# STUDIES

## Comparison of statistical models for analysing the spatial determinants of human capital concentration in Tunisian local labour markets

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Regional disparities in human capital accumulation have long been a concern, particularly in developing countries, where unequal access to education and employment opportunities exacerbates economic inequality. The geographical distribution of human capital is a key factor in its formation and accumulation. The heterogeneity of this behavior and the neighbourhood effect lead to skilled and productive individuals becoming concentrated in particular areas. This study analysed the spatial variation in the explanatory determinants of human capital concentration in Tunisian local labour markets using a spatially autoregressive geographically weighted regression approach. The rate of enrolment in tertiary education was used as a proxy for human capital. Six different models at global and local levels were used. The global models included traditional ordinary least squares (OLS) regression, spatial autoregressive lag model with spatial regimes (SARAR), and SARAR with endogenous variables. The local models were SARAR with spatial disturbance, geographically weighted regression (GWR), and multiscale GWR spatial autoregressive model (MGWR–SAR). The results suggested that tertiary education costs, transport costs, and high unemployment prevent the balanced geographical distribution of human capital in Tunisia. Skills mismatches and job search friction contribute to the spatial heterogeneity of human capital and employment in this country. The mapping of explanatory factors also showed the importance of other variables such as job matches, unemployment, productive sectors, and technological change. Finally, the MGWR model improved determination of the spatial distribution of human capital concentration compared with global regression models.

**Keywords:**
human capital,
job matching,
spatial heterogeneity,
spatial autocorrelation,
geographical weighted regression

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## Introduction

The role of human capital in driving economic growth and regional development has received considerable attention in the economic literature. Investment in education and skills development is widely recognized as a powerful tool for addressing social, economic, and health challenges. Goldin (2022) showed that investment in human capital improves economic and health resilience in crises (e.g., the Covid-19 pandemic). She underscored the critical importance of human capital, showing that regions with higher human capital accumulation tend to have higher resilience and capacity for recovery. As a result, understanding the regional distribution of human capital and its implications for economic development has become a priority for policymakers and researchers alike.

Regional disparities in the accumulation of human capital have long been a concern, particularly in developing countries where unequal access to education and employment opportunities exacerbates economic inequality. The spatial distribution of human capital is often shaped by migration patterns, with skilled individuals gravitating towards metropolitan areas that offer higher returns for their education and skills. This concentration of talent in urban centers can lead to divergent economic outcomes across regions, as rural or less developed areas experience a brain drain and face challenges in sustaining local economic growth. Studies by Coniglio–Prota (2008) and Ritsilä–Ovaskainen (2001) suggested that highly educated individuals are more likely to migrate due to them having better career prospects and higher expected returns, further widening regional disparities in human capital.

The consequences of such an uneven distribution extend beyond economic growth to social and labour market outcomes. Theoretical and empirical research has shown that inequalities in human capital can affect labour market efficiency, income inequality, and even democratic governance. For example, Park (2006) has argued that inequality in educational attainment is associated with higher income growth, while Castello–Climent (2008) found that an equal distribution of human capital is conducive to democratic stability. In labour markets, Kremer (1993) suggested that an unequal distribution of human capital reduces the probability of matching jobseekers with appropriate skills to vacant positions, leading to inefficiency and underemployment. Moreover, geographical economics theories, as discussed by Krugman (1995), highlighted the role of forces of agglomeration in amplifying these inequalities, as regions with higher concentrations of skilled labour benefit from increasing returns to scale.

Tunisia provides a relevant case study for examining the spatial dynamics of human capital and labour market outcomes. This country is characterized by high youth unemployment, significant skills mismatches, and pronounced economic disparities among its regions. Despite substantial investment in higher education, many Tunisian graduates face difficulties in finding employment that matches their qualifications, particularly in the interior and rural regions. This raises important questions about the role of the spatial distribution of human capital in shaping local labour market accessibility and job matching efficiency.

This study was implemented to address these issues by empirically examining the impact of the distribution of those enroled in tertiary education on the probability of matching jobseekers with appropriate skills to vacant positions ("job matching" hereafter) in Tunisia. Unlike previous studies that focused on general spatial factors or migration patterns, the framework employed in this work emphasizes the specific relationship between regional educational attainment and labour market accessibility. It examines whether the uneven distribution of tertiary enrolment rates contributes to inefficiencies in local job matching in Tunisia, with implications for human capital inequality and economic development.

To the authors' knowledge, this is the first empirical study to examine these dynamics in the Tunisian context, thus filling a critical gap in the literature on education-to-employment transitions in developing countries. By incorporating spatial econometric techniques, this study controls for spatial effects such as autocorrelation and heterogeneity, which may affect job matching processes and human capital accumulation. The findings have important policy implications in Tunisia and elsewhere in the developing world, particularly for regions with high unemployment rates and limited labour market integration.

The paper is structured as follows. First, a review of the literature on human capital distribution and regional labour market dynamics is presented. Then, the data, key variables, and methodological approach of this study are introduced. After describing the methodology, the empirical findings are discussed, and then, the authors compare them with the existing literature. Finally, policy recommendations and avenues for future research are concluded.

## Literature review

Various economic phenomena are driven by the distribution of human capital across or within countries, such as the distribution of income or employment opportunities. The American economist Becker (1962, 1993) provided several frameworks for understanding human capital[1]. In his book *Human Capital*, he defined human capital as "the set of productive capabilities that an individual acquires through the accumulation of general or specific knowledge, expertise, etc". Under Becker's theory of human capital, education is viewed as an investment in productivity and a catalyst for economic growth. The microeconomic foundations of human capital accumulation can be explained by the endogenous growth theory and the New Geographic Economy. Under the theory of endogenous growth, one of the sources of growth is the productivity of the factors in the production process, one of which is human capital. The accumulation of human capital is achieved through investment in skill development, which require both time and resources. According to Becker (1962), human capital appears to be more abundant where it accumulates the fastest. In terms of the model of endogenous growth, Romer (1986) and Lucas (1988) suggested that the endogenous accumulation of human capital has a direct impact on labour productivity. However, the regional integration of labour markets may induce workers to move spatially, especially from the periphery of a country to its center. Under conventional economic analysis, economic agents must localize themselves where their skills are in the highest demand. This can be explained by the effect of forces of agglomeration: human capital migrates from regions where it is scarce to those where it is abundant, rather than the reverse (Lucas 1988). As such, migration ultimately redistributes human capital spatially. It is not randomly distributed across regions and between countries, but is instead highly concentrated in particular regions and cities. Four schools of economic thought have attempted to explain the spatial concentration of human capital (Storper–Scott 2009). First, under the classical theory of creativity, Florida (2002) suggested that human capital creates and shapes a creative environment that stimulates local development and growth, attracts talent, and raises wages. Berry–Glaeser (2005) implied that climate and skills contribute to the spatial proximity of human capital. Meanwhile, Glaeser (1999) suggested that human capital prefers locations that offer a high quality and low cost of living with a supply of skilled labour. Finally, Clark et al. (2002) showed that leisure facilities such as museums, shopping centers, theaters, and art galleries are crucial for attracting skilled workers.

The unequal geographical distribution of human capital is crucial for understanding spatial disparities. In a review of empirical studies, it was discussed that the evolution of regional disparities is a result of the unequal distribution of human capital. For regions in Europe, Rodríguez-Pose–Tselios (2011) mapped the regional distribution of educational attainment. Using exploratory analyses of spatial data,

[1] Gary Becker (winner of the Sveriges Riksbank Prize in Economic Science in Memory of Alfred Nobel in 1992) was one of the first economists to broaden the scope of economic (and especially microeconomic) analysis to include social behavior. Gary Becker occupies a singular position since he contributed to opening up economic science to fields of research usually associated with sociology: education and training, racial discrimination, family decisions, criminology and deviant behavior, and even mechanisms of political pressure.

they showed that regional differences in educational attainment and human capital inequalities are driven by three factors: proximity, the north–south divide, and the urban–rural divide. This allows European cities to diverge from more peripheral regions in terms of human capital and and to converge with each other in terms of other factors. Caragliu et al. (2011) described this phenomenon as the development of "smart cities", where urban centers leverage human capital and innovation to thrive. The division fueled by distance led Erdem (2016) to demonstrate the existence of large regional disparities in human capital in Turkey from an east–west perspective. He found that tertiary-level human capital is concentrated in the provinces surrounding large cities such as Istanbul and the Sea of Marmara. Erdem (2016) and Karahasan–Uyar (2009) used exploratory spatial data analysis methods to identify the spatial distribution of human capital across Turkish regions. In addition to these spatial analysis techniques, inter-regional decomposition of the Theil index used by Kerimoglu–Karahasan (2020) clearly showed the regional disparities in human capital in Spain. Specifically, they found that agglomerations of graduates contribute to the intensification of either industrial or service economic activities and, consequently, to regional economic growth. Indeed, investment in the accumulation of human capital varies depending on the location. To demonstrate this relationship, Lopez–Rodríguez et al. (2011, 2019) used the New Geographic Economy (NEG) model of Redding and Schott (2003) (based on accessibility to the local market) to analyse the link between capital accumulation and geographical location in Romania. They found that high accessibility to the regional market is associated with an abundance of individuals with a higher level of education, while in the periphery the accumulation of human capital is blocked.

As Kano et al. (2017) considered educational level as an indicator of urbanization, they analysed the geographical distribution of university graduates across Hungarian regions. They found that the rate of enrolment on higher education courses is increasing throughout the country, even in less advanced regions, leading to a decrease in geographical disparities. This is because, in these less advanced regions, people with higher education can work in the public sector. Similarly, Czaller–Lőcsei (2018) discovered a relationship between skills distribution and regional disparities in unemployment in Hungary. They found that regions with the high accumulation of human capital exhibit lower unemployment rates, confirming the role of human capital in mitigating regional labour market disparities.

Regarding the determinants of the geographical distribution of human capital, Bihua (2018) found that tax incentives and better quality of higher education increase local rates of enrolment in higher education in China. In contrast, Heckman (2005) criticized China's human capital investments and policies on the assumption that economic performance is improved by producing an educated workforce. Meanwhile, McHenry (2013) argued that labour market size is one of the most important determinants of local human capital dynamics in the United States. He found that skills move from urban to rural labour markets through intergenerational transmission, but from rural to urban labour markets through migration. Elsewhere, Jurajda–Terrell (2009) analysed regional unemployment and human capital in transition economics, finding that regions with a higher stock of human capital tend to exhibit lower unemployment rates. Their study highlights the importance of human capital in reducing regional labour market disparities.

In the Tunisian context, there has been little research in this field. To the best of the authors knowledge, the only studies dealing with regional inequalities in education in the country were those by Trabelesi (2013) and Trabelesi–Ben Hamida (2014), which only measured the decomposition of the Gini index inequalities in human capital.

## Methodology

This study covered 268 small Tunisian administrative regions called "delegations" (see in Appendix Figure A1). The primary data used in this research were based on data collected for these 268 delegations.

### Data and variables

Several sources of data were used for this research: the 2014 Tunisian General Population and Housing Census[2] conducted by the National Institute of Statistics (INS)[3], the 2014 database of the National Agency for Employment and Self-Employment (ANETI), and the 2014 database of the Tunisian General Commission for Regional Development. The data included information on rates of enrolment in tertiary education as a proxy for human capital, spatial proximity to the main urban center (Tunis), and accessibility of jobs in local labour markets. There was also information on the job matches or placements of graduates, the unemployment rates in each delegation, the migration into each delegation for study purposes, and other important economic characteristics such as numbers of employees in different sectors, as shown in Appendix Table A1.

#### Dependent variable

To analyse the relationship between the concentration of human capital and skills matching, among other variables, only the conventional methods of measuring human capital were used. The data obtained by these methods are important for proposing and implementing policies regarding human resources. Given that human capital theory and Arrow's (1973) signal theory propose that educational attainment

[2] The 2014 Tunisian General Population and Housing Census was the last census of the Tunisian population. The next census is scheduled for January 2025.

[3] These data are available on the website of the Tunisian National Institute of Statistics.

can be used as a proxy for the level of productivity of young people (Becker 1962, 1993), Barro (1991) and Barro–Lee (1994) proposed that the rate of enrolment in school be used as a proxy for the stock of human capital, which is one of the measures of the output-based approach.[4] However, the drawback of this method is that it only measures the status of educational achievement. In the case of Tunisia and most developing countries, educational enrolment rate is used as an indicator due to the availability of such data, the simplicity of calculation, and the ease of interpretation and understanding.

The dependent variable exhibited spatial global and local autocorrelation. Figure A2 in Appendix shows the spatial clustering of enrolment in tertiary education. Specifically, such enrolment as a proxy of human capital was concentrated in the largest metropolitan area of Tunisia (Greater Tunis or Grand Tunis), in coastal regions, in the northwest of the country, and in the south. The LISA Moran scatterplot (Anselin 2003b, Moran 1950, Tilahun–Fan 2014) visualize better the spatial clustering (concentration) patterns of the enrolment tertiary rates across regions. In Appendix Figure A2 shows several high–high clusters and outliers. High–high clusters refer to regions with high enrolment rates surrounded by other regions with high enrolment rates. Otherwise, high–low outliers are regions with high enrolment surrounded by regions with low enrolment and low–high outliers are regions with low enrolment surrounded by regions with high enrolment rates.

## Explanatory variables

The independent variables used to model the accumulation of human capital are presented in Appendix Table A2. Based on previous studies and data availability, the variables were grouped into economic and spatial characteristics.

Spatial and economic characteristics are crucial for understanding how human capital is related to regional and economic dynamics. Spatial characteristics include distances, such as between the Tunis business district and other areas, and the index of job accessibility, which highlights inequalities in employment opportunities. Job accessibility refers to how easy workers can reach job opportunities. There are two key outcomes: employment returns and worker displacement (Tilahun–Fan 2014). Shen's (1998) gravity-based model, which considers employment supply and demand, was also used to estimate spatial barriers, taking into account factors such as residence, work location, and transportation (Hu et al. 2017).

[4] There are three approaches to measuring the stock of human capital: an output-based approach, a cost-based approach, and an income-based approach. School enrolment, educational attainment, adult literacy, and average number of years of schooling are the measures of the output-based approach. The cost-based approach is based on calculation of the costs paid for the acquisition of knowledge, and the income-based approach is closely related to the benefits of investment in education and training. For more details, see the book *Fundamentals of Human Resource Development* (Subhash 2019).

Meanwhile, economic attributes included graduate job placements, unemployment rates, and migration patterns influenced by educational opportunities[5] (Kain 1962). Students' migration boost the local concentration of human capital. In addition, the distribution of employment across sectors such as manufacturing, agriculture, and energy was used to obtain insights into the types of economic activity that were being performed.

## Econometric models

This paper estimated the accumulation of human capital using the rate of enrolment in tertiary education as a proxy and primary indicator. In the literature, the rate of enrolment in primary or secondary school is often used as a proxy for human capital (e.g., Mankiw et al. 1992, Levine–Renelt 1992, Borensztein et al. 1998), but this has key limitations. First, in many developing countries, primary and secondary education has increasingly become compulsory, shifting the job matching process towards highly educated jobseekers. Second, in Tunisia primary and secondary education is predominantly provided by the public sector and thus reflects public policy priorities rather than individual choice or market forces. Given the difficulties in measuring human capital directly through productivity gains or skill levels, the tertiary enrolment rate appears to be a more appropriate option for capturing the accumulation of human capital.

For the estimation of human capital accumulation, the commonly used approach is ordinary least squares (OLS) regression (model 1). Following the work of Mughal–Vechiu (2009) and Lee–Francisco (2012), this is generally expressed as follows:

$$Y_i = \beta X_i + \varepsilon_i \quad , \tag{1}$$

where $Y_i$ is the enrolment rate at delegation *i*, $X_i$ is the matrix of explanatory variables, and $\varepsilon_i$[6] is the error term. Other methods, such as two-stage least squares (2SLS) (Mughal–Vechiu 2011) and fixed or random effects panel regression (Lee–Francisco 2012), have also been employed to estimate human capital accumulation.

### Spatial indicators

The spatial location of human capital has crucial implications for its accumulation and has the potential to capture the interaction between job matching and accessibility and the concentration of human capital over time. The rate of enrolment in tertiary education is related to the underlying spatial processes governing the spatial location of human capital. Spatial indicators quantify the dependence of the human capital stock on the surrounding environment due to effects related to its spatial location.

[5] The term "educational opportunities" refers to the availability and accessibility of resources, institutions, and systems that provide individuals with the chance to acquire knowledge, skills, and qualifications. These opportunities can vary widely based on location, socio-economic factors, and policy decisions, and they play a critical role in shaping personal and societal outcomes.

[6] Hypothetically, the error term follows a normal distribution.

The most widely used technique to express the underlying spatial relationship is spatial autocorrelation (Anselin–Bera 1998), the magnitude of which can be measured by Moran's I as follows (Moran 1950):

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y}) (y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - \bar{y})^2}, \tag{2}$$

where $y_i$ and $y_j$ are the value of the variable at location i and j respectively, $\bar{y}$ is the global mean and $w_{ij}$ is the *i*th element of the standardized spatial matrix, in this case the contiguity matrix. The presence of spatial autocorrelation indicates the need to include spatial interactions in the modeling of human capital accumulation. Entekhabi (2023) extended the systematic treatment of the spatial autocorrelation between human capital formation and geographical location. This study examined the relationship between human capital accumulation and economic characteristics and spatial effects using six different models at two spatial scales: global and local. The global models included traditional OLS regression, spatial autoregressive lag model with spatial regimes (SARAR), and SARAR with endogenous variables. The local models were SARAR with spatial disturbance, geographically weighted regression (GWR), and GWR/multiscale GWR spatial autoregressive model (MGWR–SAR).

## Global spatial models

In this study, the authors used traditional OLS regression (model 1) to model human capital accumulation. The general form is the same as that used by Ward–Gleditsch (2018) as follows:

$$y_i = \beta_0 + \beta_i x_i + \varepsilon_i \tag{3}$$

where $y_i$ is the dependent variable, $\beta_0$ is the intercept, $x_i$ is the vector of explanatory variables representing the economic and spatial characteristics, $\beta_i$ is the vector of regression coefficients, and $\varepsilon_i$ is a random error term. The regression coefficients in the OLS regression were optimized by minimizing the sum of squares prediction errors. The main assumption in OLS regression is independence between observations and uncorrelated error terms (Anselin–Arribas-Bel 2013). The OLS assumes that the observations are independent and does not take into account the spatial interaction between rates of enrolment in tertiary education. The variant of OLS that take into account the spatial dependence between observations is the spatial lag model with spatial disturbance/error model (SARAR) (model 2). It is already known that (first order) spatial autoregressive models with (first order) autoregressive disturbance (SARAR) models provide general starting points for spatial analysis, since they incorporate both spatial autoregressive error (SEM) and spatial autoregressive (SAR) models (LeSage–Pace 2009). The spatial model is defined as:

$$y_i = \rho W_1 y + \beta_i x_i + \mu \tag{4}$$

$$\mu = \lambda W_2 \mu + \varepsilon \tag{5}$$

where $\rho$ is the autoregressive parameter, $u$ is an $n \times 1$ vector of autoregressive error terms with spatial coefficient $\lambda$ and spatial weight matrix $W_2$, and $\varepsilon$ is an $n \times 1$ vector of independent and identically distributed (i.i.d.) error terms. $W_1$ is the commonly used $n \times n$ spatial weighting matrix, which may differ from or be equal to $W_2$. In this study, the authors set $W = W_2 = W_1$ and defined two types of W, the first as a *k*-nearest neighbour weighting matrix with $k = 6$ and the second as a cut-off distance weighting matrix with distance of 88 km.[7]

It was assumed that the job matching of graduates determines the concentration of human capital. Therefore, the concentration of human capital plays a role in the number of job matches, which can be deduced from the unemployment rate. To address this issue, the SARAR model was estimated with endogenous variables (model 3). Following the work of Fingleton–Le Gallo (2008a, 2008b) and Drukker et al. (2013), the spatial model is defined as follows:

$$y_i = \pi y + \rho W_1 y + \beta_i x_i + \mu \quad (6)$$

$$\mu = \lambda W_2 \mu + \varepsilon \quad (7)$$

where y is an n × p matrix of observations on p endogenous variables, $x_i$ is exogenous variables, and π is the corresponding p × 1 parameter vector.

## Local spatial models

Global models such as OLS and SARAR models assume spatial stationarity when modeling the relationship between dependent and explanatory variables, where these relationships do not vary spatially. The GWR model overcomes the spatial stationarity assumption to allow the variables to vary spatially (Brunsdon et al. 1996). The mathematical notation of the GWR model is extended from equation (1) and adopted as follows (Fotheringham et al. 2002):

$$y_i = \sum_{j=0}^{m} \beta_j (v_i, u_i) x_{ij} + \varepsilon_i \quad (8)$$

where $y_i$ denotes the tertiary enrolment rate at point *i*, and $\beta_j(v_i, u_i)$ is a varying *j*th coefficient in the estimation of the continuous explanatory variables, $x_{ij}$, at each point *i* within the given spatial analysis area, and $\varepsilon_i$ is a random error term. Multiscale GWR (MGWR) is an extension of GWR that allows the conditional relationships between the dependent variable and various predictor variables to vary locally or not at all. In particular, the extension allows each variable to have a distinct bandwidth, where the data borrowing range (bandwidth) can vary across parameter surfaces. The MGWR (model 4) takes the following form (Fotheringham et al. 2017):

$$y_i = \sum_{j=0}^{m} \beta_{bwj} (v_i, u_i) x_{ij} + \varepsilon_i \quad (9)$$

where $(v_i, u_i)$ denotes the x–y coordinates of the *i*th point and $\beta_{bwj}$ denotes the bandwidth used to calibrate the *j*th conditional relationship. The spatial variability of all parameters, both the selected explanatory variables and the spatial autocorrelation term, should be tested using the Monte Carlo (MC) test for spatial variability. To assess spatial variability, the test evaluates whether the coefficients for explanatory

[7] The summary shows that the largest first nearest neighbour distance is 88 km, so using this as the upper band/threshold gives certainty that all units will have at least one neighbour because it is the maximum distance.

variables exhibit significant spatial variation rather than being constant across the entire study area.

The MC test shows whether all parameters are close together and whether there are any global factors. Based on the results regarding the MC tests, both spatial heterogeneity and spatial autocorrelation take two forms. When both spatial variability and spatial dependence occur simultaneously, the model is SARAR with spatial regimes (SARAR–MS) (model 5). With reference to global models 4 and 5, the following SARAR–MS is then obtained:

$$\begin{bmatrix} y1 \\ . \\ . \\ . \\ yn \end{bmatrix}_i = \rho W_1 \begin{bmatrix} y1 \\ . \\ . \\ . \\ yn \end{bmatrix} + \beta_i \begin{bmatrix} x1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & xn \end{bmatrix} + \begin{bmatrix} u1 \\ . \\ . \\ . \\ \mu n \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} \mu 1 \\ . \\ . \\ . \\ \mu n \end{bmatrix} = \lambda W_2 \begin{bmatrix} \mu 1 \\ . \\ . \\ . \\ \mu n \end{bmatrix} + \begin{bmatrix} \varepsilon 1 \\ . \\ . \\ . \\ \varepsilon n \end{bmatrix} \tag{11}$$

where i = 1,…,6 refers to six Tunisian regions: 1) Northeast, 2) Northwest, 3) Central East, 4) Central West, 5) Southeast, and 6) Southwest. This division helped to assess local spatial regimes.

The MGWR–SAR (model 6) reported by Geniaux–Martinetti (2018) assumes the plausibility of both worldwide and neighbourhood factors, and its general form is as follows:

$$y_i = \sum_{j=0}^{m} \rho(u_i, v_i)Wy + \beta_v(u_v, v_v)x_v + \varepsilon_i \tag{12}$$

where $(u_i, v_i)$ denotes the x–y coordinates of the *i*th point, $x_v$ are $K_v$ independent variables with spatially varying coefficients ($\beta_v$), and *Wy* is the spatial lag variable with the spatially varying coefficient $\varrho(u_i, v_i)$. In this study, the local models were calibrated based on GWR or MGWR with a Gaussian kernel function and fixed bandwidth. The GWR–SAR/MGWR–SAR models included a spatially lagged dependent variable that may introduce endogeneity by correlating with the error term *ε*. The spatial two-stage least square (S2SLS) technique was used to remove the endogenous part (Anselin 2003a).

## Evaluation of models

To compare the performance of the global and local models, the authors used the root mean square error (RMSE), which is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} y - \hat{y}}{n}}\,, \tag{13}$$

where $\hat{y}$ and y are the estimated and observed values of the dependent variable, respectively, and *n* is the number of observations.

# Results

## Aggregate human capital models

To estimate the determinants of human capital accumulation in Tunisian regions, the authors use the OLS method. The first column of Table 1 shows that the distance from the center of Tunis, the unemployment rate, and the number of workers in the agricultural and industrial sectors had significant negative associations with human capital accumulation.

Table 1

**Results for econometric models and global models of human capital accumulation**

| Dependent variable: tertiary education enrolment rate | OLS (model 1) | SARAR (model 2) | | SARAR with endogenous variables[a)] (model 3) | |
|---|---|---|---|---|---|
| | | 2.a contiguity matrix (k = 6) | 2.b distance matrix (88 km) | 3.a contiguity matrix (k = 6) | 3.b distance matrix (88 km) |
| Intercept | 32.690*** (9.480) | −14.680** (5.493) | 1.740 (2.504) | 12.020 (8.851) | 24.280* (13.277) |
| JOBINX | −9.320 (6.277) | −9.520*** (2.052) | −9.270** (3.080) | −11.070*** (2.470) | −7.320* (3.243) |
| DTUN | −1.560*** (0.441) | −0.350 (0.454) | −1.590* (0.669) | −0.950* (0.489) | −1.820* (0.895) |
| M | 0.015*** (0.006) | 0.015* (0.007) | 0.018* (0.008) | 0.008 (0.025) | 0.080*** (0.019) |
| U | −0.200** (0.106) | 0.030 (0.104) | −0.170 (0.109) | – | – |
| MRS | 1.554*** (0.566) | 1.520** (0.567) | 1.120* (0.590) | 2.100** (0.693) | 0.600 (0.883) |
| Labor AGR | −2.200*** (0.379) | −1.240*** (0.315) | −1.930** (0.659) | −1.560*** (0.421) | −1.800* (0.741) |
| Labor INDUS | −0.999** (0.470) | −0.330 (0.524) | −0.450 (0.601) | −0.260 (0.587) | −1.020 (0.698) |
| Labor MINES | 2.658*** (0.534) | 1.940*** (0.588) | 3.030*** (0.595) | 1.250* (0.521) | 2.100*** (0.604) |
| TECH | 1.630** (0.759) | 3.510*** (0.419) | 4.400*** (0.398) | 0.490 (0.881) | 2.540* (1.085) |
| $\lambda$ | – | 0.060** (0.021) | 0.001* (0.001) | 0.090*** (0.025) | −0.010 (0.001) |
| $\varrho$ | – | 0.070** (0.023) | 0.045*** (0.005) | 0.039 (0.032) | 0.050*** (0.008) |
| Moran | 6.690*** | – | – | – | – |
| LM-error | 36.680*** | – | – | – | – |
| RLM-error | 6.050** | – | – | – | – |
| LM-lag | 35.650*** | – | – | – | – |
| RLM-lag | 5.020** | – | – | – | – |
| Branch–Pagan heterogeneity test | 1.060 (0.30) | – | – | – | – |

a) Instrument = unemployment rate, instrumented = matches. Moran is Moran's I test, LM-error and LM-lag are the Lagrange multiplier tests for spatial error autocorrelation and the lagged endogenous variable, respectively, RLM-error and RLM-lag are their robust equivalents. Values in parentheses are standard errors. A more detailed description of the variables and their abbreviations can be found in Appendix Table A2.

*Note:* *: p<0.001; **: p<0.01; ***: p<0.05.

Meanwhile, the number of job matches, the number of immigrants, and the number of workers in the energy and mining sectors were significantly positively correlated with the concentration of human capital. The expected sign of the different explanatory variables were consistent. However, the magnitudes reported by the different estimation methods were quite different. Regarding the significance of the Lagrange multiplier (LM) and LM robust tests for spatial lag and spatial error, the SARAR model was estimated with both spatial lag and spatial error effects. The SARAR model confirmed the importance of regional interdependence in human capital accumulation.

Initial comparison of the estimated coefficients between SARAR with spatial $k$-nearest neighbour weighting (2.a) and SARAR with distance weighting (2.b) showed that the variables of distance to the central business district (CBD) of Tunis, the unemployment rate, the number of employees in agriculture, manufacturing, and mining, and the skills matches were all significantly associated with the rate of enrolment in tertiary education. However, the coefficients of these variables were quite similar in the two models. The significance of the correlation coefficients $\varrho$ and $\lambda$ and their evaluated impacts on the two models were also similar. Based on the Wald test, the SARAR with the $k$-nearest neighbour spatial weighting matrix appeared to be the best fitting model. The comparison between contiguity-based and distance-based weighting matrices showed consistent effects across variables, confirming the robustness of the models.

By recognizing job matches as an endogenous variable affecting human capital accumulation, the model could explicitly account for bidirectional relationships. However, the failure to account for this endogeneity led to biased results. To correct for this, the authors used an instrumental variable approach within the SARAR model. In the SARAR model (model 3), the instrumental approach isolates the exogenous variation in job matches, allowing the model to produce accurate estimates of the relationship between job matches, human capital and regional economic conditions. The other variables remained exogenous because their relationships with human capital were one-directional or stable over time. To check for robustness, the validity of the instrument unemployment was tested by performing the Sargan test (see in Appendix Table A3). The results showed that this test failed to reject the null hypothesis of the validity of instruments with a p-value of 0.099.

This suggested the value of an autoregressive model with spatial error autocorrelation, which distinguishes the direct effect of each explanatory variable from the indirect effect of the latter via the effect on the lagged matches' endogenous variable.

The results confirmed the importance of geographical distance from the center of Tunis on the rate of enrolment in tertiary education. In other words, being located in peripheral regions can reduce the incentives for individuals to invest in accumulating their own human capital. Such investment can reduce inequalities in access to education. These results are consistent with those reported by Redding–Schott (2003) and Lopez–Rodríguez et al. (2011, 2019), and with the theory of economic geography. Spatial proximity to a CBD, as a center of employment and competitiveness, elevated the concentration of individuals with a high level of education and increased spatial inequalities in education. The accumulation of high-quality human capital was positively associated with the number of skills matches and the number of workers in the mining and energy sectors. These findings are interesting in the context of job matching theory, which is described as the microeconomic basis of agglomerations of firms and individuals. The presence of centripetal forces suggests that the matching function has increasing returns to scale. Thus, the increase in job matching for graduates promotes the accumulation of human capital in large urban areas, as graduate applicants migrate to regions where capital is abundant and where the qualifications that they have are in high demand (Kremer 1993). Bound et al. (2004) investigated the same dynamics across the United States. They found that some states act as exporters of skilled labour, while others retain or attract highly educated individual to create highly skilled clusters.

The south of Tunisia exhibits a concentration of female workers in the country's automotive sector, so more highly educated individuals concentrate in these regions in order to find employment in this saturated and particularly tired sector after the revolution of January 2011. This makes the human capital of this region immobile, which favors spatial inequalities. After the revolution, widespread labour strikes and social unrest became an obstacle to Tunisia's economic growth. These strikes created an environment of instability. As a result, investors became reluctant to invest in this sector and these regions. The accumulation of skilled human capital in southern Tunisia has been reduced by layoffs in the automotive sector. It has been reported that unemployment rates are associated with income disparities, which in turn increase inequalities in access to higher education between the rich and poor and reduce the accumulation of human capital (Upadhyay 1994, Makwe et al. 2020).

## GWR/MGWR and GWR/MGWR–SAR models: spatial interpretation

According to the RMSE statistics, the MGWR–SAR (multiscale geographically weighted regression–spatial autoregressive) was the best model to account for spatial dependence and spatial heterogeneity. This finding underscores the importance of considering both global and spatial effects when analysing regional disparities in human capital accumulation. The estimation of the local regression models was specifically applied to the human capital model, as this model required a more nuanced approach to capture the spatial dynamics of human capital distribution. In this context, the SARAR model showed a significant improvement over the OLS model.

The use of GWR can lead to biased estimates when the data have multiple spatial scales. The MGWR is an extension of GWR that can overcome the scale problem by allowing each local relationship to occur at a different scale. The spatial variability of the estimated parameters was evaluated using the MC test, which could clearly indicate whether GWR or MGWR should be used.

The MC test indicated that some variables require local modeling (spatially varying) and other variables can be treated as global (spatially stationary). The explanatory variables JOBINDX, DTUN, and MRS are spatially stationary and have only a global effect on the model (see in Appendix Table A2). Therefore, the model selection (MGWR and MGWR–SAR) is justified in two ways: first, the MGWR model allows each independent variable to act as its own spatial scale; second, the extended MGWR includes a spatial autoregressive component to account for spatial autocorrelation (Table 2). This inclusion allows to understand the factors driving human capital accumulation in Tunisia.

Table 2

**Results for local models of human capital accumulation**

| Dependent variable: tertiary education enrolment rate | Mean | SD | Min. | Median | Max. | Spatial variability test (p-value) |
|---|---|---|---|---|---|---|
| | | | MGWR (model 4) | | | |
| Intercept | −0.14 | 0.06 | −0.25 | −0.12 | −0.04 | 0.145 |
| JOBINX | −0.09 | 0.01 | −0.21 | −0.09 | −0.09 | 0.155 |
| DTUN | −0.02 | <0.01 | −0.03 | −0.02 | −0.02 | 0.957 |
| M | 0.12 | 0.15 | −0.18 | 0.27 | 0.41 | 0.036 |
| U | −0.22 | 0.33 | −0.85 | −0.10 | −0.47 | 0.000 |
| MRS | 0.16 | 0.02 | 0.11 | 0.16 | 0.18 | 0.373 |
| Labor ARG | −0.35 | 0.28 | −1.03 | −0.27 | 0.22 | 0.000 |
| Labor INDUS | −0.18 | 0.04 | −0.22 | −0.19 | −0.06 | 0.098 |
| Labor MINES | 0.28 | 0.06 | 0.18 | 0.27 | 0.41 | 0.082 |
| TECH | 0.38 | 0.31 | −0.11 | 0.38 | 0.78 | 0.000 |
| | | | MGWR–SAR (model 6) | | | |
| Intercept | 24.24 | – | −14.69 | 23.24 | 55.39 | – |
| JOBINX | −11.24 | – | −33.75 | −5.32 | 206.00 | – |
| DTUN | −0.40 | – | −1.78 | −0.29 | 1.16 | – |
| M | 0.02 | – | −0.02 | 0.02 | 0.07 | – |
| U | −0.49 | – | −2.07 | −0.28 | 0.47 | – |
| MRS | 1.44 | – | −0.86 | 1.52 | 3.53 | – |
| Labor ARG | −2.67 | – | −5.82 | −2.44 | −0.69 | – |
| Labor MINES | 2.07 | – | 0.21 | 2.29 | 5.10 | – |
| TECH | 0.45 | – | −1.86 | −0.05 | 4.93 | – |
| Lambda: labor INDUS | – | – | 0.11 | –[a)] | 0.36 | – |

a) As a spatial lagged parameter, Lambda does not have a median.
*Note:* a more detailed description of the variables and their abbreviations can be found in Appendix Table A2.

The average values of the parameters of both MGWR and MGWR–SAR are not similar to the estimates of the OLS and SAR models due to the calibration of the MGWR model with several different spatial scales. The use of MGWR and MGWR–SAR allow to identify the spatial patterns and account for the spatial heterogeneity that characterize the relationships between variables that vary among Tunisian regions.

The non-stationary spatial variables with the MC test have larger differences between the minimum and maximum values in both variants of the local models. The most important explanatory variable of human capital accumulation is the job accessibility index, followed by technological change. Job accessibility is strongly associated with higher human capital levels in regions with a concentration of economic opportunities.

Another variable that affects the spatial distribution of human capital in all models is the number of job matches. The accumulation of human capital across delegations slightly favours the job matching process in Tunisian local labour markets.

Table 3

**Results of the SARAR model with spatial regimes (model 5)**

| Dependent variable: tertiary education enrolment rate | Coefficient of the model | Standard error | Dependent variable: tertiary education enrolment rate | Coefficient of the model | Standard error |
|---|---|---|---|---|---|
| Intercept_1 | 43.43* | 23.99 | Intercept_4 | 29.97 | 44.50 |
| Labor INDUS_1 | 1.68 | 2.84 | Labor INDUS_4 | 0.32 | 4.41 |
| Labor MINES_1 | −2.54 | 2.67 | Labor MINES_1 | −3.57 | 5.90 |
| Labor AGR_1 | −3.46** | 1.23 | Labor AGR_4 | −3.72 | 3.78 |
| M_1 | 0.013 | 0.01 | M_4 | 0.12 | 0.08 |
| U_1 | −0.87** | 0.31 | U_4 | 0.17 | 0.48 |
| W_Y_1 | 0.12*** | 0.02 | W_Y_4 | 0.18*** | 0.03 |
| We_1 | −0.10 | 0.06 | We_4 | −0.02 | 0.17 |
| Intercept_2 | −0.25 | 36.65 | Intercept_5 | −19.02 | 23.74 |
| Labor INDUS_2 | 5.19* | 2.42 | Labor INDUS_5 | 10.72*** | 2.88 |
| Labor MINES_2 | 1.95 | 1.41 | Labor MINES_5 | −2.62 | 2.89 |
| Labor AGR_2 | −5.18 | 4.69 | Labor AGR_5 | −2.30 | 2.78 |
| M_2 | −0.02 | 0.02 | M_5 | −0.08*** | 0.02 |
| U_2 | 0.09 | 0.46 | U_5 | 0.19 | 0.33 |
| W_Y_2 | 0.15*** | 0.02 | W_Y_5 | 0.042*** | 0.01 |
| We_2 | −0.05 | 0.10 | We_5 | −0.24 | 0.29 |
| Intercept_3 | 32.83 | 28.90 | Intercept_6 | −3.85 | 28.44 |
| Labor INDUS_3 | −0.88 | 0.69 | Labor INDUS_6 | 1.48 | 3.47 |
| Labor MINES_3 | 2.05 | 2.32 | Labor MINES_6 | 2.18 | 2.73 |
| Labor AGR_3 | −3.13 | 2.78 | Labor AGR_6 | 0.50 | 1.12 |
| M_3 | 0.02 | 0.03 | M_6 | 0.04** | 0.01 |
| U_3 | −0.50 | 0.30 | U_6 | −0.67 | 0.65 |
| W_Y_3 | 0.12*** | 0.01 | W_Y_6 | 0.09*** | 0.01 |
| We_3 | −0.94 | 0.14 | We_6 | −0.04 | 0.13 |

*Notes:* a more detailed description of the variables and their abbreviations can be found in Appendix Table A2. *: p<0.001; **: p<0.01; ***: p<0.05.

However, technological change is a crucial driver of human capital accumulation, which varies significantly across the regions of Tunisia. Marginson (2018) criticized human capital theory for considering both work and education as homogeneous domains. This criticism seems reasonable given that jobs and jobseekers in this study are relatively heterogeneous (spatial maps in Appendix Figures A3a–e of MGWR coefficients confirm this spatial heterogeneity).

The empirical results confirmed the existence of local clusters of human capital, namely, areas in which the rate of enrolment in tertiary education follows a local production econometric model. In these clusters, a higher density of economic activity emerges, supporting the presence of spatial regimes and the occurrence of the agglomeration effect (Lopez–Rodríguez et al. 2011). In other words, the results confirm the hypothesis that the presence of different spatial regimes (Table 3) is related to the existence of a variety of latent unobserved factors, which are closely intertwined with the spatial location of the observed jobs, jobseekers, technology, and employment barriers. In addition, we detected significant spatial regimes of human capital accumulation in all regions, while job matches were only significant in the fifth and sixth regions.

Table 4

**Comparison of goodness-of-fit measures for all models, retail sector**

| Models | RMSE | Wald test |
|---|---|---|
| 1. OLS model | 8.23 | – |
| 2.a. SARAR model (contiguity weight matrix) | 7.35 | 38.88 |
| 2.b. SARAR model (distance weight matrix) | 8.36 | 74.00 |
| 3.a. SARAR model with endogenous variables (contiguity weight matrix) | 7.38 | 33.91 |
| 3.b. SARAR model with endogenous variables (distance weight matrix) | 9.73 | 35.55 |
| 4. MGWR model | 10.15 | – |
| 5. SARAR model with spatial regimes | 8.24 | – |
| 6. MGWR–SAR model | 5.83 | – |

The problem of local multicollinearity occurs for some economic variables in both MGWR and MGWR–SAR models, but its impact was reduced in the transition from MGWR to MGWR–SAR. As expected, the MGWR–SAR model has a better fit in terms of RMSE estimation (Table 4).

## Discussion

The results of this study emphasize the critical importance of spatial proximity in shaping the accumulation of human capital, confirming the relevance of geographic economic principles (Redding–Schott 2003, Lopez–Rodríguez et al. 2011). Specifically, this work shows that regions closer to Tunis CBD benefit from enhanced access to tertiary education and more dynamic labour markets. Conversely, in peripheral regions, there are significant barriers, including limited access to educational institutions and fewer economic opportunities. These findings align with patterns observed in Europe (Rodríguez-Pose–Tselios 2011) and Turkey (Erdem 2016), where geographic inequalities have been reported to create significant disparities in the distribution of human capital.

Thus, the structure of the labour market is significantly associated with human capital accumulation in Tunisia. The rates of employment in agriculture and manufacturing negatively correlate with the development of human capital, highlighting the challenges faced by these traditional sectors in fostering skills advancement. These findings suggest that workers in these sectors may have limited incentives or opportunities to pursue higher education. In contrast, the mining and energy sectors demonstrate a positive relationship with human capital accumulation, reflecting their ability to attract and retain skilled workers. These industries act as localized hubs of human capital, driving regional specialization and economic development.

Furthermore, technological change in Tunisia emerged as a significant factor in human capital accumulation in this study, supporting the hypothesis that innovation and technological adoption enhance educational opportunities and labour market alignment (McHenry 2013). The findings emphasize the need for targeted investments in digital infrastructure to foster regional human capital growth and reduce disparities.

The findings of this study have important implications for policymakers aiming to address regional inequalities in human capital accumulation in Tunisia and elsewhere. The decentralization of educational resources by establishing tertiary institutions in peripheral regions can significantly reduce educational disparities (Lopez–Rodríguez et al. 2019). Additionally, improving transport networks can better connect rural areas to urban centers, thereby enhancing access to educational opportunities and labour markets.

The Tunisian government must establish new labour market reforms to align the education system with the demands of the labour market, particularly in agriculture and industry. This could improve the contributions of these sectors to human capital accumulation. Moreover, promoting job matching platforms can optimize the mobility and utilization of skilled labour (Kremer 1993).

Moreover, supporting the adoption of new technologies in underdeveloped regions can attract skilled workers, promote economic diversification, and foster the development of human capital. Investments in digital infrastructure are crucial to reducing regional disparities and improving labour market alignment.

This study's findings align with previous research by Redding–Schott (2003) and Lopez–Rodríguez et al. (2011), which demonstrated the spatial concentration of human capital in regions that are highly accessible and have a high density of economic activity. However, these findings differ from those of Kano et al. (2017), who observed declining geographic disparities in other contexts, such as in developed economies with stronger infrastructure and more evenly distributed educational resources. This contrast suggests that Tunisia faces unique challenges related to its regional economic and educational structures.

However, this research is limited by the low availability of migration data and qualitative measures of human capital, such as the quality of education and institutional factors. Future research could benefit from incorporating individual data to analyse the role of human capital characteristics in shaping labour market dynamics. Exploring the impact of specific policy interventions on the accumulation of human capital across different regions could also provide actionable insights for reducing difficulties in accessing the labour market.

Finally, the regions of Tunisia that are particularly promising economically are the urban and coastal areas, such as Tunis, Sfax, and Sousse, which attract skilled graduates. These regions benefit from better educational infrastructure and employment opportunities. In fact, human capital can be overestimated in these regions when considering only rates of enrolment in tertiary education because these regions attract skilled labour from elsewhere in the country after graduation. The concentration of high-quality jobs and proximity to economic centers amplify the agglomeration of skilled labour, making these areas net beneficiaries in the redistribution process.

Meanwhile, disadvantaged regions, such as the Central West, Northwest, and Southwest of Tunisia, suffer most from the redistribution of skilled labour. These regions experience significant emigration of students and graduates due to limited access to higher education institutions and employment opportunities, high costs associated with education and transport to urban centers, and persistent structural challenges like unemployment and skills mismatches. As a result, human capital is underestimated in these regions when performing analyses based on rates of enrolment in tertiary education, as many students migrate to urban centers, taking their potential productivity with them. These areas face a "brain drain", where the loss of skilled individuals hinders local development and exacerbates regional inequalities.

## Conclusion

The geographical distribution of human capital is a key factor in the formation and accumulation of human capital. The heterogeneity of this behavior and the neighbourhood effect allow skilled and productive individuals to become concentrated in particular places. The results of this study on Tunisia show that spatial proximity to the center of Tunis reduces the costs of education and stimulates the concentration of human capital. The authors also found that the rate of job matching process varies across the country. Limited job matching due to income inequality is a source of inequality in human capital. Analysis by the GWR model showed that the variables vary across different administrative regions within Tunisia. The number of skills matches is related to the characteristics of each region. The accumulation of human capital is obstructed by tertiary education costs, low training, transport costs, and high unemployment rates, which prevent the distribution of human capital in a spatially balanced manner.

When analysing workers by sector, the results showed that the agricultural sector is heavily influenced by investments in education, which are critical for alleviating poverty and improving the literacy levels that currently define the sector. Meanwhile, in the mining and energy sectors, which thrive on innovation and technical progress, there is underdevelopment and a need for a robust governance system. Similarly, skills mismatches, job search friction, and rural–urban migration contribute to the spatial heterogeneity of human capital and employment.

We conclude our paper by asserting that matching between jobs and skilled jobseekers is subject to the geographical behavior of the latter, which catalyzes spatial inequalities. Policymakers need to put in place policies that bring together jobs and qualified jobseekers at the level of the "delegation" or "*imada*"[8], and promote access to jobs at the micro level. For this purpose, we worked to find innovative economic solutions to ameliorate spatial heterogeneity and promote job matching by reducing spatial effects of human capital accumulation. Specifically, the authors developed a web application for accessing jobs and improving job matching, which will be discussed in a future paper.

### Acknowledgement

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[8] *Imada* is the smallest geographical unit in Tunisia after the delegation. Tunisia contains 2073 *imada*.

## Appendix

Table A1

### Descriptive statistics of the 268 delegations

| Variable | Mean | Standard deviation | Min. | Max. |
|---|---|---|---|---|
| Tertiary education enrolment rate (%) | 38.60 | 11.47 | 15.10 | 75.89 |
| Distance to Tunis (km) | 153.89 | 122.22 | 0.01 | 535.08 |
| Job accessibility index | 0.02 | 0.08 | 0.01 | 1.29 |
| Job matches | 53.46 | 98.96 | 1.00 | 678 |
| Unemployment rate (%) | 16.35 | 6.70 | 5.81 | 42.40 |
| Migration for study | 320.49 | 450.09 | 1.00 | 3,859 |
| Employees in agriculture | 1,381.93 | 1,473.01 | 19.00 | 10,898 |
| Employees in mining and energy | 260.72 | 392.27 | 5.00 | 2,897 |
| Employees in industry | 2,195.14 | 2,495.97 | 1.00 | 11,082 |

Table A2

### Description of the variables

| Variables | Description | Abbreviation | Source |
|---|---|---|---|
| Spatial variables | | | |
| Distance to CBD[a)] (Tunis) | Distance from CBD[a)] of Tunis to the rest of the delegations | DTUN | Author calculation |
| Job accessibility index | The job accessibility of delegation i is calculated by summing the job offers ($OE_{i,e}$) weighted by employment demand ($DE_{j,e}$) and the displacement impedance f ($C_{i,j}$). $A_{i,e} = \sum_j \frac{E_{j,e} \exp(-bC_{i,j})}{DE_{j,e}} = \sum_k \frac{E_{j,e} \exp(-bC_{i,j})}{\sum_k P_{k,e} \exp(-bC_{kj})}$ | JOBINDX | Author calculation |
| Economic variables | | | |
| Number of matches | The number of placements or matches carried out for qualified candidates through the employment office. | M | ANETI |
| Unemployment rate | The share of the labour force[b)] including unemployed and jobseekers. | U | INS |
| Migration for studying | The number of young people in each (outgoing) delegation belonging to the working population who have left their original delegation to study in another. | MRS | INS |
| Employees by sector of activity | Employees working in the agriculture, manufacturing, and mining and energy sectors. | AGR/INDUS/ MINES | INS |
| Number of subscribers to data transmission | Indicator of technological change | TECH | INS |

a) CBD = central business district.

b) The labour force is defined as the population of working age that is working or wants to work.

Table A3

**Instrumental variable (IV) regression with two-stage least squares (2SLS)**

| Dependent variable: ln enrolment | Coefficient | Standard error | Z-score | P-value |
|---|---|---|---|---|
| Constant | 3.71 | 0.09 | 40.71 | <0.001 |
| Matches | 0.06 | 0.02 | 3.38 | 0.001 |
| Distance to Tunis | −0.06 | 0.01 | −4.56 | <0.001 |
| Number of observations | 261 | – | – | – |

Instrumented: matches
Instruments: distance to Tunis, unemployment, job accessibility index, migration to study

**Tests of instrument validity**

Sargan (score) $chi^2 = 4.62$ ($p = 0.099$)
Basmann $chi^2 = 4.61$ ($p = 0.010$)

Figure A1

**Map of Tunisia by delegation**

Figure A2

Geographical distribution of tertiary education enrolment rates in Tunisia

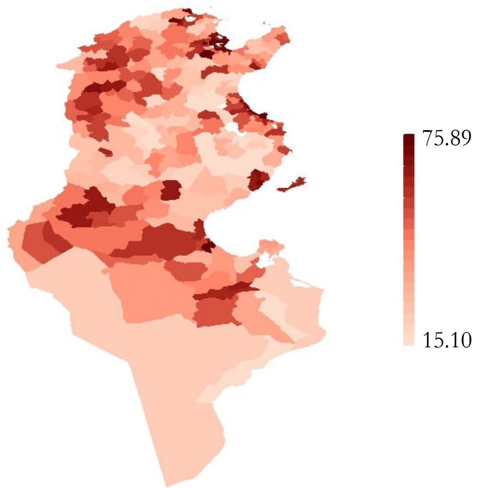
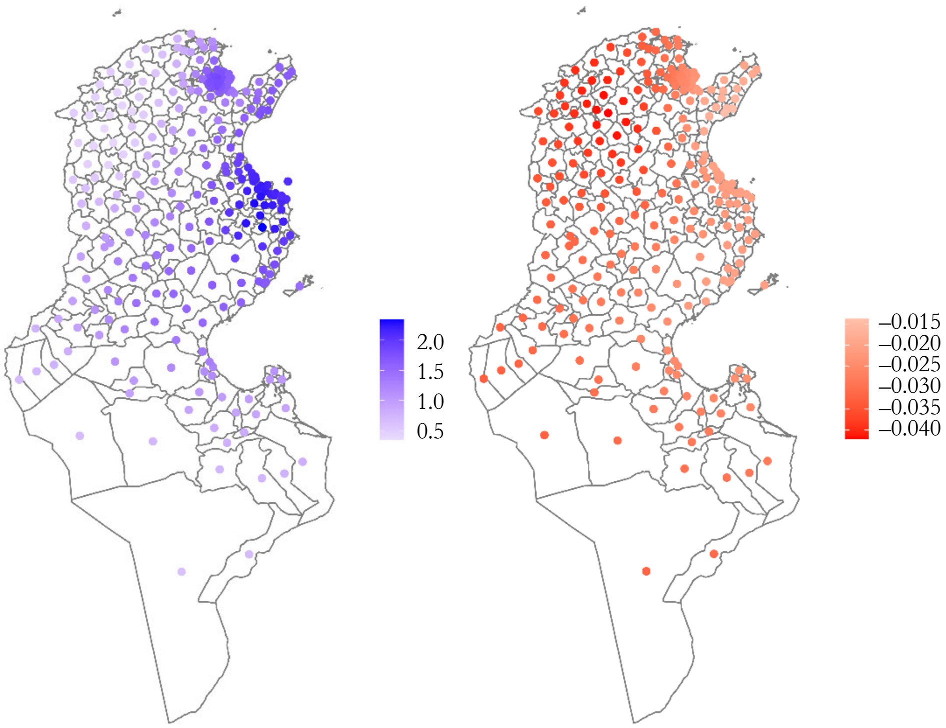



Figure A3

Spatial variation of the parameter

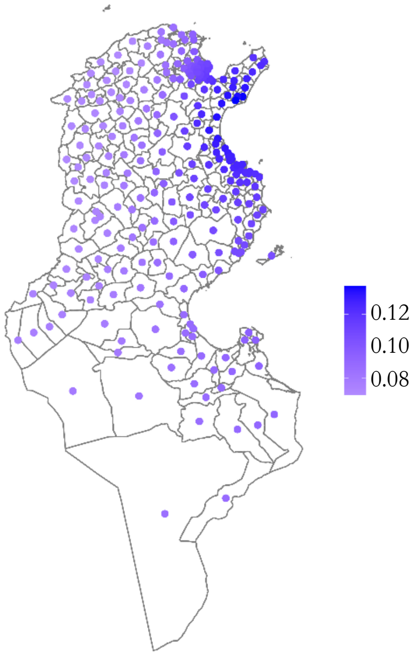
a) "qualified job matches" b) "technological change"



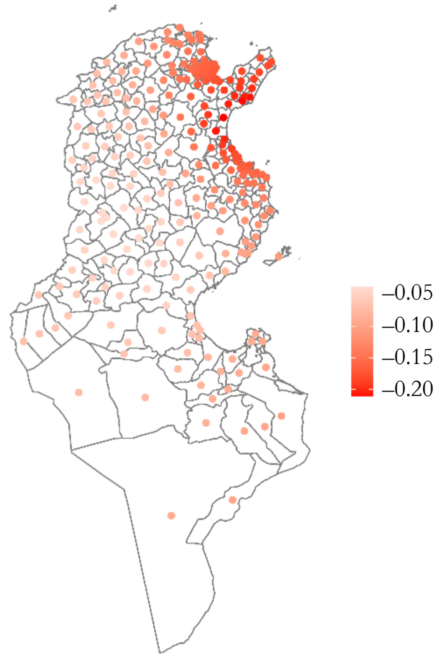

*(Figures continue on the next page.)*

*Continued.)*

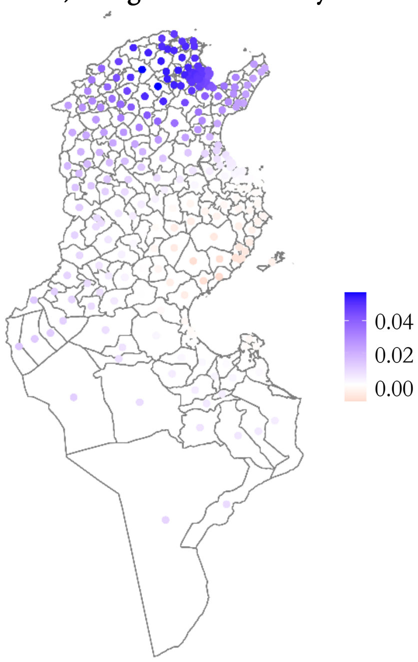
c) "employed in the mining and energy sectors"




d) "unemployment rate"




e) "migration for study"



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