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Spatial Modelling of Disparity in Economic Activity and Unemployment in Southern and Oromia Regional States of Ethiopia

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Abstract: Growth of productivity is the precondition to improve the living standard of people and maintain competitiveness in the globalized economy. However, wide regional deferential in labor force implies inefficiency as whole and might affect both aggregate unemployment and national output. The basic goal of this study was to model disparity in economic activity and unemployment in Southern and Oromia Regional States of Ethiopia, by incorporating spatial effects. Population and Housing Census data for 381 districts were used. The exploratory spatial data analysis, OLS regression model, and spatial econometric models were employed. The exploratory spatial data analysis results revealed that both economic activity and unemployment rates in a given district were directly affected by those of its neighbors. Economic activity and unemployment rates for males and females also spatially depended on that of neighboring districts. Spatial autocorrelations between unemployment and economic activity rates is negative. In modeling aspect, relying on specification diagnostics and measures of fit; spatial lag model was found to be the best model for modelling both economic activity and unemployment rates. The modelling results revealed that both estimates of spatial autoregressive parameters indicated the existence of spatial spillover in economic activity and unemployment rates. Spatial lag model analysis also demonstrated that average number of persons per household, crude birth rate, female and male unemployment rate were significant factors of economic activity rates. The factors, percentage of urban population, economic inactivity rate, percentage of self-employed population, percentage of unpaid family employers, and average number of persons per household were found as being factors behind disparities in unemployment rates across regions districts. In conclusion, as expected the economic activity and unemployment variables had the nature of correlation over space. It is recommended that most effective policy mix is required for stabilizing and alleviating disparity in both economic activities and unemployment of the districts considered in the regions.

Keywords: Economic Activity, Autocorrelation, Spatial Dependence, Spatial Econometrics, Unemployment

1. Introduction

1.1. Background of the Study

To investigate the evolution of regional productivity disparities in the countries (regions) the extent to which the existing interregional inequalities in productivity can be attributed to differences in economically active people. A great deal of effort has been expended in to the question of 'What are the most important determinants of differences in income growth rates across countries and regions over the world?' Spatially disaggregated analysis of the labor market appears to provide beneficial insights into internal forces and the ways external forces are transmitted via economic, social and political linkages (Maierhofer and Fischer, 2001). Regional sciences use spatial data to address issues and problems faced by cities and regions based on statistical or econometrics methods (Anselin, 1988). Several factors: trade between regions, technology, and generally spatial spillovers may cause to geographically dependent regions (Haining, 2003); thus, appropriate model that incorporate spatial effect must be used (Haining, 1990; Rey and Montouri, 1999; Ward and Brown, 2009). Large differences prevail in the geographical concentration of production and clusters of economic activities. Extensive literatures explain why certain countries experience greater rates of income and employment growth than others; the factors are stock of human capital, investment, trade, foreign direct investment, and low levels of political corruption (Dominicis *et al.,* 2008).

According to Kosfeld and Dreger (2006), the role of labor force is a key variable in many growth models and countries with high levels of labor force may potentially attract more firms thereby increasing the demand for labor which in turn raises wages and incomes. Study by Niebuhr (2003) revealed that a negative shock affecting regional labor markets in Europe; and unemployment can adversely affect productivity as well as productivity growth (Bräuninger and Pannenberg, 2002). In consequence, as suggested by Taylor (1996), reducing regional unemployment differentials might lead to higher national output, lower inflationary pressure, and might produce large social benefits. Girma and Vanden (2006) showed that rural poverty remains a key development challenge for Ethiopia in general and Oromia in particular. Economic growth and distribution of income are the major instruments for reducing poverty, and the nature of growth have the most significant effect explicitly incorporated in various Ethiopian government development policy (MoFED, 2010). Moreover, today reducing poverty and income inequality have been taken to be primary indicator of economic and social development in place of emphasis on economic growth; Ethiopia needs not only strong economic growth, but also robust expansion in the quantity and quality of employment opportunities particularly regional labor force which plays vital role (Berhanu *et al.*, 2005; IMF, 2009). However, negligence of spatial autocorrelation in regional data may cause misleading results. Therefore, when dealing with regional data, existence of spatial autocorrelation must be explored. If there is spatial autocorrelation in the data under study, then an appropriate model that will take it into account must be used. Taking in to account the spatial nature of the data; exploratory spatial data analysis and spatial process models would be used to analyze the data (Ward and Brown, 2009; Haining, 1990). Thus, this study has been designed to introduce measures of spatial autocorrelation and spatial econometric techniques to analyze the dependence of regional economic activity and unemployment rates in Southern and Oromia Regional States of Ethiopia as a precursor to a wider study of the importance of local interactions and social networks in regional labor market outcomes.

1.2. Statements of the Problem

Growth of productivity is a precondition to improve the living standards of people and maintaining competitiveness in the globalized economy, however, low total productivity is the key reason for persistence of poverty in developing countries. And wide regional differentials in economic activities and unemployment imply inefficiency in the economy as a whole and might affect both aggregate unemployment and national output. Little systematic analysis has explored key labor market issues in Ethiopia in terms of important policy questions about how to facilitate job creation, productivity growth, and labor market efficiency (UN, 2003). Although most of reports and research papers about the regions outline labor force status and dynamics in cross-section at household levels and over time, they didn't consider spatial dependence and heterogeneity in economic activity and unemployment of regions/districts in country level and/or regional levels. Moreover, it may add remarkable change on the outcome of policies if spatial effects are investigated while assessing disparity of labor force status. Therefore, this study has motivated to address the following research questions.

1. Is there spatial spillover in economic activity and unemployment rates?
2. What type of spatial association exists between unemployment and economic activity rates?
3. What are the statuses of spatial clusters in economic activity and unemployment rates?
4. Which model good fit to the economic activity rates and unemployment rates?
5. Which factors cause spatial variation in economic activity and unemployment rates?

1.3. Objectives of the Study

The general objective of this study was to model spatial disparity in economic activity and unemployment in Southern and Oromia Regional States of Ethiopia. The specific objectives are:-

1. To determine spatial dependence in economic activity and unemployment rates.
2. To investigate spatial association between unemployment and economic activity rates.
3. To compare spatial dependence in economic activity and unemployment rates between sex groups.
4. To explore and identify clusters of districts with significant spatial autocorrelations.
5. To evaluate model best fit to the economic activity and unemployment rates.
6. To identify prominent factors those intensify geographical variation in economic activity and unemployment rates.
7. To provide scientific information for policy makers and researchers.

1.4. Significance of the Study

Geographically close districts with similar socio-economic characteristics and vulnerability dimensions are more conducive to grouping forces, such as the formulation of parallel policy initiatives. Hence, this study may contribute to assessment and evaluation of labor force and its productivity across regions or districts. It provides information on spatial distribution of economic activity and accumulation of unemployment that can be useful for planners to distinguishing geographically targeted preparation of development plan, monitoring, and evaluation of economic and labor force policy. The study suggests policy options for policy makers and development partners to adopt enhancement of economic activity, and minimize unemployment in relation with other development indicators to solve shocks (vulnerability). If the results show spatial dependence does point to the presence of interactions between spatially proximate regions and spillovers between regions, the study provides options for local responses and national economic phenomena. It also provides basic information for researchers to conduct study using others spatial process models, on other areas, and on identified factors along corresponding areas.

2. Literature Review

According to UN system of national accounts production boundary economic activity involves the production of goods and/or services for sale or exchange and for own consumption. Activities include agriculture, any income generating services, hunting, fishing, forestry, logging, mining and quarry, and apprentices, etc. People are economically active if they are either employed or unemployed (waiting or seeking or available for job) in a particular period usually the survey reference week or year, whereas economically inactive people are people who are neither in employment nor unemployment on the International Labor Organization measure (ILO, 2006). Reasons for inactivity are attending education, household chores, too young to work, illness, old age, pensioner, etc. Two useful measures of the economically active population are the usually active population measured in relation to a long reference period such as a year, and the currently active population or equivalently the labor force measured in relation to a short reference period such as one week or one day. Economic activity rate is the percentage of the population both employed and unemployed; who constitutes the manpower supply of the labor market regardless of their current labor status (ILO, 1982 and 2000). The labor force of a country consists of everyone of working age typically above a certain age (around 14 to 16 years) and below retirement (around 65) who are actively employed or seeking employment (Hussmanns *et al*., 1990; ILO, 1998). The international definition of unemployment covers persons without work, currently available for work and seeking work during the reference period (ILO, 1982). Unemployment rate is the percentage of economically active people who are unemployed on the ILO measure. People who are either actively looking for work or waiting to return to a job from which they have been laid off are classified as unemployed. In the traditional way, unemployment rate is calculated by dividing the number of unemployed persons by the number of labor force participants limiting both numerator and denominator to the working age population (ILO, 1982).

The proportion of the working age population which is employed or seeking work (the economic activity rate) is a basic indicator of participation in the regional economy (Copus *et al.*, 2006).The dominating feature of economic activities is certainly clustering both in space and time, so the possibility of modeling the spatial dimension of economic activities is of paramount interest for a number of reasons (Arbia and Quha, 2007). The consequence of high fertility is that women's role tend to be limited to childbearing and other household activities in Ethiopia (Blen and Kimmel, 2009). From the economic point of view the level of education and additional skills play an important role as determinants of possibilities of finding a job in non-agricultural sectors, which are the base for sustainable rural development (Elhorst, 2003). Unemployment in different sectors of economic activity responds differently to various macroeconomic shocks (Berument *et al.*, 2008; Stehrer and Foster, 2009). From spatial econometric model higher proportions of the population with qualifications are associated with lower levels of unemployment (Trendle, 2006). By employing spatial Durbin models, Maria (2011) concluded that differences in labor demand, immigration rates, and urbanization were factors behind observed municipal unemployment disparities in Colombia. Elhorst (2000) included factors of regional unemployment: natural changes in the labor force, the participation rate, net immigration, wages, employment growth, the industrial mix, educational, market potential, and other characteristics of the labor market. Nijkamp *et al.*, (2007) shown that regional difference in unemployment is strictly related to disequilibrium factors than to equilibrium variables in Italy, Artis *et al.*, (1999) have found that employment and female participation have negative effect on unemployment in Spain. Regional spillovers are most likely to exist in regions tightly linked by interregional migration, commuting and trade (Topa, 2001).The empirical findings of Overman and Puga (2002) show that the unemployment rates of European regions are much closer to the rates of adjacent regions than to the average rate of other regions.

3. Methodology and Data

3.1. Sampling Design and Variables under the Study

This study was conducted in Southern and Oromia Regional States of Ethiopia. Cross-sectional secondary data spatially aggregated at district level across Southern and Oromia Regional States on all variables had used to conduct the investigation. Data for the study were extracted from 2007 Population and Housing Census database. To sample unit of analysis in fixed design especially for irregular shape polygon, the analogue of the classical situation in the case of spatial data is the surface considered as a single realization (experiment) of random spatial process (Anselin, 1988; Haining, 1990; 2003). Spatial econometrics literature mainly focuses on increasing domain asymptotic under fixed sample design (Cressie, 1993; Lahiri, 2003) and model based approach to spatial sampling (Haining, 2003). Considering these issues, and particularly by assuming increasing domain asymptotic and permutation (Griffith, 1988), 381 districts in both regional states were selected together with the following variables. The dependent variables are EA_RATE: Economic Activity Rate; is the percentage of the population age 10 years and above both employed and unemployed to both economically active and inactive people, and UNEMPR: Unemployment Rate; is the percentage of unemployed population over the total of economically active people. The independent variables and variables used in ESDA are: TOT_POP: Total population of district, SEX_RATIO: Sex Ratio, URB_TOTPO: Proportion of population in urban, EI_RATE: Economic Inactivity Rate, GOVTE_TOTE: percentage of government employers to total employed population, SELFE_TOTE: percentage of self-employed population, UNPD_FE: percentage of unpaid family workers, PROPO_TOTPO: percentage of productive population, DEP_RATIO: Dependence Ratio, AVEPRS_HSD: average number of persons per conventional household, NAC_G5: percentage of people aged 5 and above never attend school, CDR_1000: Crude Death Rate,URRU_100: percentage of population migrants from urban to rural area to total migrants lived in the place of survey for at least 6 months, UNEMPR_M: Male Unemployment Rate, UNEMPR_F: Female Unemployment Rate, MMR_100000: Maternal Mortality Rate, CBR_1000: Crude Birth Rate, RUUR_100: percentage of population migrants from rural to urban, EA_RATEM: Male Economic Activity Rate, and EA_RATEF: Female Economic Activity Rate.

3.2. Methods of Data Analysis

Standard Multiple Linear Regression Analysis

Multiple linear regression analysis is used to estimate models to describe the distribution of a response variable with the help of a number of independent (predictors). In multiple linear regressions, a linear combination of two or more predictor variables is used to explain the variation in a response (Montgomery *et al*., 2001). For cross-sectional data the basic assumptions of the multiple linear regression model analysis are: linearity, normality, homoskedasticity, and multicollinearity. Parameters are estimated by fitting model to the sample data using ordinary least square method, and to test significance of each independent variable and overall model t and F tests are used respectively at 5% level of significance. A number of checks and tests help us to ensure that analysis has proceeded within the bounds of the basic assumptions. Condition Number (K) is used to detect sever multicollinearity (Draper and Smith, 1998; Johnoston *et al*., 1997), Jarque and Bera test is used to test normality of errors (Montgomery *et al*., 2001), Breusch-pagan, Koenker-Bessett and White tests are used to test homoskedasticity (Montgomery *et al.,* 2001). To making comparison between or/ and among models in the same class but differently specified R^2, Log likelihood, AIC, SC and SE of regression are used under this study (Montgomery *et al*., 2001; Darper and Smith, 1998).

Spatial Data Analysis

In statistics, spatial data analysis or spatial statistics includes any of the formal techniques which assess entities using their topological, geometric, or geographic properties that manifest them in space: location, area, topology, spatial arrangements, distance and interactions (Anselin, 1996). Spatial data set consists of a collection of measurements or observations on one or more attributes taken at space (Haining, 1990). The spatial data structures are Raster and Vector; and there are three types of spatial data (Spatial Point Processes, Geostatistical Data, and Areal (Lattice) Data). In the context of standard spatial econometric models lattice data types are data for which aggregated value of spatial points of observation on each region at a time is used for analysis. Quantification aspect of locations of spatial data is based on location information from Cartesian space and contiguity (Lesage, 1999). Contiguity information is quantified as contiguity (spatial neighbors) matrix which contains elements of 1and 0; the matrix is denoted by W and constructed based Rock contiguity, Bishop Contiguity, and Queen Contiguity (Anselin, 1988; Lesage, 1999). Row standardized Queen Contiguity matrix called spatial weighted matrix (**W**) is used for quantification of location under this study. Lesage (1999) stated that in a regression context, spatial effects pertain to spatial dependence (spatial autocorrelation) and spatial heterogeneity. Spatial dependence is expected when sample data observed at one point in space is related to values observed at other, whereas spatial heterogeneity is simply structural instability in the form of non-constant error variances (heteroskedasticity) and/or spatial varying of model parameters (Graaff *et al*., 2001). Fundamental problems associated with analyzing spatial data and modeling spatial processes are: ecological fallacy and modifiable area unit problem (King, 1997), asymptotes in spatial stochastic processes (Anselin, 1988), boundary value and spatial sampling problem, properties of spatial connectivity, spatial non stationary, and others statistical perspective problems. In practice, these conditions are likely satisfied by most spatial weighted matrix which is based on simple contiguity, increasing domain and infill asymptotic approaches (Lesage, 1999).

Exploratory Spatial Data Analysis (ESDA) is a set of techniques aimed at, describing and visualizing spatial distributions, identifying atypical localizations or spatial outliers, detecting patterns of spatial association, clusters or hot spots, and suggesting spatial regimes or other forms of spatial heterogeneity (Haining 1990; Bailey and Gatrell 1995; Anselin 1998).Spatial autocorrelation can be defined as the coincidence of value similarity with location similarity or dissimilarity (Anselin, 2000;Anselin, 1995), which can be measured by global and local indicators. The global indicator is Moran's statistic (*I*), which measures similarities and dissimilarities in observations across space.

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{1}$$

Where, I =-1 perfect negative spatial autocorrelation, I =1 is perfect positive spatial autocorrelation, and I =0 signifies no spatial correlation. Inference on Moran's I take normal assumption and randomization or permutation approaches (Anselin 1995; Cressie, 1993). Measures of Local Autocorrelation are used when there is no global autocorrelation, and in case where measure of global does not enable us to appreciate the regional structure of spatial autocorrelation. The analysis of local spatial autocorrelation is carried out with two tools. First, the Moran scatter plot which is used to visualize local spatial instability (Anselin *et al*, 1996), and second local indicators (I_i) which is used to test the hypothesis of random distribution by comparing the values of each specific localization with the values in the neighboring localizations which is depicted by Local Indicators of Spatial Association (LISA) maps (Anselin, 1995).

In addition to the univariate, multivariate spatial autocorrelation and LISA are also analyzed by employing a bivariate Moran's I statistic and local measures. The bivariate spatial autocorrelation centers on the extent to which values of one variable observed at a given location show a systematic association with another variable observed at the neighboring locations (Smirnov *et al*., 2002). Standard multiple linear (OLS) regression model with spatially autocorrelated residuals may violate the independence assumption for error term, consequently regression parameter estimate are no longer BLUE, consistency and unbiased, so statistical inference is unreliable. Hence the important issue in empirical spatial analysis is how one can detect the presence of spatial effects, and moreover, how one can distinguish between spatial dependence as a nuisance and a substantive spatial process (Anselin and Grifith 1988).The following ESDA are applying to check the presence of spatial autocorrelation in OLS regression model residuals. Moran's Test for regression residuals (Cliff and Ord, 1981; Anselin, 1988), Lagrange Multiplier (LM) Tests: LM-error test (Burridge, 1980), LM-lag test(Anselin, 1988), Robust Lagrange Multiplier test for a spatial error process robust to the local presence of a spatial lag, and Robust Lagrange Multiplier test for a spatial lag process robust to the local presence of a spatial error. In all of these tests discussed above the null hypothesis is stated as there is no spatial autocorrelation in the OLS residuals, and large values of test statistic (χ^2) with degree of freedom one lead to rejection of null hypothesis (Anselin *et al*., 1996; Kelejian and Robinson, 1992). Spatial regression model in econometrics approach is employed to model economic activity and unemployment rates; in the spatial linear regression model, spatial dependence can be incorporated in specification in two distinct ways; as an additional regressor in the form of a spatially lagged dependent variable (Wy) provide spatial lag model, and in the form of spatial lag error structure (Wε) provides spatial error model. In a simultaneous specified model, the focus is on the explanation of the complete spatial pattern; particularly simultaneous autoregressive models assume that the response at each location is a function not only of the explanatory variable at that location but of the values of the response values at neighboring locations as well (Cressie, 1993; Haining, 2003). The simultaneous spatial lag regression model of dependent variable Y for observation i and k independent variables is:

$$Y_i = \rho \sum_{j=1}^{n} w_{ij} Y_j + \sum_{r=0}^{k} x_{ir} \beta_r + \varepsilon_i \tag{2}$$

Where, ρ is a spatial autoregressive coefficient which is scalar, the k explanatory variables and intercept are xir, r =0, 1, 2…k with associated coefficient βr, wij denote the (i, j)th element of W, and εi is the error term normally distributed. The matrix notation of the model is $\mathbf{Y} = \boldsymbol{\rho}\mathbf{W}\mathbf{Y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ where, ε is a vector of error terms which is independent and identically multivariate normally distributed with mean vector zero and constant diagonal variance-covariance matrix δ2In. Spatial lag regression model is appropriate when we believe that the values of dependent in one unit i are directly influenced by the values of dependent variable found in i's neighbors. The spatial lag term must be treated as an endogenous variable and proper estimation methods must account for this endogeneity; implies OLS estimates are biased and inconsistent due to the simultaneity. Thus, based on assumptions, the spatial process is stationary and possibly isotropic property over space and W is non-stochastic and exogenous to the model; therefore, maximum likelihood estimation with usually attractive asymptotic properties of estimators is appropriate (Anselin, 1988 and 1999; Anselin and Bera, 1998; Lee and Kammarianekis, 2004; Pace and Lesage, 2009). With similar setting in spatial lag model, the spatial error model for observation i is noted as:

$$Y_i = \sum_{r=0}^{k} x_{ir} \beta_r + \lambda \sum_{j=1}^{n} w_{ij} \varepsilon_j + \varepsilon_i \tag{3}$$

Where, λ is a spatial autocorrelation coefficient which is scalar, and ε_i independently and identically normally distributed with mean zero and constant variance. The matrix notation of spatial error model is $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ and $\mathbf{u} = \boldsymbol{\lambda}\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon}$. Thus Y =Xβ + λWu + ε, where, ε = (I –λW) u. This type of spatial regression model is appropriate when we believe that dependent variable is not influenced directly by the value of dependent as such among neighbors but rather that there is some spatially clustered feature that influences the value of dependent for single unit and its neighbors but was omitted from the specification (Anselin, 1999). The maximum likelihood estimation technique was suggested in concept of asymptotic properties of estimators for estimation of parameters (Anselin, 1988), and the estimator for spatial autocorrelation parameter is obtained from explicit maximization of concentrated log likelihood function. Most of statistical inference principally hypothesis testing in spatial models is based on Wald (W), Lagrange Multiplier (LM) and Likelihood Ratio (LR) tests that relaying on optimality properties of maximum likelihood estimators and functions of estimators(Anselin, 1988, Lesage and Pace, 2009). Each test statistic is asymptotically distributed as $\chi 2$ with 1 degree of freedom (Pace and Barry, 1997). Further diagnostics for normality, heteroskedasticity and presence of spatial dependence are also assessed for both models. Likewise for models comparison, R^2, Log likelihood, Akaike Information Criterion (AIC), Schwarz Criterion (SC) and others are often useful. The lower value for AIC and SC, and higher value Log likelihood signifies the model is best fit (Draper and Smith, 1998).

4. Results and Discussion

The analysis has been performed using data for 381 census districts. For spatial analysis, the sensitivity of our results with respect to different weights matrices was controlled, and then row standardized queen first order is found to be reasonable to study spatial effect. From descriptive summary, economic activity rate ranges from 46.00% to 94.29% with mean 73.69% and standard deviation 8.33%, and unemployment rate ranges from 0.05% to 6.88% with mean 1.53% and standard deviation 1.00%.

4.1. Exploratory Spatial Data Analysis of Economic Activity and Unemployment Rates

The theoretical mean of Moran's statistics is -0.0026 and Moran's statistics that are labeled by * are significant at 5% level of significance. The standard deviation to standardized Moran's I and pseudo significance level was obtained from reference distribution of 999 permutations. From Table 1 Moran's statistics for economic activity rates (EA_RATE) and unemployment rate (UNEMPR) are significant at 5% level of significance as it can be seen from standardized Moran's I (p-value = 0.001<0.05). For each of three variables of economic activity and unemployment rates the null hypothesis states that there is no spatial autocorrelation, and it is rejected. Which means districts with high economic activity and unemployment rates were more likely clustered together, and those with low rates were more likely clustered together in space. Comparatively in both economic activity and unemployment rates, rates for male were more likely spatially correlated than rates for female (see Table 1).

Table 1. *Univariate Moran's Statistics (CSA, 2007).*

	Variable	Moran's I	Standardized Moran's I
Economic Activity Rates	EA_RATE	0.399*	12.24
	EA_RATEM	0.402*	12.11
	EA_RATEF	0.324*	9.33
Unemployment Rates	UNEMPR	0.3895*	11.46
	UNEMPRM	0.2871*	8.98
	UNEMPRF	0.2011*	6.11

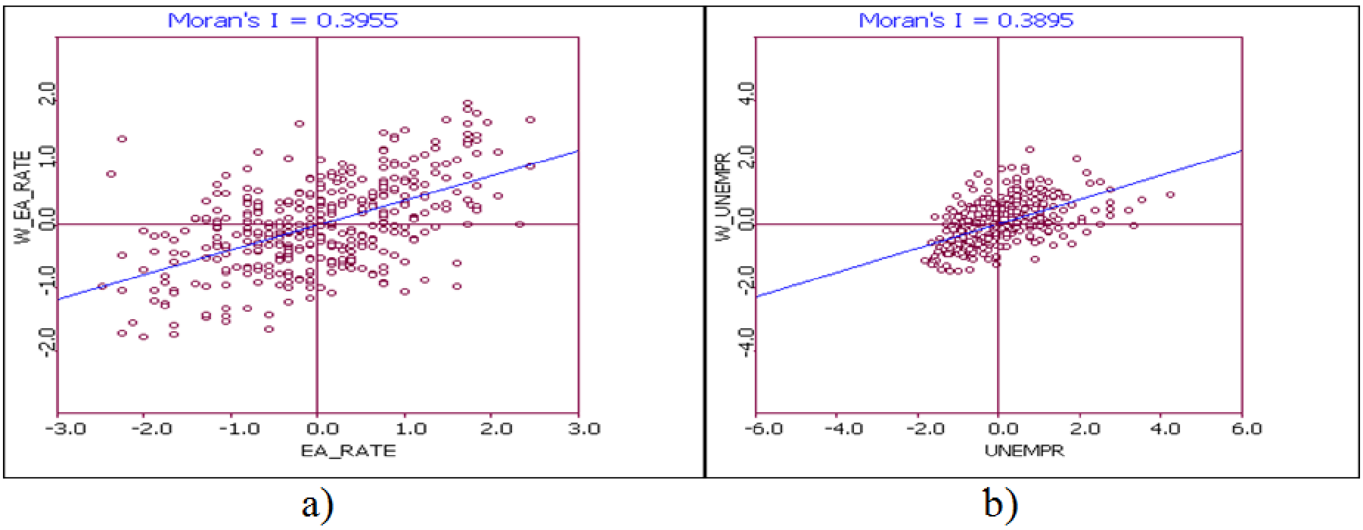

Figure 1. *Univariate Moran Scatter Plot for Economic Activity and Unemployment Rates.*

As shown in Figure 1(a) and (b) the visual level of the plots also verify the rejection of null hypothesis (no spatial clustering). Thus, the visual interpretations of Figure 1 are similar with quantitative results in Table 1, and lead us to believe that there is positive spatial autocorrelation in both economic activity and unemployment rates across the regions. Positive values of local Moran's statistic (I_i, i=1,2,…,381) indicate positive spatial autocorrelation; a given district is surrounded by the number of districts with similar rates (either high-high or low-low). Whereas negative values of I_i indicate negative spatial autocorrelation; a given district is surrounded by the number of districts with dissimilar rates (either high-low or low-high). LISA significance maps show districts whose local Moran's statistics are significant at 0.05, 0.01, and 0.001 levels of significance indicated with colors blue, green and yellow respectively, and classified by type of spatial association in cluster map (see Figure 2 (b) and (d)). The different marked locations in cluster map are indication of spatial clusters of districts with different combination of values for both economic activity and unemployment rates (see Figure 2 (a) and 2 (c)).

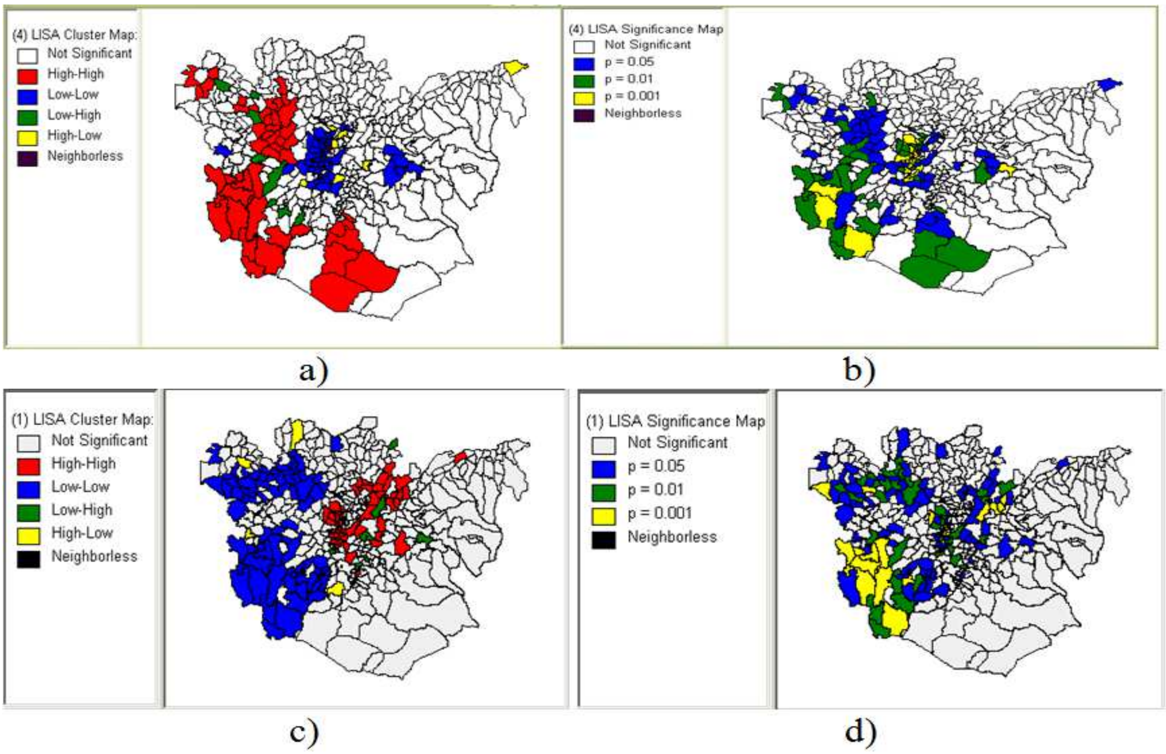

Figure 2. *Univariate LISA Maps :(a) Cluster map and (b) Significance map for economic activity rates, (c) Cluster map and (d) significance map for unemployment rates.*

Table 2 below presents bi-variate Moran's statistics between unemployment and economic activity rates. From bivariate ESDA the Moran's statistics for all pair wise variables of unemployment and spatial lagged economic activity rats are positive and significant at 5% level of significance. This indicates that there is negative spatial correlation between unemployment and economic activity rates. Moran's *I* between male economic activity/unemployment and female economic activity/unemployment rates are positive and statistically significant at 5% level of significance, which signifies districts with high male economic activity/unemployment rates are bordered by districts with high female economic activity/unemployment rates, or districts with low male economic activity/unemployment rates are bordered by those with low female economic activity/unemployment rates (see Table 2).

Table 2. *Bi-variate Moran's Statistics between Unemployment and Economic Activity Rates (CSA, 2007).*

Variable	Moran's I	Standardized Moran's I
UNEMPR vs EA_RATE	-0.251*	-7.76
UNEMPR_M vs EA_RATEM	-0.245*	-7.46
UNEMPR_M vs EA_RATEF	-0.232*	-6.94
UNEMPR_F vs EA_RATEF	-0.181*	-4.78
UNEMPR_F vs EA_RATEM	-0.144*	-4.35
UNEMPR_M vs UNEMPR_F	0.186*	5.51
EA_RATEM vs EA_RATEF	0.322*	9.54

**indicates significant test at 5% level of significance.*

4.2. Model Specification and Adequacy Tests

Here OLS regression, spatial lag and error models were fitted to economic activity and unemployment rates; aimed to explain the empirical parametric strategy that has been used to assess the main district level factors of economic activity and unemployment rates. Table 3 below presents results of OLS regression and spatial error models to identify best specification of model.

Table 3. *Tests in Ordinary Least Square Regression Model for Economic Activity and Unemployment Rates.*

Test/Model	Economic Activity Rates	Unemployment Rates
Jarque-Bera test	2.521	5.2532
Breusch-Pagan test	17.807	13.7604
Koenker-Bassett test	15.388	13.2009
White test	104.397*	124.341
Condition Number:	25.165	28.42
Lagrange Multiplier (lag)	22.5581*	57.5374*
Robust LM (lag)	6.3515*	20.7811*
Lagrange Multiplier (error)	17.4769*	37.2033*

Test/Model	Economic Activity Rates	Unemployment Rates
Robust LM (error)	1.2704	0.4470
Moron's I of OLS Residuals	0.1409*	0.206*
OLS regression model	LIK=-1258.15, AIC=2538.31, SC=2581.68, F=22.09*	LIK=-1.62, AIC=31.25, SC=86.45, F=27.51*
Spatial error model	LIK=-1250.13, AIC=2522.26, SC=2565.63, LRT=16.04*	LIK=20.13, AIC=-12.61, SC=42.94, LRT=43.504*

**indicates significant test at 5% level of significance.*

First OLS regression model is fitted to assess the presence of spatial dependence in OLS residuals, and model adequacy checking results are also discussed (see Table 3). To attain normality assumption unemployment rates were transformed using square root transformation whereas economic activity rates were not transformed. As result, from diagnostics tests results the assumption of linearity, multicollinearity, normality, and homoskedasticity were met. Among the first four tests of model adequacy, except White test of heteroskedasticity for economic activity rate variable all tests in Table 3 do not reject null hypotheses. Second we had proceeded to detect spatial dependence in OLS residuals; the tests comprise the Moran's I statistic, Lagrange Multiplier (LM) error and LM lag tests, and Robust Lagrange multiplier tests. These tests test the hypothesis states that there is no spatial dependence in OLS regression residuals. The Moran's Statistics and LM tests indicating presence of spatial dependence; however, it is difficult to discriminate dependence structure. Therefore, to identify the form of dependence in the model robust version of LM tests are relevant, and LM-lag tests for model of economic activity and unemployment rates are significant at 5% level of significance, while LM-error tests are insignificant. This indicates that a model of spatial lag dependence is appropriate rather than model of spatial error dependence (see Table 3). Finally model comparison is also made; standard measures of good fit (Log Likelihood, AIC, SC) and LRT tests are also suggest that spatial lag model is best fit to both economic activity and unemployment rates than others models (OLS regression and spatial error models).

4.3. Spatial Lag Models for Economic Activity and Unemployment Rates

A statistical model that incorporates spatial dependence explicitly by adding a spatially lagged dependent variable on the right hand side of the OLS regression model to overcome the spatial dependence found in OLS residuals is fitted to economic activity and unemployment rates.

In the spatial models specification particularly spatial lag models, interpretation of the parameters becomes more complex. The complexity arises from the simultaneous feedback nature in the spatial lag terms, because spatial lag model involves feedback between neighboring districts. That is impact of a one unit change in an independent variable in a given district depends on its connections with other districts in the spatial system, and will vary from district to district. This implies that one unit change in explanatory variable has an impact on economic activity rate in the district, which then feeds to economic activity rates in all the other districts through the spatial lag, and these then feed back to the districts again through the spatial lag, and so forth. The dependence continues until some equilibrium is reached, but the effects in the second and subsequent round of adjustments get smaller and smaller. Assuming the feedback reaches at equilibrium steady-state, the effect of each explanatory variable in spatial lag model is reasonable in contrast to OLS estimate. The significance tests of individual parameters in spatial lag model are asymptotically standard normal value which are equivalent to t-statistic; relative influence of each explanatory variable on economic activity rates. The positive estimate of spatial autoregressive (ρ=0.2255) is significant at 5% level of significance. This implies that economic activity rate in a given district directly depends on the economic activity rates in other neighboring districts. The parameter estimate of the independent variables implies that economic activity rate in one area depends strongly on the change in independent variable in the same area and its neighbors. From Table 4 male unemployment rate (UNEMPR_M), female unemployment rate (UNEMPR_F), average number of persons per household (AVEPRS_HSD), and crude birth rate (CBR_1000) have significant negative effect on economic activity rates, whereas maternal mortality rate (MMR_100000) has negative insignificant effect on economic activity rates. Percentage of self-employed population (SELFE_TOT), percentage of productive age group (PROPO_TOTE), dependence ratio (DEP_RATIO), percentage of population aged 5 and above who never attend school (NAC_G5), and percentage of rural-urban migrants (RUUR_100) have positive insignificant effect on economic activity rates. R^2 = 0.4122, measure indicates that 41.22% of variation in economic activity rates was explained due to variation in the explanatory variables and spatial lagged dependent variable. Breusch-Pagan test shows that there is no heteroskedasticity, and Moran's statistics (I =0.0043) for spatial lag model is essentially zero; signifies that spatial dependence in residuals is eliminated due to inclusion of spatial lagged dependent variable.

Table 4. *Maximum Likelihood Estimate in Spatial Lag Model for Economic Activity Rates (CSA, 2007).*

Variable	Coefficient	Std. Error(±)	Z-value	Probability
W_EARATE (ρ)	0.2255	0.05189	4.3457	0.0000
CONSTANT	59.5880	4.68508	12.7186	0.0000
UNEMPR_M	-1.4589	0.62829	-2.3221	0.0202

Variable	Coefficient	Std. Error(±)	Z-value	Probability
UNEMPR_F	-1.5222	0.48326	-3.1498	0.0016
SELFE_TOTE	0.0442	0.04377	1.0085	0.3132
MMR_100000	-0.0034	0.00340	-1.0047	0.3150
PROPO_TOTPO	0.3130	0.45443	0.6888	0.4909
DEP_RATIO	7.8044	9.15451	0.8525	0.3939
AVEPRS_HSD	-3.7612	1.10231	-3.4121	0.0006
NAC_G5	0.0392	0.02477	1.5828	0.1135
CBR_1000	-0.0242	0.00628	-3.8605	0.0001
RUUR_100	0.0436	0.04307	1.0110	0.3120
Tests and Measures of goodness of fit				
R-squared:	0.4122	Log likelihood:	-1248.21	
Moron's I of Residuals	0.0043	AIC:	2520.42	
Sigma-square:	40.583	SC:	2567.73	
Likelihood Ratio test (LRT):	19.89*	Breusch-Pagan test	17.99	

Table 5. *Maximum Likelihood Estimate in Spatial Lag Model for Unemployment Rate (CSA, 2007).*

Variable	Coefficient	Std. Error(±)	Z-value	Probability
W_UNEMPR(ρ)	0.3536	0.0490	7.2118	0.0000
CONSTANT	0.4974	0.1214	4.0978	0.0000
TOT_POP	2.72x10-7	2.47x10-7	1.1021	0.2704
SEX_RATIO	0.0039	0.0027	1.4483	0.1475
URB_TOTPO	0.0187	0.0028	6.6280	0.0000
EI_RATE	0.0139	0.0015	9.0029	0.0000
GOVTE_TOTE	-0.0181	0.0172	-1.0534	0.2921
SELFE_TOTE	-0.0065	0.0026	-2.5065	0.0121
UNPD_FE	-0.0080	0.0025	-3.2060	0.0013
PROPO_TOTPO	-0.0085	0.0158	-0.5386	0.5901
DEP_RATIO	-0.0113	0.3196	-0.0354	0.9717
AVEPRS_HSD	0.0717	0.0404	1.7762	0.0457
NAC_G5	-0.0008	0.0009	-0.8850	0.3761
CDR_1000	-0.0015	0.0034	-0.4623	0.6438
URRU_100	0.0014	0.0016	0.8778	0.3800
Tests and Measures of goodness of fit				
R-Squared:	0.5681	Log Likelihood:	23.305	
Moron's I of Residuals:	-0.0071	AIC:	-16.61	
Sigma-Square	0.0504	SC:	42.53	
Likelihood Ratio test (LRT)	49.859*	Breusch-Pagan test :	13.88	

Table 5 presents the results of analysis aimed to assess how much of the variation in an unemployment rate is explained by explanatory variables and its spatial lags. The parameter estimate for spatially weighted unemployment rates; the autoregressive parameter (ρ=0.3536) is positively significant at 5% level of significance. This implies that unemployment rate in a given district depends directly on the unemployment rate in neighboring districts; a higher/lower unemployment rate in a given district significantly increases/decreases unemployment rates in the neighboring districts. The explanation for degree of effect of independent variables on unemployment rates is made inconsideration of simultaneous feedback effect of neighboring districts' unemployment rates. Accordingly, positive sign of estimate indicates that a unit change in explanatory variable increases unemployment rate in district by magnitude of estimate of parameter for simultaneous effect of explanatory variable in that district and in all its neighbors of system. The negative sign indicates that a unit change in explanatory variable decreases unemployment rate in district by magnitude of estimate of parameter for simultaneous equilibrium effect of explanatory variable in district itself and in all neighboring districts in study regions.

As we see from Table 5 percentage of urban resident population (URB_TOTPO), economic inactivity rate (EI_RATE), and average number of persons per family (AVEPRS_HSD) are positively significant at 5% level of significance. And percentage of self-employed population (SELFE_TOTE) and percentage of unpaid family workers (UNPD_FE) have significant negative effect. Percentages of government employed (GOVTE_TOTE), percentages of productive age group (PROPO_TOTPO), dependency ratio (DEP_RATIO), percentage of population aged 5 and above never attend school (NAC_G5) and crude death rate (CDR_1000) have negative insignificant effect on unemployment rates, whereas total population (TOT_POP), sex ratio (SEX_RATIO) and percentage of urban-rural migrants (URRU_100) have positive insignificant effect on unemployment rates. R^2= 0.5681 notifies us 56.81% of variation in unemployment rates is explained due to variation in the considered explanatory variables and spatial lagged unemployment rates. And from diagnosis results (like Likelihood ratio test and Breusch-Pagan test) the model is adequately fit to data.

5. Conclusions and Recommendations

5.1. Conclusions

This study has analyzed the spatial effects in economic activity and unemployment rates for 381 districts in both Southern and Oromia Regional States of Ethiopia. The spatial effects in the data set have been analyzed by employing spatial autocorrelation methods; namely, ESDA and spatial econometrics models. From the empirical results there was evidence of positive spatial autocorrelation in both economic activity and unemployment rates. In particular male economic activity rates and male unemployment rates were more likely correlated in space as compared to that of females. The bivariate ESDA analysis revealed that there is negative significant spatial autocorrelation between unemployment and economic activity rates. Empirically, three models: OLS regression model, spatial lag and spatial error models for both economic activity and unemployment rates were compared, and spatial lag model was found to best fit to the data. From spatial lag model analysis of both economic activity and unemployment rates, estimates of spatial autoregressive parameters are found to be positive and significant; indicating that the spatial lags exert direct effects on disparities of economic activity and unemployment in the districts across the study regions. From spatial lag model analysis of economic activity rates, we concluded that the economic activity rate was negatively affected by average number of persons per household, crude birth rate, female unemployment rate, and male unemployment rate. But, dependency ratio, maternal mortality rate, percentage of migrant from rural to urban area, percentage of productive age group, percentage of self-employment, and percentage of population age 5 and above never attend school have no statistically significant effects on disparity of economic activity rates.

The factors significantly affecting unemployment rates are percentage of urban population, economic inactivity rate, percentage of self-employment, percentage of unpaid family workers, and average number of persons per household. While total population, sex ratio, percentages of government employees, percentage of productive age population, dependency ratio, percentages of population age 5 and above never attended school, crude death rate, and percentage of urban to rural migrants have no significant effects on disparity in the unemployment rates. In conclusion, as expected the economic activity and unemployment variables had the nature of correlation over space (districts). Which may indicate that economic activity created at a given location may create similar effect on that of neighboring locations, and that in turn reduces unemployment rates in the area.

5.2. Recommendations

Although a growth of productivity is a precondition to improve the living standards of people, wide regional disparity in economic activities and unemployment imply inefficiency in the economy as a whole and might affect national output. Therefore, based on findings the following recommendations can be forwarded. The implication of spatial dependences insight the ways of policy directed towards reducing unemployment and prolong economic activity needs to have a spatial dimension. For low local significance area specific policy would support and for high clusters policy to be targeted towards not merely the specific area but the group of contiguous areas to promote sustainable local labor growth which tolerate rapid labor growth of country. We suggest government to consider further policies that reduce unemployment rates, average family size and total fertility rate throughout the regions to reduce disparity of economic activity rates. From demand side create provision of local job creation strategies, and from a supply side policy perspective programs will be designed to encourage people to participate in various employments. Furthermore, most effective policy mix for alleviating disparities in economic activity and unemployment rates of districts in study regions, balancing the industrial composition and others form employment, and encouraging population to actively participate in productivity possibly stabilize spatial spillovers in both economic activity and unemployment rates. We also recommend that further study may be conducted by incorporating time data and others proxies of factors.

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