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Exploratory analysis of Regional Disparities in Household Welfare Indicators in Pakistan: Do Spatial Effects Matter?

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***Abstract*:** Pakistan is spatially a diverse state in terms of location of its economic activities and regional disparities in various dimensions of development have been a vital concern in its history. The article aims to analyze the distribution of household welfare index across 97 districts of Pakistan through exploratory spatial data analysis for periods 2004-05 and 2014-15. For this purpose, an augmented Household Welfare index is constructed for measuring Household Welfare across districts. The index consists of consist of five indicators. Final index is obtained by aggregating these indicators through Principal Component Analysis (PCA). Findings of the study indicate positive global autocorrelation and thus indicating that a district with a high (low) is linked spatially with bordering districts which also have high (low) Household Welfare level. The results also display the HH quadrant in scatterplots of Household Welfare Index includes mostly districts of Punjab and KP, while LL illustrates a cluster of most districts from Interior Sindh and Baluchistan for both 2004-05 and 2014-15 periods. Overall, the findings demonstrate the twofold structure of Pakistan's economic geography, as explained by most of the previous studies. Since geography of Household Welfare matters, it is recommended to reduce across districts inequalities by developing the social and economic institutions and infrastructure in the Baluchistan and interior Sindh.

Key words: Spatial Disparities, PCA, Household Welfare, ESDA, Dualistic Structure

1. Introduction

The concept of spatial inequality refers to the dissimilarity in economic and social indicators of welfare across different spatial or geographical locations within a country (Kanbur, 2003). One area may have access to healthcare or clean water, whereas another area does not (Gajangi, 2016). The accurate measurement of spatial disparities and the analysis of their causes and consequences are of particular significance. Spatial imbalances are vital for at least two causes. First, inequality between regions of country is a constituent of overall inequality across individuals at national level. Secondly, disparity between regions frequently goes hand in hand with ethnic and political instability, which damage political stability and social structure (Kanbur & Venable, 2005).

Inequality among individuals and between different geographic areas remains a critical challenge for development in emerging countries today just as it was in early phases of development of developed countries (Williamson, 1965). Spatial disparities in education, health and household welfare level pose key tests for developing economies and there is a growing fear in developing world about the regional and spatial inequality. It is believed that in developing and transition economies such as China, Mexico, Russia, South Africa and India, regional imbalances in economic activities, social indicators and incomes are growing (McCormick & Wahba, 2003: Kanbur & Zhang, 2005; Pose & Reaza, 2005; Friedman, 2005).

1.2 Growth and Development in Pakistan: An Overview

Despite the various above mentioned economic and political challenges at the national and international level during the last two decades, Pakistan's GDP go up from $82.69 Billion in 2000 to $346 Billion in 2021; representing around four times rise in two decades. Moreover, country's per capita income is showing three times increase in the income level. Per capita income of Pakistan was just around 570 US$ in 2000, that is around 1400 US$ now.

After the occurrence of economic growth in a state, then the question arises about the distribution of income from growth, either it assists all sections of the people equally or not. Pakistan is spatially a diverse state and its growth path has resulted in uneven social and economic development, particularly in terms of public service delivery (Easterly, 2003). With the passing of the eighteenth amendment in constitution, the seventh National Finance Commission Award (hereafter NFC)[1] has permitted the shift of further fiscal resources from the center to the provinces, which has now further influence over the provision of physical infrastructure, education and health services. This basic move toward the splitting up of power between the federation and the provinces conveys considerable long-term repercussions in the country for the policy planning, management, and implementation.

The majority of the current research studies on Pakistan economy has focused on provincial level, and overlooked the spatial disparity within the provinces among the districts. There are little facts regarding the trends in spatial disparities across districts over the previous two decades. Research at district level has become even more vital after 18th amendment passed in April 2010[2] as public and social services (such as health and education) happen to be the lone sphere of provincial governments. The district level research better explains the geographical features of socio-economic facts and provides a comprehensive investigation of the effects spatially relative to studies undertaken in the country on a provincial level.

In light of the above-mentioned challenges, the major aim of this research is to investigate the spatial pattern of household welfare level for 97 districts of Pakistan over the period of 2004 to 2015, by utilizing exploratory spatial data analysis techniques (hereafter ESDA). Thus, the study provides outcomes for clustering of socioeconomic features across Pakistani districts[3].

The paper is organized in the following mode: section 2 explains Literature review. Section 3 introduces Methodology. The section 4 presents our empirical findings and provides conclusions.

2. Literature Review

2.1 Theoretical Literature

The unequal spatial distributions of social and economic activities are one of the most incredible features of life. The dimensions of time and space always determine the economic and social activities. Theoretical economic models often integrate time, however, for a long-time mainstream economists did not pay much attention to space and geography. The significance of space was recognized recently in the literature concerning territorial imbalances, whereas older approaches about regional inequality were attributed by a relative silence about the regional level problems. Even though, the concept have been actually predicted by various theories before the New Economic Geography such as growth pole theory of Perroux (1950), the polarization and spread concepts by Myrdal (1957) and Hirschmann (1966) respectively. However, Fujita and Krugman (2004) used the idea, methods, and effects of economic integration in New Economic Geography.

2.2 Empirical Literature

The role of geography has long been ignored by economist in their research, particularly in modern growth economics and macroeconomics until 1990s. However, for the last three decades, empirical studies are focusing on

[1] The NFC award is the allocation of fiscal assets by the federal government among the provinces of Pakistan annually. The award is constituted in 1973 Constitution of Pakistan under the Article 160.

[2] The eighteenth constitutional amendment to the 1973 constitution has raised the autonomy of provinces to great extent.

[3] The only other exceptions include (Burki *et al*. 2010) and (Ahmed, 2011) that have considered explicitly in their studies spatial dependencies.

the association between geographical factors and territorial imbalances. The empirical literature on spatial distribution of socio-economic indicators across countries or regions can be further categorized into case studies of developed countries and developing countries.

For developed world, studies on spatial disparities across regions found mixed results. In the case of the European Union, majority of research studies found that poor areas tend to fall behind while most well-off regions reveal unrelenting growth (Canova & Market, 1995; Magrini, 1999; Magrini, 2004). In the case of European Union and United States, it is recognized that innovation is highly concentrated in a very few regions (Carlino et al., 2001; Crescenzi et al., 2007) indicating that fundamental features for innovation to succeed are distributed highly unequally. In the same way, it has been found that the capability of European regions to translate knowledge into significant economic activities vary across space in accordance with different qualitative local social structures and innovation systems across regions (Rodriguez-Pose, 1999; Crescenzi & Rodriguez-Pose, 2008).

For developing countries, the localized nature of economic development and the role of social and institutional aspects emerge even more essential as favorable locality and contexts become less likely. Regional spatial disparity was widespread in some countries such as Brazil, but decreases over the period 1981-1997 (Azzoni et al., 2005). However, regional inequality remained steady at lower levels comparatively in other countries. While calculating inequality for Peru by using literacy and expenditure, Torero and Escobal, (2005) investigated that inequality was low across regions for the period 1972–93. Balisacan and Fuwa (2006) examined that the regional disparity in the Philippines and concluded that regional disparity condensed between 1985 and 2000. Similar findings were made for South Africa between 1990 and 2000 (Friedman, 2005), and Indonesia between 1984 and 1999 (Krugell & Naude, 2003). Meanwhile, in the case of China, it was recognized that geographic factors are significant statistically in revealing the spatial disparity largely between seashore and non- seashore (Chang, Bao, & Woo, 2002).

Currently, most of the studies focusing spatial disparity are based on a technique known as ESDA. A number of ESDA based analysis have been conducted on the subject of regional disparities (For instance, Battisti & Di Vaio, 2008; Ezcurra et al., 2007; Voss etal., 2006; Jensen et al., 2006; Magalhaes et al., 2005). The only ESDA analysis performed on the Pakistan case is Ahmed (2011). For Pakistan, for the first time Ahmed (2011) studied the agglomeration of growth, income inequality, human development and education spatially across 98 districts. Ahmed found that bordering districts share growth and development levels of each other’s, proving that economic topography does influence growth, development, and territorial disparities of Pakistan. The study further analyzed that the district wise distribution of growth, income inequality, human development and education, demonstrates a major trend for levels of development and socio-economic disparities to cluster in Pakistan.

Most of the research on socio-economy of Pakistan has focused on a provincial level (for example, Hamid & Hussain, 1992; Pasha et al, 1996; Khan & Jamal 2003; Aamir & Jamal 2003; Naqvi, 2007; Siddique, 2008; Burki et al., 2010; Arif, 2010). These studies overlook the significance of social interactions among the districts within the provinces. The above empirical evidences clearly indicate that there is an abundance of work in assessing the issue of spatial inequality in the rest of the world over the past three decades; only limited studies have focused the issue for Pakistan. This not only draw attention towards investigating regional differences within the country in order to discover the most isolated subset of the people in terms of health, literacy and income, but in addition to support in the formulation of course of action that can eliminate these problems of dissimilarities in income and development. So, the study provides some of the first logical study on clustering of household welfare indictors across districts of Pakistan.

3 Methodology

This section discusses research methodology and data base applied for analyzing data**.**

3.1 Model

The use of spatial econometric methods has achieved popularity with this bigger attention on issues of regional development and improvement of spatial data analysis (Arbia, 2006). There are several methods used to discover correlations in space. The commonly used technique is ESDA. This study utilizes technique ESDA.

3.1.1 Mapping the Distributions

Prior to estimation of models with data, GeoDa (one of diverse software packages for performing ESDA) is utilized to create scatter plots, box-plots and quartile maps. It maps the variables that are utilized in the study and examine spatial patterns visually through map.

3.1.2 Exploratory Spatial Data Analysis

A subgroup of exploratory data analysis is ESDA. When using EDA, the researcher gives the data a closer look and attempts to interpret it. During the year 1977, John Tukey created the EDA. The ESDA methodologies used in this work include investigation at the local level (LISA) and computation of global level indicators (Moran's *I* spatial autocorrelation). The creation of a spatial weight matrix is the initial stage in the spatial autocorrelation analysis process.

ESDA is a subgroup of Exploratory Data Analysis (hereafter EDA). In this study, the ESDA techniques employed comprise the computation of Global level indicators (Moran's *I* spatial autocorrelation) and analysis at local level (LISA). For spatial autocorrelation analysis, the first step is to define a spatial weight matrix.

3.1.3 Spatial Weight Matrix

For defining neighborhood in this study, two fundamental approaches utilized in this study are common borders (contiguity) and distance. Weights matrices based on contiguity consist of rook and queen. According to the rook criterion, districts are considered neighbors if they share a boundary, not a set of vertices. K nearest neighbors and distance bands make up weight matrices based on distance. Four weight matrices are developed based on the aforementioned two ideas in order to analyze the spatial distribution of the household welfare index. The four weight matrices include; a rook contiguity matrix, k_7 nearest neighbor matrix, k_4nearest neighbor matrix, and W-150 miles matrix, which define neighbors as all the districts located inside a great circle distance with a cut-off of 150 miles. The matrices are finally row standardized, which is a suggested practice when the distribution of the factors under deliberation is probably biased because of errors in designing of sample or because of a forced aggregation method.

Because of space limit, we only discuss the k_7 nearest neighbor matrix:

$$w_{ij}(k) = 0 \ \ if\ i = j$$

$$w_{ij}(k) = 1 \text{ if } d_{ij} \leq D_i(k) \text{ and } w_{ij}(k) = w_{ij}(k)/\sum j\, w_{ij}(k) \text{ for } k = 7 \qquad \textbf{(1)}$$

$$w_{ij}(k) = 0 \text{ if } d_{ij} > Di(k)$$

From Equation (1), d_{ij} is great circle distance between centroids of district i and j and $Di\ (k)$ is the 7th order minimum distance between districts i and j, so that each district i has seven neighbors accurately.

After defining the weight matrix, next we estimate some spatial statistics that discuss the spatial distribution of household welfare index.

3.1.4 Measures of Spatial Autocorrelation

Spatial autocorrelation basically refers to a methodical spatial dissimilarity in values across a map, or with the given locations patterns in values recorded at locations (Fingletonm & Upton, 1985). When features are alike in location, then it would be regarded as spatially positive autocorrelated. When features were different in location, then it would be considered as spatially autocorrelated negatively. When characteristics were not dependent on location, they are regarded as zero autocorrelation (Holt, 2007).

3.1.5 Global Spatial Autocorrelation

To discover the global spatial autocorrelation in the data, this study uses Moran's statistics. Originally, it was proposed by Moran in 1948, and the standard work by Ord and Cliff popularized it in 1973. Primarily, the Moran's *I* is the widespread employed measure due to its simplicity in understanding and its further splitting into a local statistic alongside presenting graphical data regarding presence or absence of spatial clustering. It is judged by mean of a null hypothesis test of random locality. Null hypothesis negative response advocates a spatial structure, which gives further insights into distribution of data. For the household welfare index, it measures the strength of the linear relationship between its value at one location and the spatially weighted average (mean) of adjacent values and is formalized as:

$$I_t = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(k) x_{it} x_{jt}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{it} x_{jt}} \tag{2}$$

From Equation (2), w_{ij} is the degree of association between the districts *i* and *j* and the variable of interest in district *i* at year *t* is represented by x_{ij} (determined as a deviation from the mean value for that year). Positive spatial autocorrelation is pointed out, if values of *I* is bigger than the expected value $E(I) = -1/(n-1)$, while negative spatial autocorrelation is indicated, if values of *I* is lesser than the expected value.

3.1.6 Local Indicators of Spatial Association

The Moran's *I* is used to measures the presence of global spatial autocorrelation only; it does not give data on the accurate locations of spatial patterns (Holt, 2007). So, *local indicators of spatial association* (here after LISA) is essential to measure the magnitude and location of spatial autocorrelation (Anselin, 1995). Thus, this research employs LISA method. The technique displays the presence or absence of significant spatial outliers or clusters for each district. It also specify local clusters that are significant (low–low or high–high) or spatial outliers locally (low–high or high–low). The mean of the Local Moran statistics is related to the value of Global Moran's *I* (Anselin et al., 2007).

$$I_i = \left(\frac{x_i}{m_o}\right) \sum_j W_{ij}\, x_j \quad with \quad m_o = \sum \frac{x_i^2}{n} \tag{3}$$

From Equation (3), w_{ij} represents the elements of the weights matrix *W* (row-standardized) and x_i (x_j) is the observation in district *i (j)*.

3.2 Variables Description and Data Source

3.2.1 Variables Description

The use of per capita output as a measure of living standard has been criticized by several economists, as it fails to explain the wider aspect of welfare (Sen, 1983; Stiglitz et al., 2009; Todaro & Smith, 2011; Roy & Bhattacharjee, 2009 Schepelmann et al., 2010). So, in this study, we attempt ESDA analysis for 97 districts by using household welfare index for periods 2004-05 and 2014-15. The index is composed of five indicators. Principal Component Analysis (PCA) is employed to aggregate the weights obtained from these indicators (Basel et al., 2020). The list of indicators used to compute sub-indexes is given in Table 1.

3.2.2 Data Source

Data for the study is taken from PSLM Surveys covering the period 2004-05 and 2014-15. PSLM surveys cover data on socioeconomic indicators for 116 districts across four provinces of Pakistan.

Table 1: List of Indicators of Household Welfare Level

S. No	Indicators of Household Welfare Index
1	Households by housing ownership.
2	Household with Gas.
3	Households with electricity
4	Households with flush toilet.
5	Households with RCC Roof.

3.2.3 Data Limitations

PSLM surveys cover data for 116 districts across four provinces of Pakistan. Due to missing observations, 20 districts are dropped from the data for this study. The detail of the dropped districts is given in Table 2.

Table 2: List of districts dropped from data due to missing observation

	Provinces			
	Punjab	**KP**	**Sindh**	**Balochistan**
Districts	Chiniot, Nankana Sahib	Tor Ghar	Tando Allah Yar, Tando Muhammad Khan, Kashmore, Shahdadkot, Sujawal, Umerkot, Matiari, Jamshoro	Derabugti, Sheerani, Washuk, Ketch, Panjgur, Kohlu, Nushki, Harnai

4. Results and Discussion

4.1 Mapping the Distributions

The first step for our analysis is to map and examine the data. The mapping gives important information about outliers and the directions of spatial autocorrelation.

4.2 Quartile Maps

Quartile map is category of quantile map that sort values for a variable that are then grouped into four bins that each have the same number of observations. In quartile map, higher values are explained by darker colours, whereas lower values are illustrated by lighter coluors. Figure 1-2 comprises two quartile maps that display household welfare index for period 2004-05 and 2014-15.

The quartile maps display the majority of Punjab's Eastern and Northern districts have the highest level of household welfare level. Southern/South-Eastern Punjab districts are underdeveloped relative to the developed eastern and central districts of Punjab. In Khyber Pakhtunkhwa most of the districts belong to the category of high household welfare level, whereas, districts of Northern and southern Khyber Pakhtunkhwa are the least developed districts. With the exception of Quetta, Balochistan's districts lies in the low household welfare level category. The distribution of districts in Sindh is heavily skewed toward low medium levels of household welfare. With the exception of Karachi and Hyderabad, Southern Sindh is home to the least developed districts. Overall, the maps showed that there is slight improvement in spatial clustering of household welfare level from 2004 to 2015.

Figure 1: Quartile Map for Household Welfare Index (2004-05)

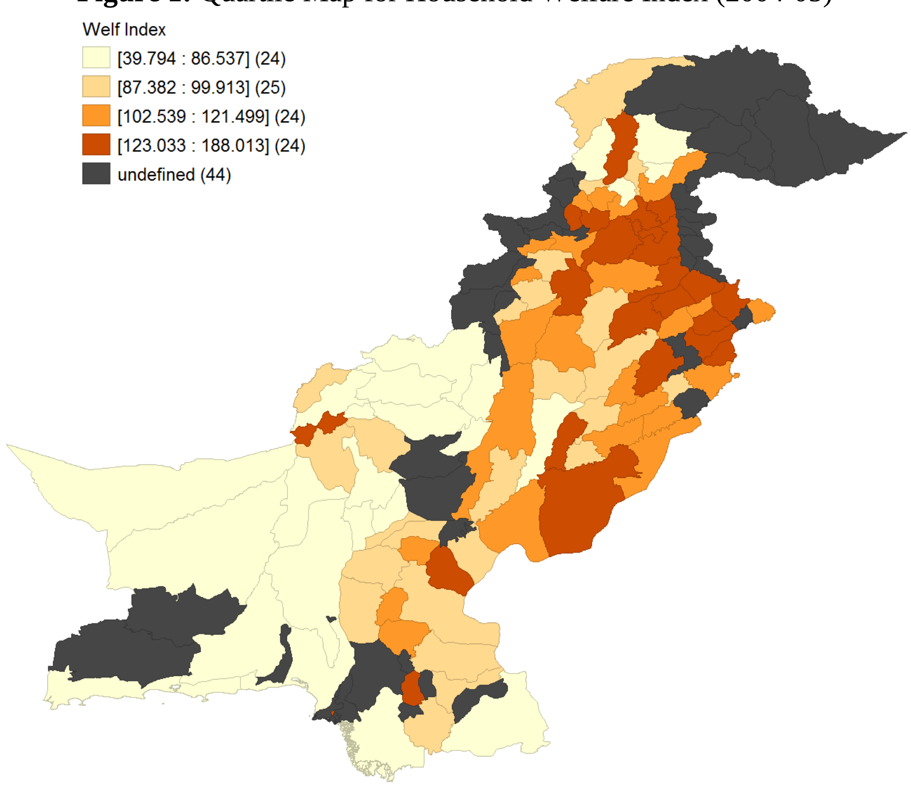
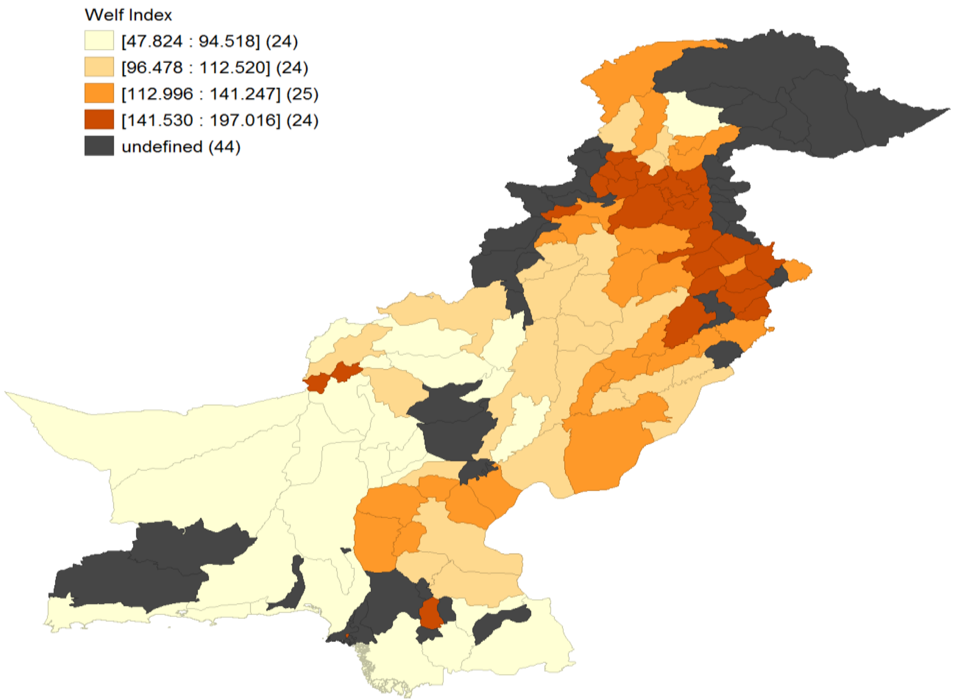


Figure 2: Quartile Map for Household Welfare Index (2014-15)



4.3 Box Plots

For mapping of data distribution, another necessary tool of ESDA is the box plot that presents five vital facts regarding a dataset: the lower quartile of the distribution expressed as Q1 representing 25 percent of the cumulative distribution, the Q2 representing median, the upper quartile expressed as Q3 represents 75 percent of the cumulative distribution, and Q4 representing topmost value. The main advantage of a box plot is to show the outliers, which are defined as values above or below a certain multiple of the difference between the first and third quartiles (randomly determined by GeoDa to 1.5). Such as, a lower outlier signifies a value below [$Q1-1.5*(Q3-Q1)$] and an upper outlier refer to the value over [$Q3 + 1.5*(Q3 - Q1)$]. The first quartile of the distribution is located in the lowest portion of the dark area. The median is indicated by the bar in the center of the dark region. The third quartile of the distribution is located in the upper section of the dark area.

The ‘‘box plots’’ listed in figures 3-4 give a first look of spatial distribution of household welfare index across Pakistan’s districts. The box plot figures 3 and demonstrate the spatial pattern for the scores in 2004-05 and 2014-15. The box plot figures for 2004-05 revealed Islamabad, Lahore and Karachi as upper outlier for overall household welfare. Whereas, for the year 2014-15, the box plots shows Bolan, JhalMagsi, Sibbi (Baluchistan) and Kohistan (KP) as the lower outlier for the period 20014-2015.

Figure 3: Box plot for Household Welfare Index for the period 2004-05

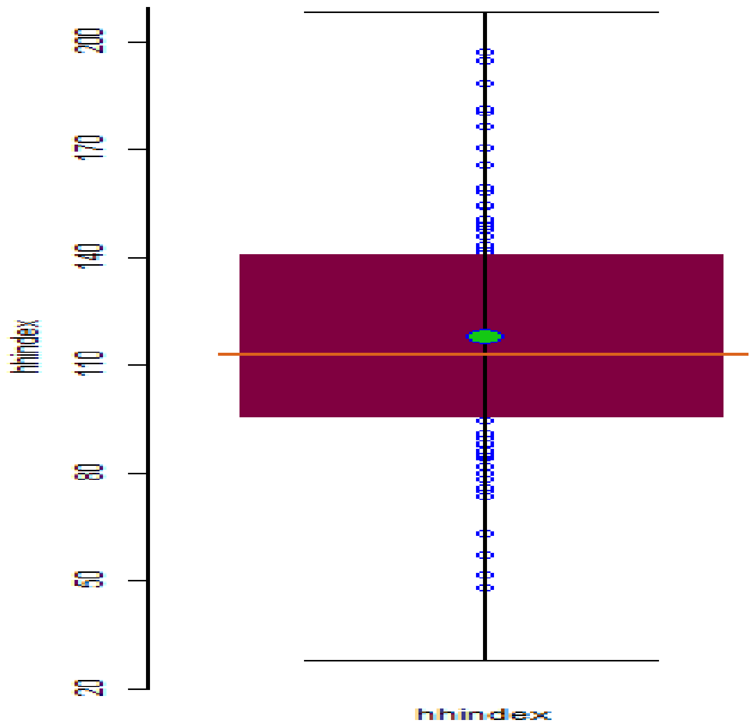
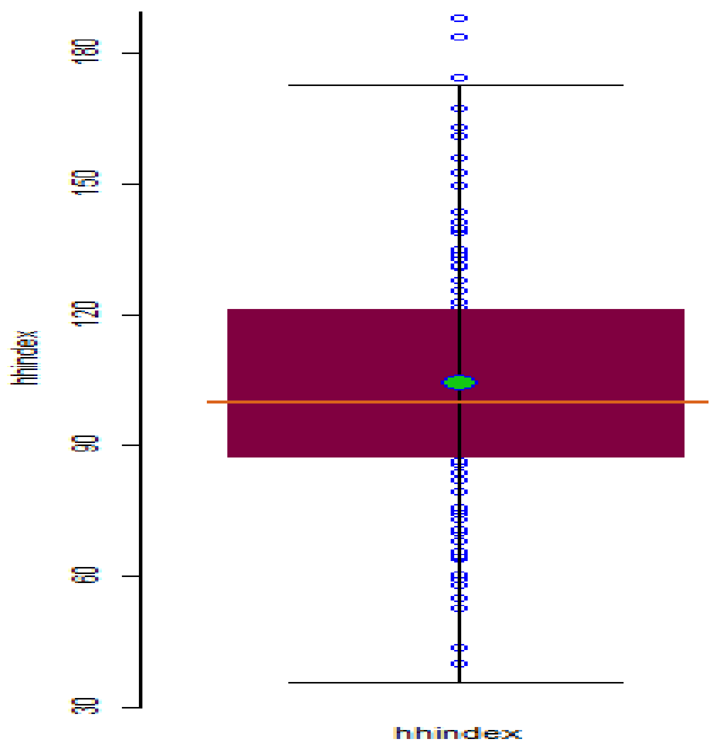


Figure 4: Box plot for Household Welfare Index for the period 2014-15



Overall, the quartile maps and box plot revealed that overall districts from Balochistan and Interior Sindh have experienced the greatest stagnation in terms of household welfare level over the period 2004-2015, as box plot revealed most of districts in lowest quartile belong to Sindh and Balochistan. Likewise, quartile maps also show that clusters of least developed districts belong to the provinces of Balochistan and Interior Sindh. On the other side, majority of districts of Punjab and KP are mapped as developed in both periods.

4.4 Spatial Autocorrelation

Box plots and quartile maps are useful tools for determining how the household welfare index is distributed among districts. On the other hand, they do not adequately research whether a household welfare index's spatial distribution is random or not. We believe that the household welfare index may not be distributed evenly between districts for a number of reasons. For instance, the preceding data show that the distribution of the household welfare index throughout Pakistan's districts is characterized by dissimilar clusters.

4.5 Global Spatial Autocorrelation

The concept of spatial autocorrelation or spatial association is essential to ESDA. Moran's *I* is the most common test for spatial autocorrelation (Cliff & Ord, 1981; Upton & Fingleton, 1985). It is judged through a test of a null hypothesis of random location. A spatial structure is suggested in case of rejection of this null hypothesis, which leads to more insights into data distribution.

Tables 3 and 4 below present the results of Global Moran's I for the years 2004–2005 and 2014–15, respectively. At the 1% level of significance, all four matrices support the existence of a significant positive global spatial autocorrelation. The district with a high (or low) level of household welfare level tends to be bordered by districts with a high (or low) level of household welfare level, as demonstrated by significant positive global spatial autocorrelation. We employ a weight matrix based on rook contiguity for the remainder of our study because all four weight matrices show a considerable positive global spatial autocorrelation.

Table 3: Moran's I and P-Value under Different Spatial Weights (2004-05)

Variables	Queen	Rook	K_4	K_7	W-150 miles
Household Welfare Index	0.375 (0.001)	0.375 (0.001)	0.399 (0.001)	0.366 (.001)	0.268 (0.001)

Note: The values in parentheses are the p-values.

Table 4: Moran's I and P-Value under Different Spatial Weights (2014-15)

Variables	Queen	Rook	K_4	K_7	W-150 miles
Household Welfare Index	0.469 (0.001)	0.469 (0.001)	0.465 (0.001)	0.482 (.001)	0.370 (0.001)

Note: The values in parentheses are the p-values

The Moran's *I* result for Household Welfare Index clearly indicate the increasing level of spatial dependence from 2004 to 20015, as given in Table 3 and Table 4.

4.6 Local Spatial Autocorrelation

4.6.1 Moran Scatter Plots

The global indicator "Moran's *I"* is helpful to identify global spatial autocorrelation, but it cannot detect local patterns of spatial association, for instance local spatial clusters or local spatial outliers of high values or low that are significant statistically. Moran scatter plot detect the groups of districts categorized in clustering of high or low values. Following the suggestion of Anselin (1996), it displays the distribution of household welfare index for each district on the horizontal axis against the standardised spatial weighted average (spatial lag, which is the average of the neighbors' values) on the vertical axis. So, the Moran's scatter plot help us to investigate both local spatial association and global spatial association (as the slope of the line is the Moran's *I* coefficient).

According to the four types of local spatial relationships between a district and its neighbors, the Moran scatter plot is divided into four distinct quadrants:

1. Quadrant I (expressed as HH representing top right) explains that the household welfare value of the district and "neighboring" districts are high and the spatial difference is not significant.
2. Quadrant II (expressed as LH representing top left) explains that the household welfare value of the district is low, whereas that of the "neighboring" districts is higher, with large spatial differences.
3. Quadrant III (expressed as LL representing bottom left) explains that the household welfare values of the district and "bordering" districts are low and the spatial difference is not significant.
4. Quadrant IV (expressed as HL representing bottom right,) explains that the household welfare values of the district are higher, whereas that of the "bordering" districts are low and the spatial difference is large.

Figure 5: Moran Scatter Plot of Household Welfare Index for period 2004-05

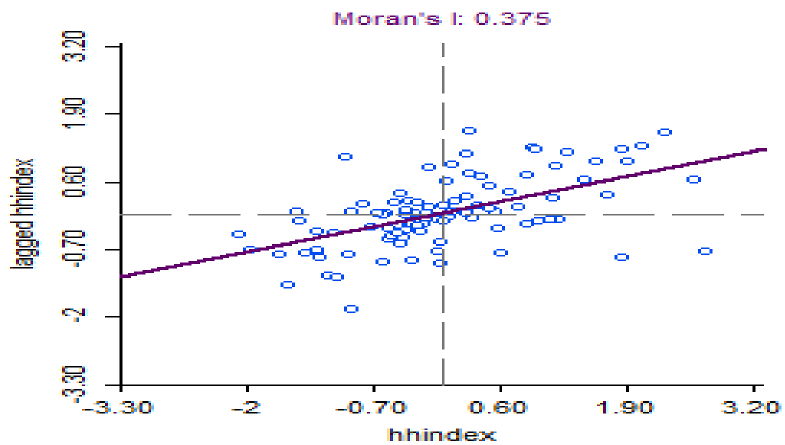
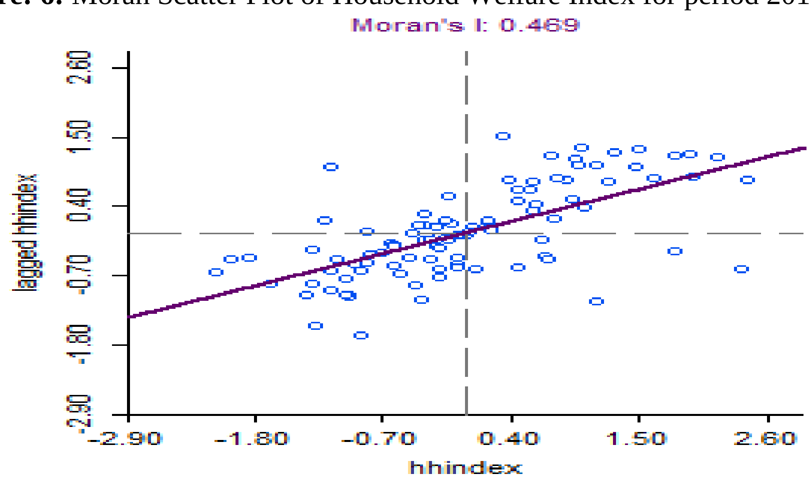


Figure: 6: Moran Scatter Plot of Household Welfare Index for period 2014-15



The Moran scatter plot is just exploratory of clusters or outliers and cannot explain significance. The Moran's scatter plot of household welfare index for period 2004-05 and period 2014-15 are demonstrated by the figures listed in Figures 5 and 6. Districts located in first and third quadrants indicate positive spatial autocorrelation, representing the spatial clustering of same values. While, the districts located in second and fourth quadrants denote negative spatial autocorrelation representing spatial clustering of unlike values. Both figures indicate positive global spatial autocorrelation, which was observed before by value of Moran's *I*. Moran scatter plots displayed that most of the districts are located in first and third quadrants (HH & LL), with first quadrant (HH) showing a cluster of districts mostly from Punjab and KP, while third quadrant (LL) shows a cluster of the majority of districts from interior Sindh and Balochistan.

Overall, the differences of household welfare index across districts in Pakistan are caused mostly by the "HH" and "LL" agglomeration effects, while the "HL" and "LH" agglomeration effects are not evident. Moran Scatter plots also show that with the passage of time, "LL" and "HH" accumulation areas tend to expand. These findings reflect the twofold structure of Pakistan's districts.

Table 5: Distribution of spatial autocorrelation for Household Welfare Index (2004-05)

Var	HH (34)	LH (14)	LL (35)	HL (14)
Household Welfare Index	Abbottabad, Hafizabad, Bhakhar, Chakwal, Faisalabad, Gujrat, Attock, Gujranwala, Hangu, Islamabad, Haripur, Jehlum, Kasur, Khanewal, Kohat, Lahore, Mansehra, Mardan, Mianwali, Narowal, Naushahro Feroze, Nowshera, Pakpatten, Peshawar, Rawalpindi, Sargodha, Sahiwal, Toba Tek Sheikhupura, Sialkot, Sukkur, Swabi, Singh, Vehari	Buner, Charsada, Jhang, Karak, Khushab, LakkiMarwat, Lasbilla, Lodhran, Mithi, Muzaffagarh, Okara, Sanghar, Thatta, Upper Dir,	Awaran, Badin, Bannu, Barkhan, Batagram, Bolan, Chaghi, Dadu, Dera Ismail Khan, Dera Ghazi Khan, Gwadar, Jafarabad, Jakobabad, JhalMagsi, Kalat, Kharan, Khairpur, Khuzdar, Kohistan, Larkana, Loralai, Mastung, Mirpur Khas, MusaKhel, Nasirabad, Nawab Shah, Pashin, Qilla Abdullah, Qilla Saifullah, Rajanpur, Shangla, Sibbi, Tank, Zhob, Ziarat.	Bahawalnager, Bahawalpur, Chitral, Ghotki, Hyderabad, Karachi, Layyah, Lower Dir, Malakand, Multan, Quetta, RahimYarKhan, Shikarpur Swat.

Table 6: Distribution of spatial autocorrelation for Household Welfare Index (2014-15)

Var	HH (36)	LH (10)	LL (40)	HL (10)
Household Welfare Index	Islamabad, Abbottabad, Chakwal, Charsada, Faisalabad, Attock, Gujrat, Gujranwala, Hafizabad, Hangu, Haripur, Jehlum, Karak, Kasur, Khanewal, Khushab, Kohat, Lahore, Mansehra, Lakki Marwat, Malakand, Lower Dir, Mardan, Mianwali, Narowal, Naushahro Feroze, Nowshera, Okara, Peshawar, Sheikhupura, Rawalpindi, Sargodha, Sialkot, Swabi, Sahiwal, Toba Tek Singh	Bhakhar, Buner, Jhang, Kohistan, Lasbilla, Pakpatten, Sanghar, Thatta, Upper Dir, Vehari	Awaran, Badin, Bannu, Bahawalnager, Bahawalpur, Barkhan, Batagram, Bolan, Chaghi, Dadu, Dera Ghazi Khan, Gwadar, Jafarabad, Jakobabad, JhalMagsi, Kalat, Khairpur, Kharan, Khuzdar, Lodhran, Loralai, Mastung, Mirpur Khas, Mithi, MusaKhel, Muzaffargarh Nasirabad, Nawab Shah, Qilla Saifullah, Pashin, Qilla Abdullah, Rahim Yar Khan, Rajanpur, Shangla, Shikarpur, Sibbi, Tank, Zhob, Ziarat.	Chitral, D.I.Khan, Hyderabad, Karachi, Larkana, Layyah, Multan, Quetta, Sukkur, Swat.

The presence of local spatial autocorrelation is proved by LISA findings and it shows spatial heterogeneity in the shape of two different spatial clusters of high and low level of household welfare index (see Figure 5 & Figure 6).

5. Conclusions and Recommendations

The study analyzed spatial distribution of household welfare index for 97 districts of Pakistan for periods 2004-05 and 2015-15.

5.1 Conclusions

The main findings the study is given as under:

- Quartile maps clearly display that there exists a vast gap in household welfare level across the districts of Pakistan.
- Moran's *I* indicate significant positive global autocorrelation and thus indicating a districts with a high (low) household welfare level are associated spatially with bordering districts which also have high (low) household welfare level.
- The findings of Moran's Scatterplots show that, most of districts of Punjab and KP lie in the HH quadrant, While the LL quadrant shows a cluster of the of districts mostly from interior Sindh and Balochistan for both periods.

- On the whole, these findings prove the twofold structure of Pakistan's economic geography, as explained by previous literature. Along with spatial heterogeneity, spatial autocorrelation among districts is also witnessed by the findings of the study.
- Overall, the findings confirm the twofold features of Pakistan's economic geography, as explained by many studies previously.

5.2 Recommendations

Following main recommendations come out from our results.

- The procedural implication of the findings is that studies that employ OLS to analyze socio-economic issues across districts may provide statistical judgments that are not reliable. By assuming spatial-independence, they may lead to estimates that are biased and overestimated.
- The main policy implication is that development policies need to focus cluster development that can cater to large segments of the population. Since geography of household welfare matters, it is recommended to reduce across districts inequalities by enhancing spending in education and the training of out of work labor force in the under developed districts of Pakistan. It is also recommended that development of the social and economic institutions and infrastructure in the Balochistan and Interior Sindh should be on the priority list of government.

5.3 Future research Possibilities

- In light of the spatial nature of the above study, additional research can be done on the factors responsible for non-convergence of development and other Indexes across the districts of Pakistan.
- These spatial econometrics techniques could be extended to other economic, social and environmental issues for Pakistan and developing world as portrayed by the literature on developed countries.

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Appendix

Figure A1. Provincial Administrative Map of Pakistan

Figure A2: District Administrative Map of Pakistan

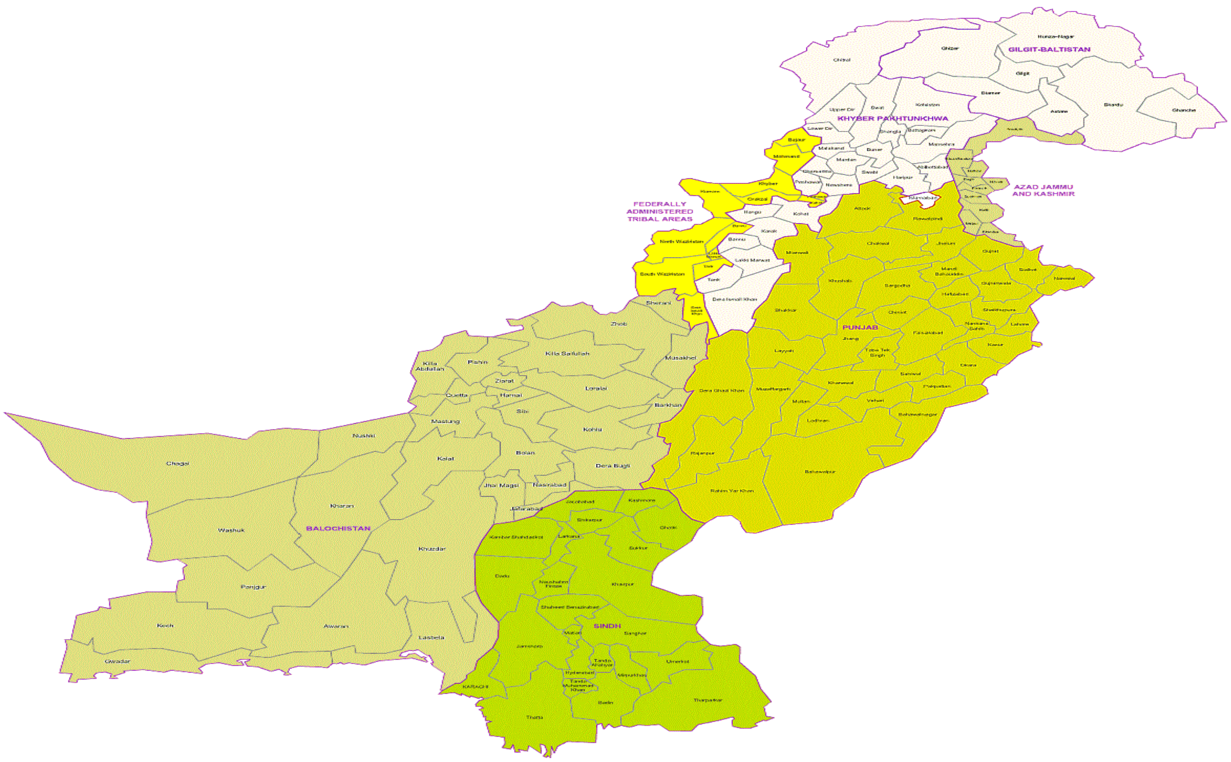

Table A: Sample Binary Contiguity Weight Matrix

	Attock	Chakwal	Gujranwala	Gujrat	Hafizabad	Jhelum	Mandi Bahuddin	Rawalpindi	Sialkot
Attock	0	1	0	0	0	0	0	1	0
Chakwal	1	0	0	0	0	1	0	1	0
Gujranwala	0	0	0	1	1	0	1	0	1
Gujrat	0	0	1	0	0	1	1	0	1
Hafizabad	0	0	1	0	0	0	1	0	0
Jhelum	0	1	0	1	0	0	1	1	0
Mandi Bahuddin	0	0	1	1	1	1	0	0	0
Rawalpindi	1	1	0	0	0	1	0	0	0
Sialkot	0	0	1	1	0	0	0	0	0

Table: Sample Binary Contiguity Weight Matrix
*Full matrix is available in *GWT file format* from the author upon request.