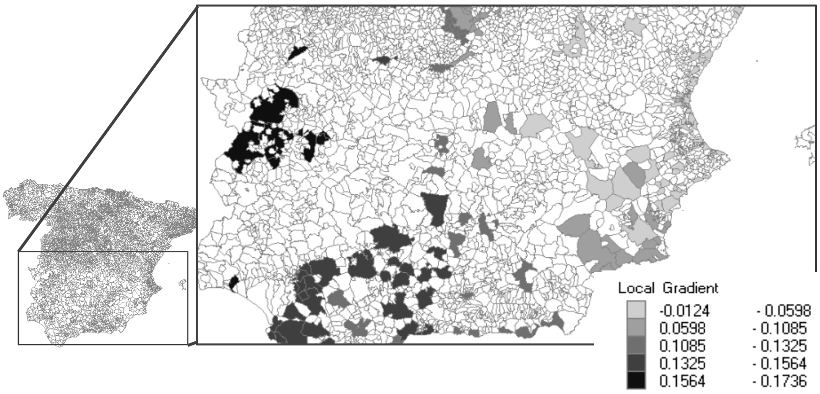
Figure 4. Influence of people with non-manual supervision activities (%$\mathbf{SUPNM_{i,2001}}$) on employment

Figure 5. Influence of people in mon-manual supervision activities (%$\mathbf{SUPNM_{i,2001}}$) on employment (Detail: Barcelona, Balearic Islands).

4.1.4 Manufacturing human capital (%$MAFAC_{i,2001}$) as a factor of employment growth

At the global level throughout the territory, the coefficient (β=0.1542) quantifying the impact between human capital focused on manufacturing (%$MAFAC_{i,2001}$) and the variation in employment ($\Delta EMP_{i,2001-2011}$) is positive and significant ($p<0.01$). This suggests that the higher the proportion of employment in manufacturing in municipality *i*, the greater the growth of employment there. In contrast, at local level, the map (Figure 6) distinguishes differences in the impact of this variable on employment growth between the east and west of the country, which leads to the conclusion that the manufacturing industry is far from the Mediterranean coast and that its impact is more prominent in the western regions of the country. So its impact as a generator of jobs is thus greater in those areas.

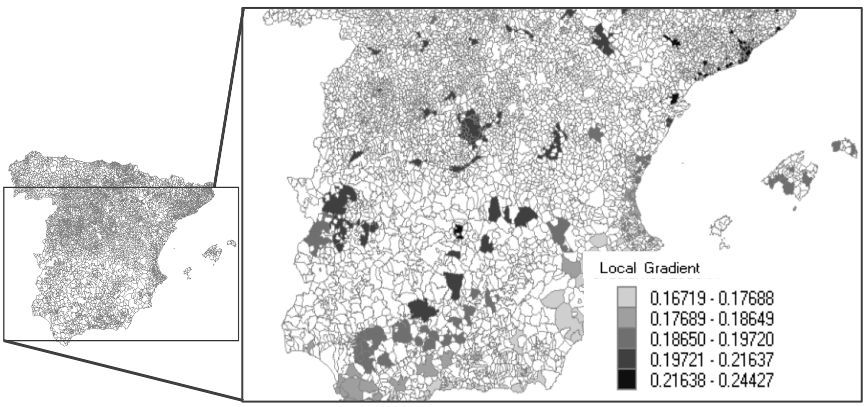
Figure 6. Influence of human capital employed in manufacturing ($\%\mathbf{MAFAC_{i,2001}}$) as a factor of employment growth.



4.1.5 Skilled manual workers ($\%MANC_{i,2001}$) as a determinant of employment growth

Again, at the global level throughout the country, the relationship between the variables employment growth ($\Delta EMP_{i,2001-2011}$) and proportion of skilled manual workers ($\%\mathrm{MANC_{i,2001}}$) is positive and significant. This suggests a directly proportional relationship between the variation in employment as an effect of the spillovers of the human capital of skilled manual workers. This same effect can also be observed at the local level, because all the coefficients are positive in the 317 municipalities in the sample (Table 4), ranging from a minimum of $\beta_i = 0.274$ to a maximum of $\beta_i = 1.21$ The impact becomes greater as the municipalities are closer to the centre of the peninsula and are away from both the north coast and the Mediterranean coast, (Figure 7). The same happened with the variable $\%SUPNM_{i,2001}$, which leads us to assume that economic activities on both coasts are mostly focused on tourism, hospitality and fishing activities.

Figure 7. Influence of skilled manual worker ($\%\mathrm{MANC_{i,2001}}$) on employment

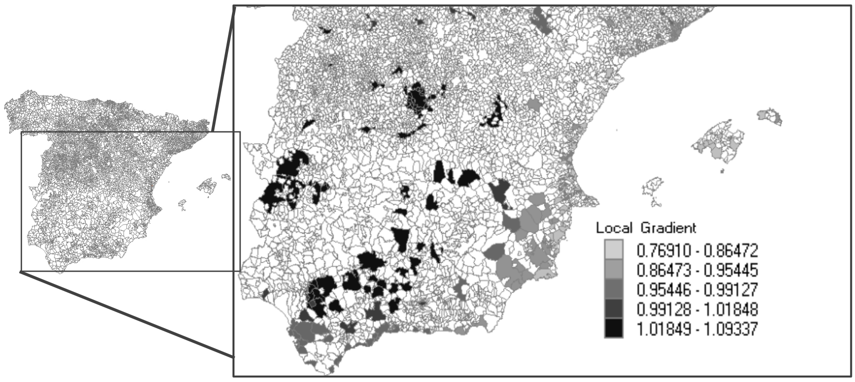


4.1.6 Influence of people with tertiary education ($\%EDU3_{i,2001}$) on the economy

The overall impact (Table 2) of the variable tertiary education ($\%EDU3_{i,2001}$) on employment ($\Delta EMP_{i,2001-2011}$) is positive, with a coefficient of β=0.9606. This coefficient is the largest in the model, which testifies to the relevance of education at both the global and local levels. The local coefficients (Table 4) are also the highest and range from the minimum β_i=0.7691 to the maximum β_i=1.093. These coefficients show (Figure 8) that education is more relevant as municipalities are further from the coast, although 75%

of the 317 municipalities had the highest coefficients for β_i in the model (tertiary education=1.01), which is evidence of the importance of promoting and investing in education, particularly at the university level and above throughout the territory.

Figure 8. Influence of People with Tertiary Education ($\%\mathbf{EDU3}_{\mathbf{i,2001}}$) on Employment



5 Discussion

Interaction between Human Capital and Other Factors (Labour Market Conditions and Government Policies)

It is essential to acknowledge the effect of economic policies on employment through the interaction captured between variables. The econometric results in the work of Kamar et al. (2019) confirm the impact of various policies on employment. Specifically, they evaluated policies addressing skills mismatches in the labour market, fiscal and monetary incentives aimed at directing investment towards labour-intensive projects, and policies promoting the development of SMEs and recognise their potential for significant employment growth. Woo et al., (2017) also tackles the employment issue by measuring the relationships between variables and suggests capturing the different levels of complementarity between investment in capital and in education, or between education and technological progress, as introduced by Lin (2003). He mentions that these relationships may vary across regions. Such heterogeneity could provide insight into specific policies regarding technical progress and physical capital, as well as human capital accumulation.

In their case study, Calderon & Serven (2010) conclude that their results are not only statistically significant but also economically relevant, as decompositions of observed changes in growth and inequality suggest that infrastructure policy development contributed to both growth and equity across nearly all world regions. There are several cases of study where individual policy variables are considered, empirically exploring the impact of trade on employment: associated with external demand sources (Greenaway et al., 1999), and with both internal and external demand (Felbermayr et al., 2011; Lo Turco and Maggioni, 2013). Ianchovichina et al. (2013) study the potential of infrastructure investment to create employment. Finally, Jude & Silaghi (2016) assess the effects of foreign direct investment (FDI) on employment, associated with productivity sources.

Specific Circumstances Affecting Employment in Different Contexts: Regional Policies, Qualitative Data, and Local Experts

Romer's (1994) models emphasise that human capital is one of the main drivers of economic growth. Biagi & Lucifora (2008) reach similar conclusions using models based on worker surveys from ten European countries. However, there may be regional exceptions deviating from general behaviour. For example, Calderon & Serven (2010) find particularly large deviations in infrastructure policy impacts in East and South Asia, and smaller ones in Western Europe, explained by differing levels of infrastructure development.

In another econometric evaluation of the European Cohesion Policy (aimed at growth and convergence in lagging regions), Pellegrini et al. (2013) observe a positive impact. They estimate it at 0.6 to 0.9 percentage points annually, equivalent to over a quarter of the average annual per capita GDP growth in the assessed regions during 1995–2006.

This evidence and our findings suggest that policies intended to promote regional balance must take spatial patterns into account (Mohanty & Bhanumurthy, 2018). In other words, regions require differentiated political treatment. For instance, since FDI tends to flow towards states with a high spatial concentration of manufacturing, services, and infrastructure, liberalisation and investment attraction policies for lower-status regions should include a strategic focus on creating labour-related knowledge externalities by improving transport and communication infrastructure, alongside human capital enhancement (Mohanty & Bhanumurthy, 2018).

There is a recognised issue with data availability for capturing econometric relationships. For example, Gutiérrez Posada et al. (2018) refer to factors difficult to measure due to their substantial qualitative components, which complicate statistical quantification and evaluation (Doloreux et al., 2001). These factors include the local institutional context (Cooke et al., 2004), the presence of specific actors such as groups, organisations, and communities (Galaway and Hudson, 1994), or the existence of inter-firm dynamics and knowledge diffusion (Malecki and Oinas, 1999; Porter, 1990). Innovation studies researchers describe how certain regions have managed to develop local innovation systems by combining these factors in specific ways (Cooke et al., 2004). Numerous case studies also describe how these elements can drive local employment growth.

Infrastructure Quality, Access to Finance, and Specific Policies as Regional Job Creation Factors

Ziberi et al. (2022) suggests that a 1% increase in education expenditure positively affects economic growth in North Macedonia. In a study of 76 countries, Hall (2002) also find that financial sector development is essential concerning the sustainability of the employment system.

Wang & Li (2022) highlight that some Chinese regions were more resilient to external shocks, likely due to lower income inequality, higher levels of innovation, human capital, and financial development.

Ke et al. (2020) also emphasises that improving road and rail quality and modernising transport infrastructure (measured by the increasing share of public spending on transport in China) significantly contributes to growth. Calderon & Serven (2010) agree on the importance of infrastructure quantity, quality, and accessibility, concluding that infrastructure development accelerates poverty reduction in Sub-Saharan Africa by driving growth and reducing inequality.

In another case, Luo et al. (2022) examine the hypothesis that in China, broadband infrastructure boosts entrepreneurial activity by concentrating and improving the quality of human capital and supporting regional financial development.

Regional Characteristics (Socioeconomic, Cultural, and Political) as Effectiveness Factors in Development Policy

Mohanty & Bhanumurthy (2018) conclude that regional per capita income, growth, and employment outcomes exhibit spatial characteristics, as do the growth drivers—manufacturing, FDI, infrastructure, and services. This spatial pattern assigns a regional character to development policies. Tödtling & Trippl (2005) agree, suggesting that each region must develop and adapt their political strategies to its own circumstances. Policies intended to promote regional balance must, therefore, consider spatial growth patterns (Mohanty & Bhanumurthy, 2018), implying the need for differentiated political treatment due to the diversity of contexts.

This opens opportunities for dynamic and specific regional strategies. Howells (2005) highlights the diversity of approaches in regional innovation policy. Tödtling & Trippl (2005) stress the need for differentiated regional innovation policies, demonstrating that no universal model is ideal.

Mohanty & Bhanumurthy (2018) argue that policies should target the specific causes behind spatial variation. For instance, differences in business and regulatory environments might cause spatial clustering or growth determinant variability. In such cases, policy must aim to create a favourable regulatory and business environment. Autant-Bernard et al., (2013) mention that effective local policymaking depends on understanding regional scientific and technological potential, industrial structures, distribution systems, local demand characteristics, and knowledge diffusion channels.

Nevertheless, it is important to explore the possibility of universal recommendations. Autant-Bernard et al. (2013) advocates leveraging regional assets by promoting local knowledge flows between science and industry, between firms, and within firms, as well as opening local systems to national and international networks. Education policy plays a central role in each of these areas. Criscuolo et al. (2014) propose databases with more detailed sectoral breakdowns, and Autant-Bernard et al. (2013) calls for improved access to harmonised regional datasets—especially regarding their temporal and spatial dimensions—to enable interregional comparisons over time. He also advocates removing institutional barriers and encouraging SME participation in European programs.

Special attention to regions with specific local dynamics

In the case of Odeleye (2012) , focused exceptions are found in the relationship between GDP and education spending. Their model shows that in Nigeria, a 1% increase in education expenditure leads to a 0.17% decrease in GDP. This behaviour illustrates that there are regions with specific dynamics that require special attention, as their model contradicts conventional economic theory (Ziberi et al. 2022).

Mohanty & Bhanumurthy, (2018) propose focusing on the most lagging regions, as well as outliers, since they may require particular consideration in policy design. This is exemplified in the study by Teixeira & Queirós (2016) which find that the only cases with a negative relationship between education expenditure and growth are: in the relatively short term (20 years) and for less developed countries, being determined mainly by the lack of technological development.

This type of exceptional behaviour also appears in Gutiérrez Posada et al. (2018), who observed a reversal in the socio-economic status index between their two samples (1991–2001 and 2001–2011). Their study shows that self-employment growth was negatively related to that of neighbouring regions in the first decade but reversed in the second. Similarly, Mohanty & Bhanumurthy (2018) also reports opposing growth trends between own-region and neighbouring regions, suggesting the need for individualised studies on specific groups or regions that exhibit spatial outliers, at a disaggregated level, in order to understand each region's unique growth process. Significant, even opposing, effects for certain determinants may exist depending on the time period considered (Gutiérrez Posada et al. 2018).

Along the same research lines, Chang et al. (2009) note that although trade openness appears to be beneficial to economic growth on average, its effect varies considerably across countries and depends on a variety of conditions related to the structure of the economy and its institutions. Consequently, Gutiérrez Posada et al. (2018) stress that universal recipes for local growth do not exist, and that local policies must be designed with careful consideration of local characteristics. They must also account for the temporal dimension, as the influence of any factor may change (or even reverse) depending on the time frame. Gutiérrez Posada et al. (2018) conclude that their results align with the flexible framework set out by the EU's new Cohesion Policy and the Smart Specialisation philosophy (see McCann and Ortega, 2013, 2015; and Thissen et al., 2013), highlighting the need for more localised development policy projects with shorter review timelines.

Analysis of temporal dynamics (evolution of employment and human capital) in response to economic changes (2008 crisis)

Gutiérrez Posada et al. (2018) address the challenges of time-specific data in capturing temporal dynamics by analysing two different decades (1991–2001 and 2001–2011). Their findings show that both the initial endowment of human capital (measured as the percentage of the population with higher education) and that of neighbouring regions had a positive and significant effect on local employment growth in both decades. However, the overall effect was greater during the 1991–2001 period, likely due to the Spanish economy's heavy dependence on the construction sector. The subsequent sample (2001–2011) includes the 2008 crisis, which altered general employment dynamics. Furthermore, as shown in their study, human capital proved to be the most resilient variable, though to varying degrees depending on the region analysed.

In a similar vein, Criscuolo et al. (2014) show that, in terms of age, younger firms were more affected by the 2008 crisis compared to established firms—both in terms of job creation and job destruction. However, the main drivers of the overall decline in employment were established firms, due to their larger presence in the economy. Moreover, the contribution of young firms to net employment growth remained positive during the crisis, indicating their resilience during economic downturns.

Additionally, Scarpetta et al. (2002) highlight that burdensome business regulations and high labour force adjustment costs appear to negatively impact the entry of small firms. Similarly, Criscuolo et al. (2014) note that during this period, a further decline in the rate of new firm entry occurred, continuing a trend observed in most countries since the early 2000s. Given the importance of new firm entry for a range of economic outcomes beyond job creation (e.g., innovation, competition, and productivity), this finding raises particular concern. It may suggest the temporary need to lower barriers to entry for new firms during times of crisis.

Predictive models (factors: human capital and entrepreneurship) as tools for simulating regional policies

Woo et al. (2017) carries out counterfactual simulations to assess three alternative policies: a fiscal expansion in investment; greater efficiency in the accumulation of regional human capital; and a modified migration pattern based on investment. Woo et al. (2017)conclude that among the three proposed scenarios, the policy focusing on improving the quality of human capital has a more significant impact than the one focusing on expanding the quantity of human capital. Therefore, the top priority should be to improve labour productivity through increased government investment in education and R&D activities in lagging regions (Woo et al., 2017). Given the results related to the education variable in our own study, this recommendation appears to be consistent.

Fingleton, (2001), meanwhile, uses NUTS 2 regions in his simulations for modelling and analysis. These regions are small enough to capture subnational variation and represent the EU's unit for allocating financial assistance. His simulations (across 178 EU regions) show that productivity levels and growth rates are higher across all EU regions when those receiving financial assistance experience faster production growth. The results of these models (Woo et al. 2017 and Fingleton 2001), along with those of the present study, suggest the need for targeted policies in lagging regions, with a special focus on human capital and R&D. For example, offering tax incentives for establishing R&D departments in each company, with higher tax relief in the most underdeveloped regions.

6 Conclusions and Policy Implications

This study found that there are regions that require different types of assistance due to their unique and unrepeatable individual contexts. Of all the variables analysed, tertiary education is the most significant and has the greatest overall and regional impact, even in times of crisis, demonstrating resilience. Therefore, incentivizing it through public spending with more readiness in lagged regions and R&D through regionally differentiated fiscal policies that encourage an R&D department in each company again with more readiness in lagged regions seems advisable. Case studies were found in which different growth policies are evaluated, with differentiated responses based on regional characteristics. This leads us to believe that a more in-depth regional analysis is necessary to make specific policy recommendations for each region. Although the GWR appears to be a good tool for this purpose.

In more detail, in this study we modelled the variation in the number of jobs based on the proportion or ratio of the professional characteristics of people living in each region. Diverse local responses were found across the territory; in other words, human capital has spatially differentiated effects on employment growth.

In this context, the variable of unskilled manual workers showed significant deviations from the general gradients (with lower β_i coefficients) in the country's major cities (Madrid, Barcelona, and Zaragoza), where the impact of these workers on employment is lower. This reduced impact may be due to the greater economic diversification found in large cities, implying that unskilled manual workers have a lesser degree of influence in these areas. This suggests the usefulness of support policies, educational promotion (in the secondary sector), and guidance aimed at unskilled manual workers, with a particular focus on larger cities, as this group appears to be more vulnerable to unemployment in urban environments.

It was also found that the spillover effects of specialised workers (non-manual supervisors, skilled manual workers) generate less impact on employment along coastal areas, and the same was observed for those employed in manufacturing (with greater influence in the western part of the country). It is possible that the skills of these groups generate more value in municipalities where economic activity is more diversified, unlike coastal municipalities, which tend to focus on tourism services or fishing.

Case studies have also shown that investment in education and infrastructure improves economic growth (Ziberi et al. 2022; Ke, 2020; Calderon & Serven, 2010), and broadband infrastructure promotes entrepreneurship through human capital and financial development (Luo, 2022). Availability of financing is a regional determinant for new firm formation, with significant regional variation (Armington & Acs, 2002).

According to Ziberi et al. (2022), investment in education promotes economic growth. Following the 2008 crisis, human capital demonstrated resilience, even though employment fell due to the downturn in the construction sector (Gutiérrez Posada et al. 2018). Our findings confirm this, as tertiary education showed the greatest impact among the variables studied as a generator of employment. Therefore, promoting, investing in, and developing human capital through this type of education appears advisable across the entire country. On the coasts in particular, tertiary education should aim to diversify economic activity beyond hospitality (in the south) and fishing (in the north). This also highlights the need for economic development policies that are targeted and differentiated according to regional characteristics – for example, to encourage business creation in areas where job numbers are decreasing. Similarly, understanding regional employment variations provides deeper insight into regional consumption, which could be useful for planning both public and private policies. A standardised strategy to counter the effects of unemployment – one that does not account for regional differences – does not appear advisable based on the findings of this study.

Reforms in education, infrastructure, financing, and regulation may boost entrepreneurial growth in the short and long term (Rashid et al., 2025). However, it is also essential to raise awareness among decision-makers about the importance of systematically considering potential geographical influences to develop more comprehensive and effective strategies, as the development of successful local economic strategies requires knowledge of local socio-economic processes and the dynamics of employment (and consumption) growth at the regional level. This phenomenon necessitates the creation of non-uniform economic development strategies across the territory (Mathur, 1999). In this regard, Mohanty & Bhanumurthy (2018) emphasise the need for regionally differentiated policies, as local dynamics influence the effectiveness of such policies.

That said, it is important to consider that the reallocation of funds is only partially effective when there are complementary factors that enhance its impact, such as a high-quality institutional environment or decentralised government structures; the presence of an industrial base; and a certain intensity in R&D, as well as human and territorial capital. Policies aimed at improving the quality of human capital (education, R&D) have a greater impact than merely increasing its quantity (Woo et al., 2017). This supports the idea of targeted policies in lagging regions, with incentives for R&D and education as central elements. This article aligns with the current literature in that it identifies the regions where funds need to be reallocated, while also analysing an essential factor – human capital – for growth in these areas. However, to determine where the reallocation of funds is most effective, it would also be necessary to assess the intensity of regional R&D and the quality of local government structures. The spatial variations identified call for a reorientation of fund reallocation policies so they may contribute to the convergence of regional economic growth.

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