The Effect of Spatial Unemployment on the Neighbouring Regions' Economies: A Regional Case Study of KwaZulu-Natal in South Africa

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This article investigates the degree of spatial dependence of unemployment on neighbouring economies with possible implications for cross-border community development initiatives. The local municipalities within the KwaZulu-Natal province in South Africa are used as a case study. Spatial econometric techniques are employed that incorporate dependence between regions in close geographical proximity. Disaggregated data and knowledge about the dynamics at a sub-regional level are usually unavailable for designing employment policies, especially for regional economies in under-developed countries. The results suggest an absence of spatial unemployment clustering and autocorrelation between neighbouring economies. The absence of externalities implies that little mutual dependence exists between adjacent economies, and therefore municipal unemployment patterns can be viewed as spatially random. The economy of a region is therefore fundamentally heterogeneous in that its unemployment rates are determined and influenced by its unique and diverse factors rather than neighbouring unemployment trends or patterns.

Key Words: regional unemployment, labour, spatial regression models, spatial dependence, regional impact and influence, neighbours, spatial weights, spatially lagged dependent variables, spatial autocorrelation
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Introduction

Investment within the built environment is recognised as influencing the 'neighbourhood effect' and ultimately contributes to community development (Wang 2019). In contrast, a continuation of prolonged unemployment could signal the opposite and delay investment. Investigating if the level of unemployment in a particular economy affects the economic activities, level of employment, growth and business profits in an adjacent economy are investigated. Analytical spatial analysis is applied to investigate the plausible spatial clustering and autocorrelation on nearby or proximity economies resulting from regional unemployment. Data from neighbouring economies within the KwaZulu-Natal province in South Africa is applied for this analysis. Understanding these spatial relationships proves to be important, specifically in identifying if there is such a relationship and secondly, if there is, the perceived value that can be gained in breaking the trends to foster community development across boundaries.

Regional or city economic activity may not always be static, suggesting periods of higher employment levels in one region might result in either draining development from its neighbours or simultaneously supporting the development of all the cities or regions in a particular area (Marais and Cloete 2017). In other words, higher employment occurs in one region because of the additional investment, while constraining investments from nearby cities, which subsequently experience higher levels of unemployment (Patacchini and Zenou 2007). Firms will probably locate in economically successful places, resulting in a clustering effect with the associated agglomeration advantages (Sharifzadegan, Malekpourasl, and Stough 2017). Spillover benefits can also accrue from nearby regions because of capital, knowledge, technology, entrepreneurship, and an expanded market (Caragliu and Nijkamp 2016; Delgado, Porter, and Stern 2010; Kleynhans 2016). However, suppose higher economic activity and investments in a city attract funds from abroad in such a way that it arouses interest in all the cities in that part of the area. In that case, all neighbouring cities and regions will benefit.

Regression analysis usually rests on the assumption that the error terms of indicators do not correlate, but when studying nearby regions, such economic data are seldom independent (Bhattacharjee, Holly, and Mur 2018). This study applies spatial analysis, which circumvents these violations associated with observations of nearby or adjacent regions or towns.

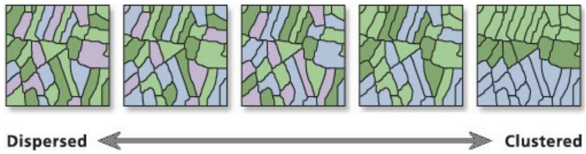
Disaggregated data and knowledge about the dynamics at a subregional level are usually unavailable for designing employment policies, especially for underdeveloped countries (Mishra and Singh 2019, 176). Thus, this article makes an important contribution relating to KwaZulu-Natal, designing the necessary instruments and deriving important information. Three statistical models will be used to assess the effect from neighbouring cities. It utilises the usual ordinary least square regressions, a spatial lag model, as well as a spatial error model, and derives two models to study the influence of economic activity and figures of other cities in the region nearby.

The second presents the theoretical basis illuminating the concepts of spatial dependence, clustering, and agglomeration. The third section provides the theoretical departure on the possible spatial correlation between unemployment rates, while the urban and rural unemployment realities in the Province of KwaZulu-Natal are presented in the fourth section. The fifth section explains the spatial regression models, starting with the basic spatial autoregressive model, designing the spatial lag regression Y, spatial lagged regression X, and spatial error regression models. The sixth section explains the data used, analysis methods, and the methodology employed during the research. This section also includes developing a spatial proximity or spatial closeness matrix. The application of the Moran's I statistic covers in the seventh section. The empirical results of the research are presented in the eighth section, including the regression model and the estimation of the spatial lag and spatial error models. The summary and conclusions are provided in the last sections.

Theoretical Setting

Spatial autocorrelation is purely investigating how closely (as proxied by distance) objects (variables) correlate with other nearby objects across a spatial area (Coetzee and Kleynhans 2021). Similar or related values located close to each other are associated with positive autocorrelation. On the other hand, negative or inverse autocorrelation holds that dissimilar or non-related values are found close to each other. The relevance of spatial autocorrelation allows or enables the researcher to conceptualise (model) how relevant spatial characteristics (dynamics) is impacting a pre-selected object in space and whether or not a definite relationship (i.e. dependency/association) of objects with spatial properties are present. Significant positive/negative outcomes propose a prominent spatial property in the object with a 'high' correlation. The spatial autocorrelation

FIGURE 1
Spatial Autocorrelation Range



range is illustrated in figure 1.

Spatial data, or geospatial data, refers to data linked or referenced to a particular location on Earth. Spatial data is significant because it is not just data, but data that can be visualised, located, followed, patterned, and modelled based on other spatial data. Close spatial reliance exists when the spatial characteristics (in the form of data) of a particular area are inferred or impacted by another area (Moralles, Silveira, and Rebelatto 2019). These interactions are best explained through agglomeration or clustering effects. Location's role in agglomeration has only recently been examined within the South African context (Naudé and Krugell 2006). Krugell and Rankin (2012) found that factors beyond firm-level contribute to clustering. Their results suggest that dimensions of distance are important to economic activity and recommend further research focused on the distance over which agglomeration economies work. Cheruiyot (2020) explores this further, this time within the urban context, and found that spatial sector clustering exists near key international transport nodes. Aiming to build on these results, this paper applies spatial analysis to measure if this interconnectivity remains on a regional level.

When studying spatial data, the derived spatial relationships may prevail between the variables and/or error terms (Sharifzadegan, Malekpourasl, and Stough 2017). Agglomeration may be a logical consequence (Vermeulen 2017).

Equation 1 (using ordinary least squares (OLS)), represents the relationship between the dependent (γ) and independent (X) variables as:

$$\gamma = X\beta + \varepsilon. \tag{1}$$

Assuming the best linear unbiased estimator (BLUE), minimising the sum of squared deviations from the 'true' values leads to estimating the object or variable β. To achieve the BLUE principle and derive statistical inference regarding the estimated coefficients requires assumptions regarding the error terms (ε).

The general rule or assumption is that the average random error terms are zero (Anselin 2005), proposing the absence of systematic misspecification or bias. Adherence to the non-bias assumption implies the lack of correlation between the error terms, and confirms constant variance, i.e. homoscedasticity, and normally distributed error terms.

Theoretical Departure on Spatial Correlation between Unemployment Rates

Unemployment in a region is often a symptom of low economic development and growth. Usually, low levels of development are associated with structural challenges in regions, causing low levels of productivity and a mismatch between supply and demand (Temple 1994). This might cause labour to migrate to adjacent regions to find employment elsewhere. Often, adjacent regions also experience similar unemployment, but those that do find work reduce unemployment in both regions (Barnes, Peck, and Sheppard 2012). This might lead to convergence of employment and growth trends in both regions (Coetzee and Kleynhans 2018a) and that is what this article aims to assess, the answers to which may direct economic development planners towards higher levels of development and better living for their citizens.

Patacchini and Zenou (2007) developed a theoretical model that explains the spatial nature of unemployment. The model is built on neoclassical explanations of wage differentials, low productivity and related structural impediments that cause poor convergence rates in regional labour markets. The model also relies on the Blanchard and Katz (1992) model. Barrett (2014) indicates that the Blanchard and Katz model assumes that different bundles of goods and services are produced and consumed by different regions under constant returns to scale and that both firms and workers are perfectly mobile.

In the Patacchini and Zenou (2007) theoretical model two regions or areas, $i = 1, 2$ and $j = 1, 2$, are used. A worker can, irrespective of the place of residence, consider employment in any of the two areas. Area *i*'s (or area *j*'s) total number of employed and unemployed workers (normalised to the population of 1) can then be expressed by the equation:

$$E_i + U_i = E_{ii} + E_{ij} + U_{ii} + U_{ij} = 1, \tag{2}$$

for $i = 1, 2$ and $j = 1, 2$, where $i \neq j$; where U_{ij} represents the total unemployed workers that reside in i and search in j and E_{ij} the total employed workers that reside in i and search in j.

Patacchini and Zenou (2007) further state that finding a job follows a random Poisson process that suggests several matches or contacts between the two sides of the market in area i per unit of time. The matching efficiency is expressed as a parameter (m_0) that expresses the relationship between the total unemployed workers ($U_{ii} + U_{ij}$) that search for work in area i and the total job openings (V_i) in the area. The matching parameter in area i is further linked to the tightness of the labour market (θ) in area i (or j), which inherently embraces the effects of all the exogenous variables influencing the levels of unemployment, such as the average population characteristics and dynamics of the area (i or j).

The model then proposes that the total unemployment in region i at period t is a function of the total unemployment in both areas i or j, but at period t equals minus one (one period lagged) and/or the labour market tightness in both areas i or j but at time $t - 1$ (one period lagged) such that:

$$U_{i,t} = f(U_{i,t-1}, U_{j,t-1}, \theta_{i,t-1}, \theta_{j,t-1}). \tag{3}$$

The theoretical model argues that the spatial nature of unemployment is relevant because people both work and search in the area where they do not reside. There are exogenous factors inherent within each area (Coetzee and Kleynhans 2018b).

Urban and Rural Unemployment Realities

Unemployment is a very serious problem in South Africa. It has been identified as one of three key priorities for the government to address. To this end, the national government has developed several policies and strategies focusing on economic growth and job creation. The Provincial Government also has some key responsibilities in the national effort to decrease the national unemployment rate and trajectory (The KwaZulu-Natal Provincial Planning Commission, Office of the Premier 2016). Both these spheres of government have important contributions to make. However, they do not operate at a local level and thus local government must be a vital component in the fight against unemployment. This is especially relevant given that many of the most fundamental economic activities take place at the local level.

In the Province of KwaZulu-Natal (see figure 2), the unemployment rate (official definition) ranged between 15 and 50% in 1996 among the 51 municipalities located in KwaZulu-Natal. This picture worsened to between 20 and 50% in 2019. Unemployment is particularly severe in the more rural areas of the province. On average, the divide between urban and rural (as defined by their contribution to gross provincial product) varied between 25% for urban municipalities and 40% for rural munici-

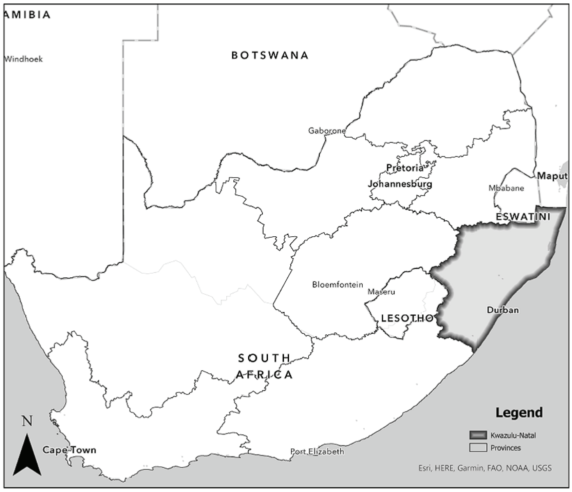


FIGURE 2
Map of Kwazulu-Natal Province, South Africa

palities (Global Insight n.d.). One would expect that if only the National and Provincial governments are important and relevant in terms of unemployment, the unemployment rate range would not be this significant. If local factors did not play a role then there would be no reason for such significant differences in local unemployment rates. Therefore, given the wide range of unemployment rates amongst the municipalities, local factors seem to be both important and relevant. These studies to a large degree test this assumption using spatial regression models.

Policy by itself does not create agglomeration effects or clustering of activity. Instead, it promotes the conditions to benefit economies where interconnectivity occurs (Cortright 2006). The KZN provincial government has at its disposal policy instruments to steer economic development within its borders which the Provincial Growth and Development Strategy (PGDS) aims to achieve. The PGDS aligns with various international and national development goals such as the United Nations Sustainability Development Goals and the National Development Plan (2013) which encourages a clear plan for growth and development throughout the province to improve well-being.

As previously mentioned, this responsibility extends to the local government level. Various policy instruments are at their disposal to facilitate land development, of which the most prominent is land use management through spatial development planning, culminating in an Integrated Development Plan (IDP). The content of the IDP represents the most critical governance needs of the local government for near-term strategic planning which require attention for economic development. Beyond the planning tools at the disposal of local government, the spatial location of the administrative area could affect how successful these are.

Spatial Regression Models

The Basic Spatial Regression Concept

Observational data emanating from random cities and/or regions can readily suggest the dependence of the observations because of spatial proximity (Shimeles and Nabassaga 2018, 121). LeSage and Fischer (2008) argue that accounting for the regional dependence between data can be facilitated via spatial regression methods. This is because the economic data of regions are often similar to the neighbouring data.

The spatial correlations between cities or regions in close proximity can be linked to several standpoints. The Ertur and Koch (2007) theoretical model, for instance, proposes both human and capital technological interdependence and externalities as possible reasons. This requires including growth rates from neighbouring regions when locational growth rates are estimated (Coetzee and Kleynhans 2018a).

Time dependency recognition is essential when working with time-series data. To this end, it is most probably advisable to include cost adjustments, behavioural frictions and time lags. According to Ertur and Koch (2007), it is also relevant to focus on 'spatial diffusion with friction.' This validates spatial lags due to trends in neighbouring regions (LeSage and Fischer 2008).

Spatial econometrics models spatial dependence, considering the economic geography between nearby regions. To this end, ordinary least square (OLS) regression analysis can be modified to include the spatial dependence of nearby regions (Anselin 2005; LeSage 1999).

Spatial autoregressive models are generally represented as:

$$\gamma = \rho W_1 \gamma + X_1 \beta + \mu, \tag{4}$$

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

$$\varepsilon \sim N(0, \sigma_2, In), \tag{6}$$

where γ is a dependent variable.

This incorporates a vector of cross-sectional dependent variables, i.e. $n \times 1$, while X forms a matrix of the dependent variables, i.e. $n \times k$. W_1 and W_2 are variables expressed as a weighted nxn spatial matrix. These also contain contiguity relationships and/or distance functions. λ represents the spatial observed value lag coefficient and μ is a random error for region i.

Special models can then be designed with the inclusion of specific limitations. A first-order spatial autoregressive model may, for instance, be developed when X and W_2 are adjusted to zero ($X = 0$ and $W_2 = 0$), yielding:

$$\gamma = \rho W_1 + \varepsilon. \tag{7}$$

In this equation, the linear variations in the data of neighbouring regions are accommodated (but other explanatory variables are ignored). This approach is like first-order autoregressive models, but now accommodates spatial aspects, yielding the equation: $\gamma_t = \rho\gamma_{t-1} + \varepsilon_t$, where historical data explain the variation in γ_t.

This can then be changed to a mixed regressive-spatial autoregressive model adjusting W_2 to zero, yielding the linear equation:

$$\gamma = \rho W_1\gamma + X\beta + \varepsilon. \tag{8}$$

This corresponds to lagged dependent variable models used in time series data analysis. In the spatial model, variation in y can be better explained when another explanatory variable is incorporated in the matrix X. When the variable W_1 is also adjusted to zero, spatial autocorrelation can be incorporated in the disturbances, and this can be represented as:

$$\gamma = X\beta + \mu, \tag{9}$$

$$\mu = \lambda W_2\mu + \varepsilon. \tag{10}$$

The Spatial Durbin Model is a related approach that applies spatial lags to the dependent and independent variables. It applies the explanatory variable matrix X to normal regression analysis:

$$\gamma = \rho W_1\gamma + X\beta_1 + W_1X\beta_2 + \varepsilon. \tag{11}$$

The dependent variable is then represented by an n by 1 vector y, while parameter ρ is a scalar. W is a spatial weight n by n matrix: $\rho W\gamma$.

Matrix P displayed below is a $n \times n$ binary indicator matrix. The rows coincide with observations of regions 1 to 5. In the matrix '1' represents data from 'neighbours' associated with each row, the 2nd and 3rd observation or region. Measuring the distance from the centre of each location, the '1s' represent the nearest two locations. As an illustration, $P(1,2) = 1$ and $P(1,3) = 1$ implies they are the closest regions, where #2 and #3 are the closest neighbours of region #1, meeting the distinction of $m = 2$ neighbours. Similarly, $P(2,1) = 1$ and $P(2,3) = 1$ represent regions 1 and 3 in row 2 ($m = 2$), with region #2's closest neighbours, and it is also shown that regions #3 and #4 are neighbouring region #5.

$$P = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix}. \tag{12}$$

In the P-matrix, the diagonal shows all zeros because a region cannot be its neighbour. By dividing all the figures in the P-matrix by the figures of its neighbours, it is possible to normalise it to obtain all the row-sums equal to one. This changes it to a spatial weight matrix W, with a *row stochastic* form, which will be convenient when the spatial regression models are estimated.

$$W = \begin{pmatrix} 0 & 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 0.5 & 0 \end{pmatrix}. \tag{13}$$

Multiplying the W-matrix with the y-vector of observations of any particular variable of the five regions yields matrix Wy displayed below. This product matrix yields an n by 1 vector that represents the mean of a particular variable of the neighbours and is referred to as the 'spatial lag' (LeSage 1999; Higazi, Abdel-Hady, and Al-Oulfi 2013).

$$Wy = \begin{pmatrix} 0 & 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 0.5 & 0 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{pmatrix} = \begin{pmatrix} 1/2y_2 + 1/2y_3 \\ 1/2y_1 + 1/2y_3 \\ 1/2y_2 + 1/2y_4 \\ 1/2y_3 + 1/2y_5 \\ 1/2y_3 + 1/2y_4 \end{pmatrix}. \tag{14}$$

Following the above, it can be proposed that regions perhaps may be allied to nearby regions in the below distinct ways:

- The y value in a specific region might influence (or be related to) a similar variable in an adjacent region, or

- The x's values in a specific region might influence (or be related to) a similar variable in an adjacent region, and
- The residuals (ε) might influence (or be related to) the residuals in a nearby region (spatial heteroscedasticity).

DESIGNING THE SPATIAL LAG REGRESSION y

When there is reason to assume that the variables of an indicator (y) are directly influenced by the data (y) of a neighbouring region or city, it may be appropriate to estimate a spatially lagged y model (Wang and Lee 2018).

This excludes any influence of other covariates specific to i, and there is reason to assume that any other variables might influence the values of y (Diop 2018, 276). In this case, it is assumed that other spatial aspects exist that are not specified, which cause some clustering and the value of indicators y and its unitary size I. To determine this spatially lagged model, the dependent variable y must be continuous.

The spatial lag regression may be represented by:

$$y_i = \rho W_i y_i + x_i \beta_1 + e_i, \tag{15}$$

which can be rewritten as:

$$(I - W_i) y_i = x_i \beta_1 + e_i. \tag{16}$$

In this case, the independent variables are those that are not determined by regions nearby. The ρ (rho) variable is the spatial dependence parameter indicating spatial lag. When ρ is positive it may be assumed that both the values of the region's dependent variable y and that of its neighbour are high, if not higher (Higazi, Abdel-Hady, and Al-Oulfi 2013).

SPATIAL LAGGED REGRESSION X

The model thus far developed is befitting when the spatial variables' behaviour or fate responds to the exogenous observable characteristics of neighbours in so far as:

$$y_i = x_i \beta_1 + W_i X \theta + e_i, \tag{17}$$

where θ (theta) represents the spatially weighted independent variables of the nearby regions.

The spatially lagged independent variables are included in the model (Higazi, Abdel-Hady, and Al-Oulfi 2013).

SPATIAL ERROR REGRESSION

In the spatial error regression model, spatial influence from neighbouring regions or cities is determined by considering the error terms instead of the systematic components. This model may now be represented as:

$$y_i = x_i\beta_1 + e_i, \tag{18}$$

$$e_i = \lambda W e_i + \varepsilon_i, \tag{19}$$

where λ (lambda) is the spatially weighted errors of the neighbours. The spatial autocorrelation term in this spatial error regression model then captures spatial dependency (Higazi, Abdel-Hady, and Al-Oulfi 2013).

Methodology

DATA UTILISED

The empirical analysis of this study employed unemployment, population growth, production (income), and literacy figures for 1996, 2003, 2009, and 2015 for the 51 KwaZulu-Natal municipalities (figure 3). This implies that the whole population was included, and the periods were chosen based on the availability of comparable data, ranging over two decades.

This data encompassed average per annum figures for the various municipalities of their:

- Unemployment rate as derived from Global Insight (n.d.) and cross-referenced by Statistics South Africa (n.d.). This entails the number of unemployed people divided by the total population;
- Population growth rate (number of people), as derived from Global Insight (n.d.) and cross-referenced by Statistics SA's annual population estimates;
- Gross domestic product growth rate from the Global Insight (n.d.) database, which is verified by the provincial GDP estimated by the KZN Treasury model (constant 2010 prices);
- Literacy growth rate published by Global Insight (n.d.), which is the number of people with matric and more, divided by the total population.

METHODS OF ANALYSIS

Geographical clusters and/or regions can be analysed and described through the various regional statistics, but also visually. The visual presentation provides a fast perception of the situation, which also intuitively

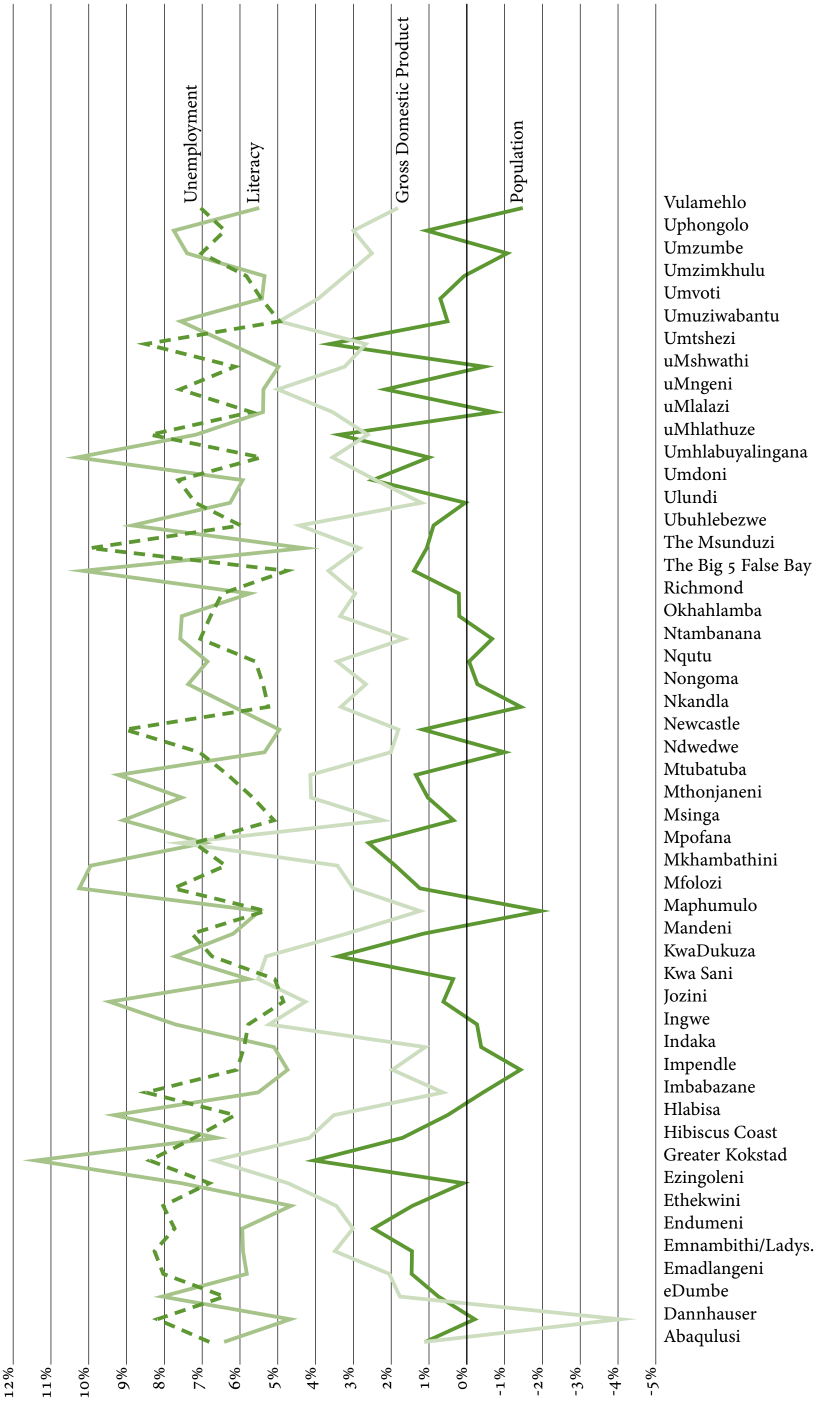
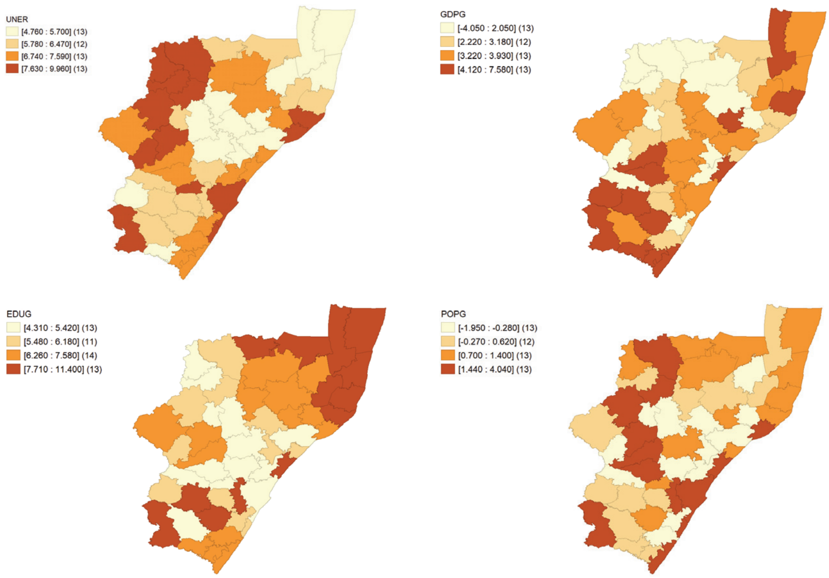


FIGURE 3 Four Variables per KZN Municipality over the Period



NOTES UNER = Unemployment rate, GDPG = Gross domestic product growth rate, EDUG = Literacy growth rate, POPG = Total population growth rate

FIGURE 4 GIS Images per Variable per KZN Municipality over the Period (%) (based on data from Global Insight (n.d.), Statistics South Africa (n.d.) and KZN Treasury (2021))

provides insight into the situation. The individual images in figure 4 represent a coloured picture enabling the spatial pattern visualisation of the variables. The geographical information system (GIS) software QGIS was employed. High/Low levels (rates or growth) are presented in dark/light areas (Thongdara et al. 2012).

Some spatial association seems evident, such as the clustering of dark-shaded regions and the clustering of light-shaded regions. The spatial association seems to support the findings of Yates and Casas (2012) that the average unemployment and literacy rate per municipality are key determinants.

On the other hand, the average GDP and population growth rate variables per municipality seem more dispersed. The images propose that nearby or neighbouring areas are more alike, suggesting a spatial relationship.

The GIS software package GeoDa (see https://geodacenter.github.io/) makes it possible to estimate the spatial lags for the variables (ρW) (Li et al. 2009). GeoDa is an internet computer-based software tool for spatial

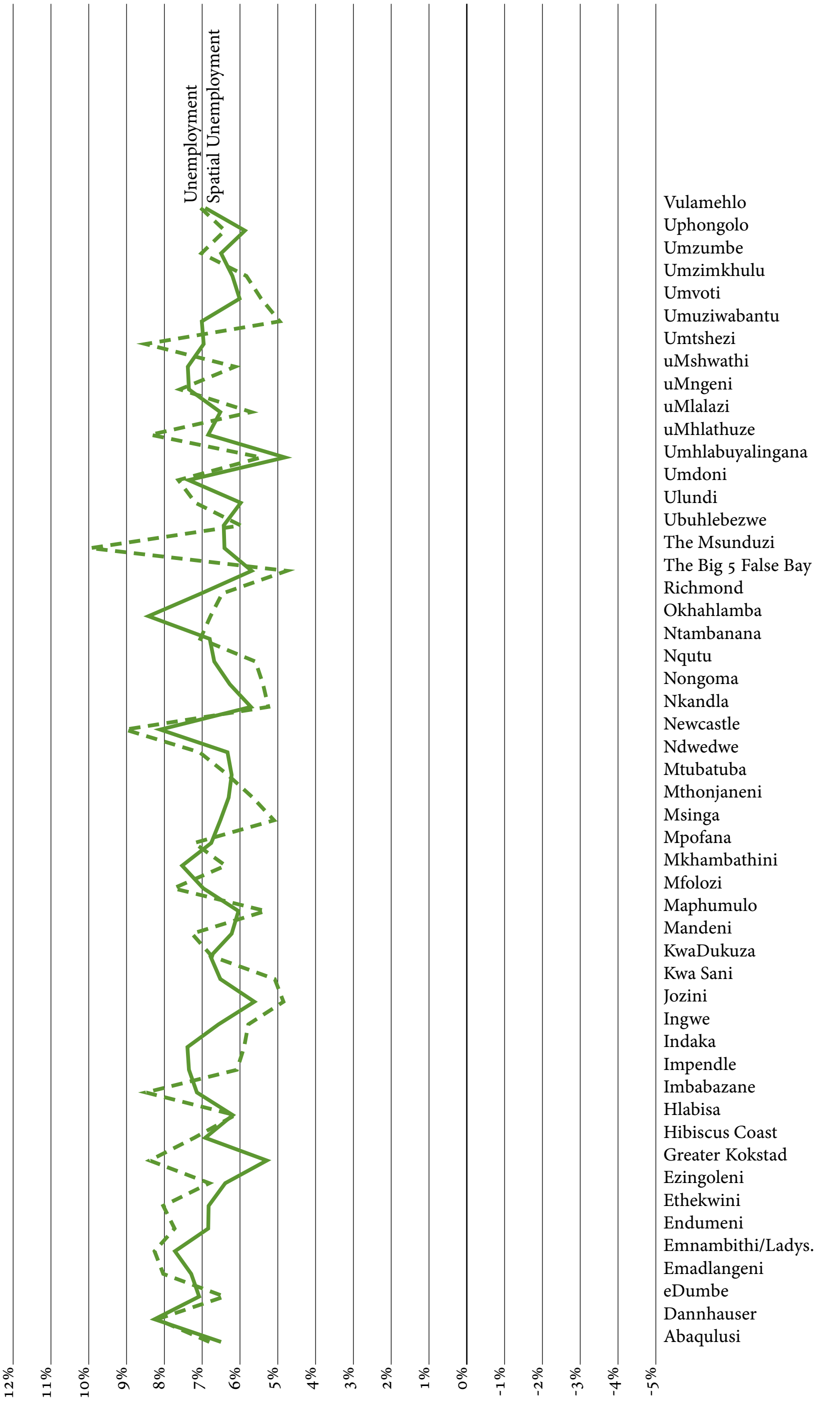


FIGURE 5 Spatial Lag and Average Unemployment Rate per Region

TABLE 1 Covariance and Correlation Analysis of KZN

Variable	Unemployment rate		Unemployment rate*	
	Correlation	t-statistic	Correlation	t-statistic
GDP	−0.229	−1.647	−0.357	−2.679***
Literacy growth rate	−0.304	−2.239***	−0.441	−3.445***
Population growth rate	0.427	3.305***	0.008	0.061

NOTES * Spatial lag average. *** $p < 0.001$

data analysis, which applies the most recent methods and perspectives of exploration and modelling of spatial trends. For example, figure 5 displays the average unemployment and the spatial lag average unemployment rate per municipality.

Following figure 5 and the associated descriptive statistics (not included), it seems that the actual time series is less smooth than the spatial lag operator. This is also the case for the other variables. Testing for normality (associated p-values) confirms that the data of the variables (except for GDP growth rate) are normally distributed. Table 1 presents the covariance and correlation analysis for the variables. Also included is the associated t-statistic.

DETERMINATION OF THE SPATIAL WEIGHTS MATRICES

A spatial proximity matrix represents a deterministic transformation of a spatial weights matrix (Smith 2008). Through such a weight matrix, the weighted dependence of n spatial units, where a unit j has a 'spatial influence' on unit i in the order of w_{ij}, can be assessed or estimated. The spatial proximity matrix C with n elements can be developed within a geographical system as:

$$C = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{pmatrix}, \tag{20}$$

where the range and nature of influence and distance of the data from nearby units are proxied by cell c_{ij}, commonly between locations i and j (Coetzee and Kleynhans 2021). Constructing a spatial weights matrix yields the following:

$$W = \frac{C}{C_0} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix}, \tag{21}$$

where

$$C_0 = \sum_{i=0}^{n} \sum_{j=0}^{n} C_{ij}, \sum_{i=0}^{n} \sum_{j=0}^{n} w_{ij} = 1. \tag{22}$$

The starting point in specifying the spatial proximity weights is to express whether units share common borders (Coetzee and Kleynhans 2021; Anselin 2005). Defining a group of points on the boundary (*bnd*) with unit i by $bnd(i)$, i.e. neighbours are classified as two units that share a common boundary, refers to Queen contiguity weights:

$$w_{ij} = \frac{1,}{0,} \frac{bnd(i) \frown bnd(j) \neq \emptyset}{otbnd(i) \frown bnd(j) \neq \emptyset}. \tag{23}$$

The k-nearest neighbour weights (Anselin 2005), are relevant when the centroid, i.e geometric centre of a plane figure, distances between unit i to all units $j \neq i$ sorting as: $dij(1) \leq dij(2) \leq \cdots \leq dij(n1)$, then for each $k = 1, \ldots, n-1$, the set of $Nk(i) = j(1), j(2), \ldots, j(k)$ comprises the k closest units to i (in general ties are disregarded, see Anselin 2005). For every given k within the k-nearest neighbour weight matrix W, the spatial weights can then be represented as:

$$w_{ij} = \frac{1,}{0,} \frac{j \in Nk(i)}{\text{otherwise}}. \tag{24}$$

Radial distance weights are necessary if and when the distance between units d is important. The minimal influence will be assigned after the spatial threshold distance or bandwidth if the distance is too far (Coetzee and Kleynhans 2021; Anselin 2005). The weighted radial distance matrix W can be presented as:

$$w_{ij} = \frac{1,}{0,} \frac{0 \leq d_{ij} \leq d}{d_{ij} > d}. \tag{25}$$

Actual distance values propose that distance (between two or more units) is commonly a significant criterion (Anselin 2005). In this case, the actual distance ($1/d$ = inverse of the distance) will have a strong influence on the weighted actual distance matrix W, which is:

$$w_{ij} = \{1, \frac{1}{d_{ij}} > 0\}. \tag{26}$$

The current study will mainly apply the Rook-based Contiguity Weight Matrix (Ord and Getis 1995).

Applying Moran's I-Statistic

Moran's I-statistic can be used to measure spatial autocorrelation. The associated methodology is not dissimilar to OLS regressions (Moran 1950; Wu and Liu 2017) with values ranging from minus to positive one, i.e. $-1, \ldots, +1$. If zero, no spatial relationship exists (Mehrotra, Bardhan, and Ramamritham 2020), while positive/negative values represent positive/negative spatial relationships (Coetzee and Kleynhans 2018a). When the expected Moran's I-statistic's value is $E(I) = -1/(N-1)$ then it proposes the absence of spatial autocorrelation (De Dominicis 2014).

Figure 6 shows a scatter plot of Moran's I-statistics showing the average unemployment rate per municipality. The unemployment rates of the municipalities (non-standardised) are given on the horizontal axis, while the vertical axis gives their mean unemployment rates, which implies a lagged Spatial Poverty indication (W) from the nearby municipalities that the Moran's I weight matrix provides (Edwards et al. 2018). Estimating the Moran's I correlation coefficient 'I(d)' can be done using the following equation:

$$I(d) = \frac{\frac{1}{W}\sum_{h=1}^{n}\sum_{i=1}^{n} W_{hi}(y_h - \overline{y})(y_i - \overline{y})}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2} \text{ for } h \neq i, \tag{27}$$

where n is the sample size, h and i are the locations, W_{hi} is the matrix's size, and W is the sum of values.

The distance function is w_{hi}; y_h equals one and the particular distance groups are y_i where $y_h \neq y_i$ and 0 in all other cases; y_h, y_i are the values of the variables (Coetzee and Kleynhans 2018a; Zierahn 2012).

In his research, Anselin (1996) estimates the global Moran's I-statistic slope of the unemployment rate to be 0.237, indicating a spatial cluster where unemployment is concerned. The associated Moran's I-statistic probability of 0.01 suggests that the chance that such clustering could just be coincidental and thus non-existent is less than one per cent (Stojčić and Orlić 2020; Voss et al. 2006).

Figure 6 shows several municipalities with an unemployment rate above average and adjacent to those whose unemployment rates are also above average situated in the upper right quadrant (Torrens 2008). Those that are bottom left are municipalities with below-average unemployment surrounded by similar neighbours. Those municipalities whose unem-

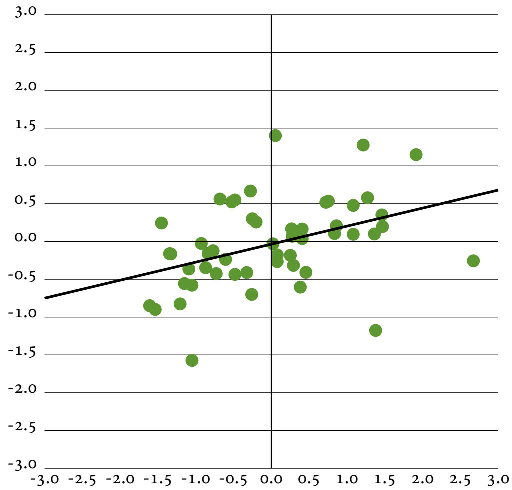


FIGURE 6

Global Moran Scatter Plot, Average Unemployment Rate in KZN

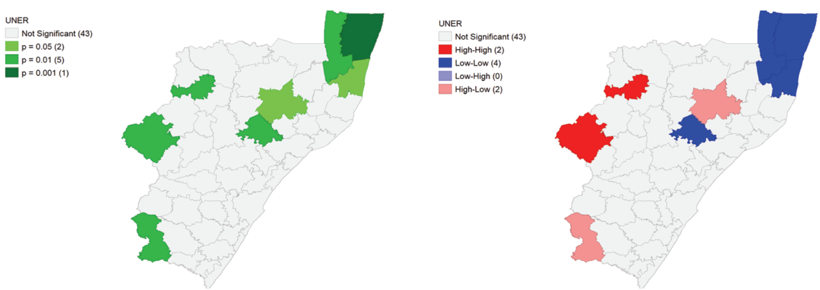


FIGURE 7 LISA Spatial Dependence in KZN

ployment rates are above average and located near cities with unemployment rates below average are situated in the quadrant on the bottom right. The municipalities with unemployment rates below average and located near cities with unemployment rates above average are situated in the top left quadrant (Meliciani and Savona 2015; Li, Calder, and Cressie 2007).

Autocorrelation as a spatial dependence test is rather equivocal. The coloured section on the map of KwaZulu-Natal province in figure 7 indicates autocorrelation. This was indicated by the Univariate Local Indicators of Spatial Autocorrelation 'LISA,' but not all these clusters were statistically significant.

The coefficients of the Global Moran autocorrelation statistic between the average unemployment rate and each explanatory variable per mu-

TABLE 2 Global Moran I-Statistics

Variable	Moran I	Significance Level
Average GDP growth rate	0.097	0.085
Average literacy growth rate	0.403	0.001***
Average population growth rate	−0.060	0.330

NOTES *** $p < 0.001$.

TABLE 3 Results for KwaZulu-Natal Municipalities (OLS Model)

Variable	Estimates	p-value
Constant	8.732***	<0.001
GDP	−0.272***	0.002
Population	0.640***	<0.001
Literacy	−0.236***	0.005
Adjusted R^2	0.467	
F-statistic	15.616***	<0.001
Log-likelihood	−64.13	
Akaike info criterion	136.26	
Jarque-Bera norm. test	3.093	0.212
Koenker-Bassett test	0.228	0.972
White test	13.316	0.148
Multicollinearity condit. number	10.850	Extreme Multicollinearity

NOTES *** $p < 0.001$.

nicipality over the period are displayed in table 2. Also displayed are the coefficients' levels of significance.

Results of the Empirical Analysis

SPECIFYING THE REGRESSION MODEL

The classic or standard regression analysis excluding spatial weights is the starting point (using GeoDa, see below). The regression is usual:

$$y_t = \beta X_t + \varepsilon_t, \tag{28}$$

where y is the average unemployment rate per municipality, X is the vector of explanatory variables per municipality (average GDP, average population, and average literacy growth rates), and ε is the usual random error variable. The period ranges from 1996 to 2014, and the results for KwaZulu-Natal municipalities are given in table 3.

TABLE 4 Spatial Autocorrelation Test

Variable	Tests with spatial weight	p-value
Moran's I-stats. (error)	0.387	0.698
Lagrange lag multiplier	1.222	0.268
Robust lag LM	3.102	0.078
Lagrange multiplier (error)	0.000	0.995
Robust LM (error)	1.880	0.170
Lagrange multiplier (SARMA)	3.102	0.211

NOTES *** $p < 0.001$.

Perceiving the χ^2 statistic distribution with 2 degrees of freedom, the Jarque-Bera test suggests serious errors in normality ($p > 0.05$). No heteroscedasticity exists according to the Koenker-Bassett ($p > 0.05$) test. Heteroscedasticity among random variables with a specific functional form and trend surface specifications are considered as the residuals of the Koenker-Bassett test are studentised, implying robustness to non-normality.

To test the robustness of the specifications for heteroscedasticity, the White test was conducted as this disregards the heteroscedasticity of specific functional form and the results support the evidence of no-heteroscedasticity shown above. A large group of possibilities are considered by the White test, as it squares all the powers and cross-products of the variables in the model. The plain revealed acceptable results indicating the X-variables coefficients that are statistically significant, both individually, as well as jointly. However, nothing has yet suggested a possible special relationship, if any at all.

Adding weights to the ordinary regression analysis (rook continuity estimates that include the spatial weight matrix), gave similar results, but tests for spatial autocorrelation were also conducted. Spatial autocorrelation was assessed using five diagnostic tests and the results are given in table 4. Logically, Moran's I-statistics were determined first. The spatial error Lagrange multiplier and the robust Lagrange multiplier error models were estimated, followed by the Lagrange multiplier lag test (LM-Lag) and a robust Lagrange multiplier lag test as an alternative. Finally, a SARMA Lagrange multiplier model was developed and tested, which represents a higher-order model that includes spatial lags and spatial error terms.

One degree of freedom existed in the data and was distributed as χ^2,

TABLE 5 Spatial Lag Estimates – KZN Municipalities

Model	Spatial lag	*p*-value
Constant	8.733***	<0.001
GDP	−0.272***	<0.001
Population	0.640***	<0.001
Literacy	−0.236***	0.002
Lambda	−0.001	0.995
R^2	0.499	
Log-likelihood	−64.13	
Akaike info criterion	136.26	
Schwarz criterion	143.987	
Breusch-Pagan test	0.204	0.976
Likelihood ratio test	0.000	0.995

with the SARMA LM model having two degrees. The order in which the estimations are done is important and to ensure statistical significance only the robust models and estimations are noted and investigated further. The analysis considered only those that were found to be statistically significant and robust. When the ordinary LM-Lag and LM-Error models are insignificant, the robust models are also insignificant. Most test statistics given in table 4 are statistically significant, implying the absence of spatial autocorrelation.

ESTIMATING THE SPATIAL LAG MODEL

When studying spatial regression models, the traditional measures of regression analysis, for example, the R^2, are not applicable (Anselin 2005). Statistical measures, such as the coefficient of determination, are a kind of pseudo-R^2, which cannot be compared to the usual statistics. In spatial analysis, the Log-Likelihood, Schwarz criterion and Akaike info criterion measures are more appropriate (Breitung and Wigger 2018).

When the results of the Log-likelihood and Akaike info criterion statistics of the ordinary regression analysis (−64.13 and 136.26) are compared to the spatial lag model (−63.47 and 136.94) (tables 3 to 5), the inclusion of a spatial lag specification did not have any effect. The results showed that the spatial auto-regression indicator (ρ) equals 0.19 but is insignificant ($p > 0.05$). Testing for heteroscedasticity using the Breusch-Pagan test in the error terms also revealed no heteroscedasticity.

TABLE 6 Estimation Results Using the Spatial Error Model

Variable	Spatial lag	p-value
Constant	7.184***	<0.001
GDP	−0.248***	0.002
Population	0.613***	<0.001
Literacy	−0.205***	0.008
Weight matrix (ρ)	0.191	0.212
R^2	0.515	
Log-likelihood	−63.470	
Akaike info. criterion	136.940	
Breusch-Pagan	0.205	0.976
Likelihood ratio test	1.320	0.250

To improve the spatial autoregressive coefficient of the asymptotic significance test, an alternative test was conducted. As part of the specifications of classic regression analysis, the likelihood ratio test relates the null hypothesis to an alternative spatial lag model. The low probability value also indicated that the spatial autoregressive coefficient is statistically insignificant. The graph in figure 8 displays the spatial lag model, depicting the values of the actual, predicted and residual values of the average unemployment rate per municipality.

ESTIMATING THE SPATIAL ERROR MODEL

Similar results were obtained when estimating the spatial error model. When the results of the log-likelihood and Akaike info criterion statistics of the ordinary regression analysis (−64.13 and 136.26) were compared to the spatial error model (−64.13 and 136.26) (tables 3 to 6), it indicated that the inclusion of a spatial lag specification still had no effect.

The value of lambda, which is the spatial autoregressive coefficient, equals minus 0.0011, reveals to be highly insignificant, and no heteroscedasticity exists among error terms according to the Breusch-Pagan test results ($p > 0.05$). The next test was not a spatial autocorrelation test, while the classic likelihood ratio test substantiated the notion that the spatial autoregressive coefficient has very weak statistical significance ($p > 0.05$). The graph in figure 9 (actual vs. predicted and residuals) displays the spatial error model.

The model results confirm that spatial correlations can indeed be estimated. It measures or assesses which nearby municipalities experience

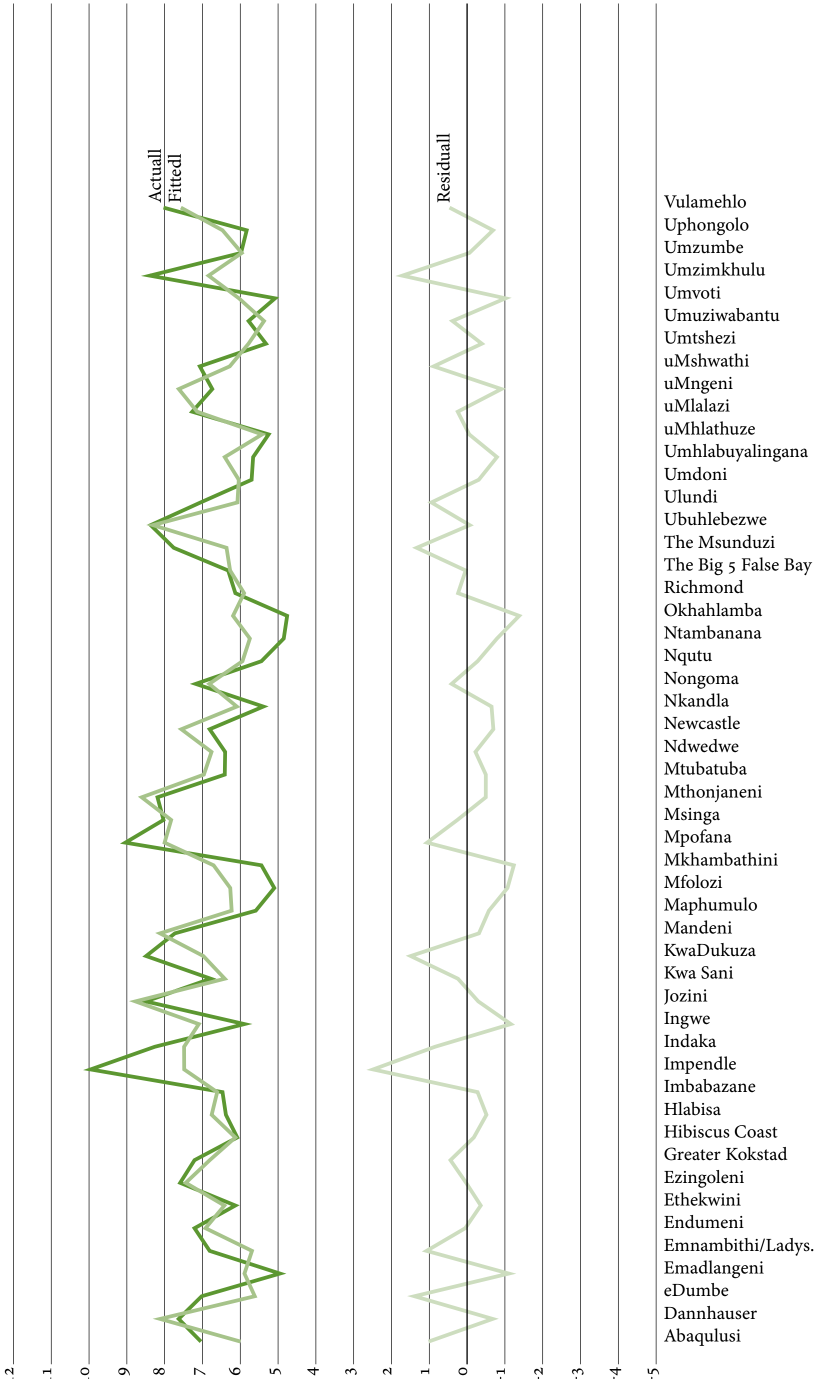


FIGURE 8 Spatial Lag Model

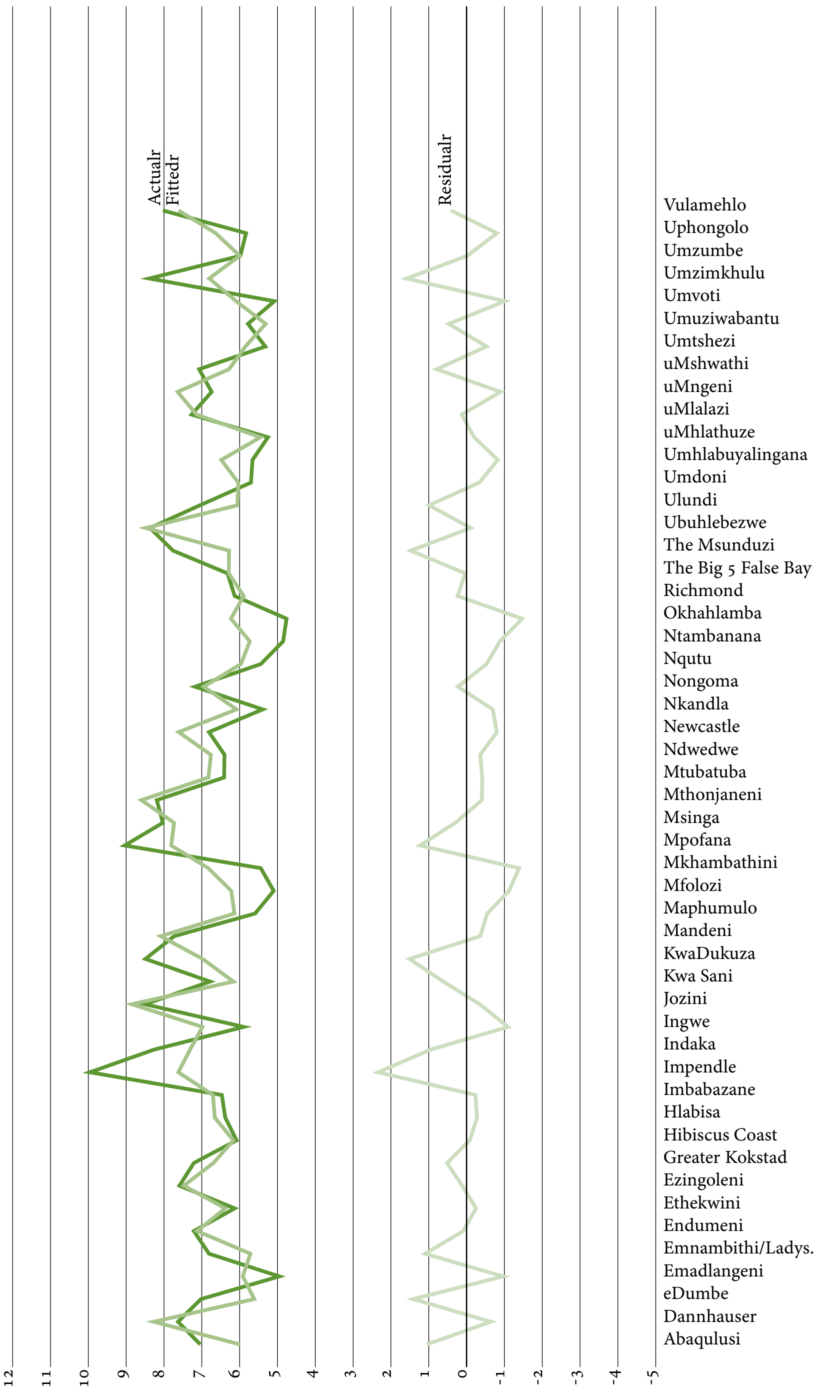


FIGURE 9 Spatial Error Model

similar unemployment characteristics and the degree of influence on one another. The study results suggest that the unemployment rate in a particular municipality is not spatially dependent on or influenced by the economic situation of its neighbours. The evidence suggests complete spatial randomness. This suggests that municipalities are fundamentally heterogeneous, and their unique and diverse municipal factors influence the unemployment rate.

Findings

Unemployment is a critical focus of the Province of KwaZulu-Natal. Amongst the 51 municipalities located within the Province, they register different unemployment rates and changes thereof. To this end, it is relevant to understand the unemployment interaction or relationship between the 51 municipalities and especially the spatial interaction and relationship.

The Moral I spatial autocorrelation of the average municipal unemployment rate proposes the existence of spatial unemployment clusters. Autocorrelation as a spatial dependence test is rather equivocal, although not all the identified clusters were statistically significant.

Based on the spatial regression analysis, the unemployment rate in a particular economy seems not to be spatially influenced by the economic situation of its neighbours, but rather due to spatial randomness. In essence, the spatial analysis proposes that spatial proximity is not a significant determinant or factor, i.e. 'space does not matter.' Thus, the unemployment rate in one municipality is not related to what happens in a neighbouring or nearby municipality.

Conclusions

Rural economies with prolonged unemployment are often associated with low economic growth. This could be a result of structural challenges, low levels of productivity or even a mismatch between supply and demand. However, if this trend is also observed in the neighbouring economies, the question comes to mind whether these economies influence one another.

To measure this, the study employed three statistical models, the usual regression analysis applying least square (OLS), the spatial lag model (SLM) and the spatial error model (SEM) investigating the spatial statistical relationship between contiguous economies (local authorities).

The results reveal that the unemployment rate in a particular economy is not spatially influenced by the economic situation of its neighbours, but rather due to spatial randomness. In essence, the spatial analysis proposes that spatial proximity is not a significant determinant or factor, i.e. 'space does not matter.' Thus, the unemployment rate in one municipality is not related to what happens in a neighbouring or nearby municipality. From a theoretical and logical point of view, this does not make total sense since, in general, the assumption is that leading regions have some influence or impact on lagging regions. This might be an indication of underdevelopment and weak linkages between various districts in the region. This inherent heterogeneity has implications for local- and provincial-level policymakers in terms of governance and economic development policy and projects. A one-size-fits-all agenda for spatial development would not succeed. When designing job creation and economic development programmes and policies this necessitates unique programmes for each authority and urban region.

The results might seem counter-intuitive since it seems plausible that the unemployment rates of neighbouring municipalities should to some degree correlate. Authorities are not autonomous entities operating as closed economies with no movement of labour or capital between them (Coetzee and Kleynhans 2018a). In terms of the theoretical background, and regarding policy and legislation, this is unique to South Africa. According to South Africa's Constitution (1996), every authority is responsible for its development, including economic and spatial policies. Although over-arching national and provincial economic policies exist, every local authority must compile custom and relevant policies every five years, and these policies must be translated into their spatial impact in terms of national legislation and by-laws. When seen in this context, the conclusion of the current study that 'space does not matter,' makes sense to some extent and can even be correlated to authorities that enact the relevant policies and legislation, and those who do not.

The results do, however, need further investigation and analysis which give cause for follow-up studies. It is therefore recommended that further studies include both time series and panel series analysis to augment the current cross-section analysis and either verify or refute the initial results of this particular study.

The current study is nonetheless important since it gives an initial conceptual framework for further study of the spatial relationship between the economic variables of neighbouring economies. It sets the stage to call for a further research agenda on this particular topic, especially looking at the role of existing policy and legal documents and their appropriateness in encouraging economic development for regional economies, possibly supporting agglomeration or clustering of economic activity to reduce unemployment.

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