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Exploring Spatial Patterns and Determinants of Poverty: New Evidence from Pakistan

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This study aims to explore two types of spatial determinants of district level poverty in Pakistan: factors that have direct effect, and indirect or spillover effect, on poverty levels of neighbouring districts. The Spatial Autoregressive (SAR) model has been applied to estimate previously mentioned objectives. Data of 148 districts were collected from the National Socio-Economic Registry (NSER), and provincial development statistics. The Small Area Estimation (SAE) technique provides district level poverty estimates. Empirical results reveal that spatial autocorrelation arises owing to the lag effect of outcome variables, and autocorrelation of error terms with neighbouring districts. Moreover, results are suggestive of factors that have direct influence on poverty levels of respective districts. These include urbanisation, population growth rate, average family size, education, road infrastructure as well as climatic factors (i.e. monthly temperature and rainfall). Apart from direct effects, some determinants of district level poverty have spillover or indirect impact on poverty levels of neighbouring districts. Such factors include level of employment, road length, literacy rate, and climatic factors. Poverty in one district itself has a spillover impact on determining poverty level of adjacent districts. The findings of this paper suggest that the government should enhance regional connectivity, which may be helpful in exploiting the spillover effect of road, health, and education infrastructure to reduce regional poverty levels in Pakistan.

1. INTRODUCTION

Poverty is a complex and multidimensional phenomenon because of two notable features. First, despite various efforts to address it, globally about 902 million people live below the poverty line as per the money metric measure, whereas 1.6 billion people are facing multidimensional poverty. Second, the incidence of poverty not only varies across regions and countries, but also varies within a particular country. For example, the highest poverty level is noted in Sub-Saharan Africa (35.2 percent), followed by South Asia (13.5 percent), Latin America (5.6 percent) and East Asia Pacific (4.1 percent) (World Bank, 2018).These estimates reveal that challenges to addressing poverty across regions remain inadequately addressed.

Despite various reforms, addressing poverty remains an unfinished task in Pakistan because 24.5 percent of the population is living below the poverty line, whereas 12.5

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percent and 30.5 percent population is estimated to be poor in urban and rural areas respectively. Provincial estimates as per multidimensional poverty markers indicate that Baluchistan at 71 percent is the poorest province of Pakistan, while the populations of KPK at 50 percent, Sindh at 43 percent, and Punjab at 32.5 percent are multi-dimensionally poor (GoP, 2017-18). Documented studies conducted by researchers also suggest disparities in the prevalence of geographical poverty levels in Pakistan (e.g. Cheema, 2010; Arif, 2015; Begum, 2015; Iqbal & Nawaz, 2016).

Multiple socioeconomic factors may also significantly impact the prevalence of poverty in Pakistan. Some of these factors include dependency ratio and financial constraints to households, while unemployment, inflation, macro-economic instability, political instability, population growth, and adverse impacts of climate change are macro-level determinants of poverty[1]. These studies have some limitations. Firstly, all studies have employed OLS to estimate determinants of poverty, which gives biased and inefficient parameters if spatial autocorrelation is ignored. Secondly, the spillover effect of some spatial determinants is missed regarding Pakistan.

Spatial autocorrelation arises owing to spatial dependence across locations. In order to make a spatial analysis of poverty levels, researchers pay a lot of attention to tackling spatial dependence. So that they may estimate unbiased and efficient determinants of poverty, (e.g. Petrucci, et al. 2004; Amarasinghe, et al. 2005; Higazi, et al. 2007). Anseline (1999) have suggested that spatial dependence comes into existence owing to autocorrelation of error terms, lag effect of outcome variable, and covariates of the model. It causes econometric problems like *Heteroscedasticity* and *Autocorrelation*, if parameters are estimated by OLS estimator (Higazi, et al. 2007).

Contrary to OLS, researchers apply the Spatial Autoregressive (SAR) model, which provides unbiased and efficient parameters even in the presence of spatial dependence across regions. Furthermore, SAR decomposes the total effect of a variable into direct and indirect impacts of a variable on the outcome variable. Indirect impact means the spillover effect of a variable for a neighbouring location. Spatial lags are quite different from a time series analysis, while in the context of spatial analysis, lags indicate adjacent location. These lags are specified by employing a spatial weighting matrices scheme. For that reason, SAR models are being widely used to estimate spatial determinants of poverty levels in developing countries (e.g. Anseline, 1995, 1999; Amarasinghe, et al. 2005; Farrow, et al. 2005; Higazi, et al. 2007).

This study aims to investigate spatial determinants of district level poverty in Pakistan by applying Spatial Autoregressive (SAR) model. The specified objectives are outlined as follows.

1. To explore factors which have a direct effect on district level poverty.
2. To explore factors which have a spillover effect on poverty levels of neighbouring districts.

This paper contributes to literature in two ways. Firstly, it applies the spatial autoregressive model to decompose the impacts of spatial determinants of poverty into direct and spillover effects which are missed by previous studies for Pakistan. Secondly,

[1]See e.g. (Ma, *et al*. 2018; Pervaiz and Rizvi, 2013; Yousaf and Ali, 2014; Jan, et al. 2008; Aftab, et al. 2002; Arif, et al. 2011, 2015; Arif & Iqbal, 2009; Awan, et al. 2011; Iqbal & Awan, 2015).

district level consumption-based poverty of 148 districts of Pakistan is predicted by combining HIES and the National Socio-Economic Registry (NSER). The NSER is the largest data set comprising a truly representative sample of districts of Pakistan including FATA, AJK, and Gilgit-Baltistan.

The rest of the paper is organised as follows:

Section 2 briefly reviews the literature.
Section 3 discusses data design and construction of variables.
Section 4 presents the methodological framework.
Section 5 presents empirical results and discussions.
Section 6 concludes and gives some policy recommendations.

2. LITERATURE REVIEW

Initially Anseline (1986, 1994, and 1995) suggested the use of the spatial regression model. Later, the model was developed into a geographically weighted model. It has been widely applied by researchers to obtain unbiased and efficient parameters (Marshal, 1991; Bailey and Gatrell, 1995; Anseline, 1999; Anseline and Bao, 1997; Fotheringham, et al. 2000; Anseline, et al. 2002a).

A study conducted by Petrucci, et al. (2004), employs the spatial regression model to estimate the spatial determinants of poverty for Ecuador. Study findings indicate that infant mortality rate, birth rate, population growth rate, and percentage of adult literacy are the main drivers of poverty. Environmental factors such as temperature and rainfall, slippery roads, and landslides are also estimated as spatial determinants. Moreover, distance from the main road, cereal production, irrigated area, and arable land are significant spatial determinants of regional poverty.

Amarasinghe, et al. (2005) has identified spatial patterns of food poverty in Sri Lanka. They apply the Spatial Autoregressive (SAR) model to estimate spatial determinants of food poverty. The results of their study indicate such factors as agricultural employment, better access to roads, and water availability for irrigation and average landholding size. Further findings unleash the spillover impact of employment level on adjacent regions. Farrow, et al. (2005) estimate similar results for Ecuador.

Kam, et al. (2005) have estimated the spatial determinants of poverty for Bangladesh using the spatial regression model. Their findings show that the proportion of landless households, agriculture area under tenancy, livestock holding, schooling, modern irrigated facilities, road infrastructure, access to amenities, and structure of agriculture land are the factors affecting rural poverty in Bangladesh.

Palmer-Jones and Sen (2006) explored spatial determinants of poverty in India. The results demonstrate that dependency ratio, population growth, cultivatable area of land, climatic variables, physical infrastructure, and financial constraint are the important determinants of poverty. Similarly, Okwi, et al. (2007) & Ma, et al. (2018) also have applied the spatial regression model to estimate spatial determinants of poverty in Kenya and China respectively. Some recent studies (e.g. Owada, et al. 2019; Tong and Kim, 2019; Maalsen, 2019) have used the SAR model also.

Mainly, two factors affect poverty in Pakistan: macro-level, and household level. The household level determinants of poverty include education, housing conditions, household occupation, level of employment, financial constraints, land ownership, and idiosyncratic shocks. Moreover, demographic factors like household size, dependency ratio, and gender composition are significant determinants of poverty in Pakistan (i.e. Yusuf, et al. 2017; Sadiq, 2010; Arif and Ahmed, 2001; Mcculloch and Baulch, 2000). Macro-level determinants of poverty are inflation, unemployment, exchange rate volatility, poor infrastructure of health and education, political instability, and poor quality of human capital. In addition, covariate shocks such as floods, climatic changes, and vulnerability to key economic factors are estimated as significant determinants of poverty in Pakistan (i.e. Arshed, et al. 2017; Pervaiz and Rizvi, 2013; Yousaf and Ali, 2014; Hashmi, et al. 2008; Jan, et al. 2008; Anwar and Qureshi, 2002; Amjad and Kemal, 1997).

Arif (2015) has assessed Pakistan's poverty profile. The two definitions of poverty used are multidimensional poverty and PMT score by using NSER. Results indicate that districts of FATA and Baluchistan have a high poverty rate. Begum (2015) has simulated district level poverty by combining both HIES and PSLM survey datasets for the year 2010-11. Estimated magnitude of district level poverty are observed to be quite a bit less than assessed by Arif (2015), however, ranking of poverty remains the same. Similarly, Cheema (2010) also calculated district level poverty in Punjab by using SAE approach. Findings suggest that districts of South Punjab are poorer than the districts of central Punjab.

The literature review above highlights that those studies regarding Pakistan (e.g. Arshed, et al. 2017; Pervaiz and Rizvi, 2013; Yousaf and Ali, 2014; Jan, et al. 2008; Akram, et al. 2008; Aftab, et al. 2002) have missed tackling spatial variation and dependence across regions which may provide biased and inefficient parameters. This study attempts to overcome the deficiencies of previous studies regarding determinants of poverty in Pakistan.

3. DATA SOURCE, VARIABLES AND DESCRIPTIVE STATISTICS

3.1. Data Sources

Data of 148 districts of Pakistan including FATA, Gilgit-Baltistan (GB), and Azad Kashmir (AJK), are compiled from multiple data sources such as the National Socioeconomic Registry (NSER)[2], and development statistics of respective provinces (2010-11). In addition, data on the share of urban population are collected from Arif (2015). District level poverty estimates are calculated by combining NSER and HIES household datasets. NSER provides us with an opportunity to compute district level predicted estimates of poverty for 2010-11 through the application of SAE. In brief, the present study is based on cross-sectional data, because we do not have panel data of district level consumption-based poverty in Pakistan. Finally, spatial information for all districts is generated by using shape files.

[2]NSER is a census type household data, collected by BISP during 2010-11 to identify beneficiaries of a program on the basis of PMT score. It covers over 27 million households that constitutes more than 150 million people across the country. Provincial coverage shows that 14.88 million households of Punjab, 6.6 million from Sindh, 3.6 million of KP and 1.1 million of Baluchistan were surveyed. NSER also covers around 0.588 million household of AJK, and 0.15 million household of Gilgit-Baltistan, and 0.40 million are covered from FATA.

3.2. Methodological Framework

3.2.1. *Conceptual Framework*

In order to estimate unbiased and efficient parameters, a growing body of literature has suggested the application of spatial regression (i.e. Anselin, 1988; Bailey and Gatrell, 1995; Weiss, 1996; Kim, et al. 2002; Farrow, et al. 2005). These studies argue that Ordinary Least Squares (OLS) estimator violates BLUE property owing to the presence of spatial dependence in the model. This means that when a value is estimated for one location, it may depend on the neighbouring location as well. There are three main sources of spatial dependence, which are: spatial autocorrelation of error terms, lag of outcome variable, and effects of covariates. Spatial dependence, which occurs due to spatial error terms, suggests that error terms of neighbouring locations are auto-correlated. Lag of dependent occurs when the outcome variable of one region is affected by the lag of outcome variable of neighbouring locations. Spatial lags are quite different from time series analysis. Nonetheless, in spatial analysis, lags indicate adjacent location. These lags are specified by creating a spatial weighting matrices scheme. Similarly, covariates of one location have significant impacts on outcome variable of adjacent locations (e.g. Anselin, 1999; Higazi, et al. 2013).

Another benefit of spatial analysis is the decomposing of total spatial effect into direct and indirect effect. Direct effect establishes influence of one variable on the outcome variable of the same location. Likewise, indirect impact indicates that spillover effects of one variable determines outcome variable of neighbouring location. Incorporating spatial considerations provide significant variations in the model which validates reliability of estimated findings (i.e. Owada, et al. 2019; Tong and Kim, 2019; Maalsen, 2019; Okwi, et al. 2007).

3.2.2. *Econometric Specification of Spatial Autoregressive Model (SAR)*

The previous section identifies three sources, which determine spatial dependence. In order to capture it, three specifications of SAR are required: spatial lag model, spatial error model, combination of both models along with lag of covariates [i.e. Liu (2017); Drukker *et al* (2013); Haining *et al.* (2000)]. These models are specified as follows.
We start with the linear regression model. After that, spatial regression specifications will be introduced in the original linear model.

$$Y = \beta X + \in \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (1)$$

In Equation (1), Y is outcome variable, X represents vector of independent variables, β is also vector of parameters, and whereas $\in$ error terms of respective district.

District level poverty, in this paper, is set as the outcome variable. Explanatory variables include average family size, dependency ratio, female ratio, the different age groups of family members, and asset ownerships by households in respective districts. Moreover, district level educational variables, infrastructure (roads, health and educational institutions), and urbanisation, climatic (temperature and rainfall), regional dummies.

Adding spatial lag of outcome variable in above equation makes it the spatial lag of outcome variable. Specification of SAR lag model is given as follows.

$$Y = \beta X + \lambda Wy + \in \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (2)$$

Equation (2) has the additional term, λWy which stands for lag of dependent variable. Here, W is weighting matrix. Weighting scheme is generated based on distance between locations. Λ is the spatial estimated value lag coefficient. Similarly, spatial error lag model gets the following specification.

$$Y = \beta X + \lambda Wy + (1 - \rho)^{-1} \in \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \qquad (3)$$

In the above equation, ρ is coefficient of spatial autocorrelation in the spatial error model. Equation (3) comprises both specification SAR outcome lag and error lag model jointly. Finally, the third specification of SAR captures spatial dependence by allowing lag of covariates to be correlated with outcome variable of neighbouring districts.

$$Y = \beta X + \beta WX + \lambda Wy + (1 - \rho W)^{-1} \in \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \qquad (4)$$

Term, βWX is added in above model, which captures allowing lag of explanatory variable to be correlated with dependent variable of adjacent locations. Above specified models are estimated by employing Maximum Likelihood (ML) approach (Haining, et al. 2000).

3.3. Variables Construction

District Level Poverty: consumption based poverty is calculated by applying official poverty line, PKR 3030 per adult equivalent monthly consumption for Pakistan. District level poverty head count ratio (%) is simulated through Small Area Estimation (SAE) approach because one-dimensional poverty estimates for 148 districts of Pakistan are not available due to lack of data on district level household consumption.

SAE simulates monthly per adult equivalent consumption by combining both HIES and NSER. A large amount of literature suggests application of SAE to map poverty estimates at smaller administrative units of developing countries owing to unavailability of household consumption data (e.g. Elbers, et al. 2002; Minot and Baulch, 2002a; World Bank, 2000; Alderman, et al. 2002; Henninger and Snel, 2002).

SAE comprises two stages. First stage is to use HIES dataset to estimate monthly per adult equivalent consumption. The specified model is given as follows.

$$logy_{ch} = X_{ch}\beta + U_{ch} \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \qquad (5)$$

Where, log y_{ch} is log of monthly expenditures per adult equivalent, X_{ch} is vector of explanatory variables, which are common variables in both household surveys HIES and NSER. For example, family size, age of the head of family, gender of the family head, dependency ratio and household asset related. And β stands for vector of estimated coefficients, and u_{ch} is error term. Error term comprises two effects i.e. cluster effect and household effect. From equation (5), unbiased and efficient parameters are estimated.

The second stage of the SAE is to impute the parameters estimated from the first stage with NSER. It simulates monthly household consumption. From simulated per adult equivalent consumption, poverty head counts for all districts are calculated including districts of AJK, GB, and FATA.

District Level Family Demographic Profile: From NSER, district level average of family size, female to male ratio, and dependency ratio are generated.

Total number of females are divided by the total number of male members in a family. Based on household information, district level average of ratio is computed. If the ratio is found equal to 1, then the number of male and female members in a family is equal. Likewise, a ratio above 1 indicates that households have more females than males.

The dependency ratio is constructed by taking the ratio of non-working age groups to working age groups. The higher value of ratio suggests a higher age dependency ratio. Finally, age composition is also measured by categorising it into different age groups[3] of population.

District Level Education Groups: household education is categorised into illiterate, primary, middle, matriculation, intermediate, and above intermediate education. Unit and percentage measure these categories. Illiterate households (%) are specified as reference group.

District Level Employment: three variables related to employment are constructed from NSER such as percentage of population having government job, percentage of population engaged with private jobs, and percentage of pension receiving household members.

District Level Household Asset Ownership: district level household asset ownership is categorised into durable assets, capital assets, and livestock ownership.

District Level Infrastructure: the study employs district level road, health, and education infrastructure related variables. These variables are comprised of per kilometres road length, availability of basic health centres, and total number of schools at district level.

District Level Urbanisation: district level urbanisation is measured by taking a percentage of urban population to total population.

Climatic Variables and Regional Dummies: Ten-year averages of monthly temperature and rainfall for districts are measured. Similarly, square terms of both temperature and precipitation are also used to identify non-linear impacts of climatic variables. Provincial and agro-climatic zone binary variables are constructed to control regional effects. Agro-climatic zones are generated according to studies by Arif (2015) & Ahmed *et al.* (2015).

For a quick view, a description of abovementioned variables is given in Table 1.

Table 1

Definitions of District Level Variables

Variables	Description of Variables
District Level Poverty	District level poverty (%) is predicted by using SAE approach
Family Size	Average Family size of HHs at district level
Female to Male Ratio	% of ratio of females to male members
Dependency Ratio	Ratio of non-working to working age groups
Primary Education	Percentage of individuals having primary education
Middle Education	Percentage of individuals having middle education
Metric Education	Percentage of individuals having metric education
Intermediate	Percentage of individuals having intermediate education
Above Intermediate	Percentage of individuals having above intermediate
Govt Job	Percentage of HHs who have Govt. job
Private Job	Percentage of HHs who have private job
Pension	Percentage of HHs who receive pension amount
Durable assets	Percentage of HHs owning TV, AC, Air cooler, etc.
Capital assets,	Percentage of HHs owning tractor, car, scooter, etc.
Livestock	Percentage of HHs owning livestock
Health Units	Availability of basic health centres per person
Schools	Primary, middle and secondary schools per person
Urbanisation	Percentage share of the urban population
Temperature	District level 20 years average of temperature
Rainfall	District level 20 years average of rainfall
Population Growth	Population growth rate of each district
Roads Lengths	Total road length (km) in respective districts

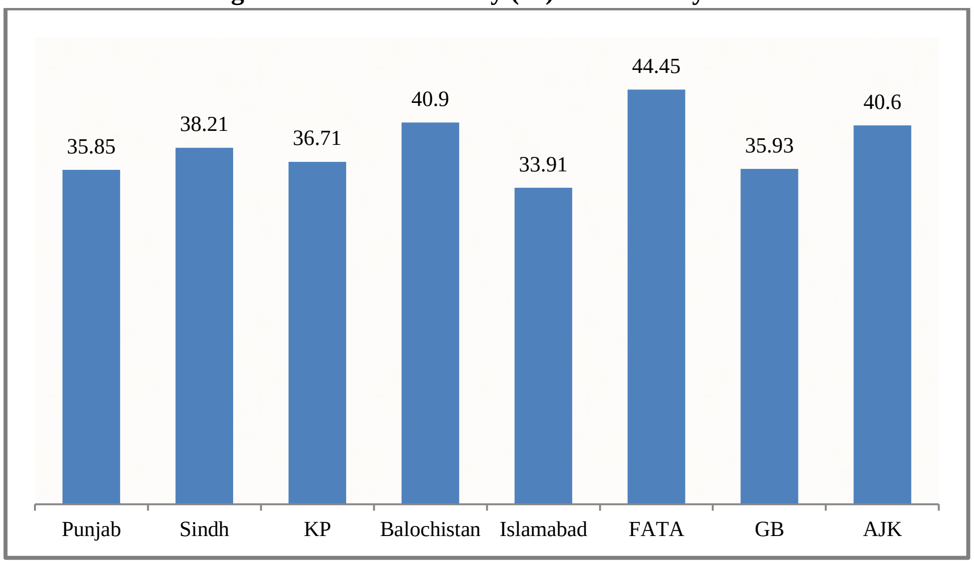
[3] Six groups of district level percentage of population are generated such as below 5 years, between 6 to 15 years, 16-25 years, 26 to 35 years, 36 to 50 years, and above 50 years old.

4. RESULTS AND DISCUSSION

4.1. Analysis of Predicted Poverty

Figure 1 compares simulated poverty estimates across provinces. Provincial comparison employs the official poverty line, PKR 3030 per adult equivalent monthly consumption. Predicted poverty estimates demonstrate that Punjab appears to be the province with the lowest poverty levels (35.85 percent). Sindh (38.21 percent), KPK (36.71 percent), and Balochistan (40.9 percent) are relatively poorer provinces while Islamabad has 33.91 percent poor households. Furthermore, simulated poverty estimates for other regions of Pakistan show that FATA (44 percent) AJK (40.6 percent) and Gilgit-Baltistan (35.93 percent) are respectively much poorer. In conclusion, FATA and Baluchistan are the poorest regions amongst the provinces. This paper does not capture rural and urban differences because NSER dataset does not identify rural and urban households (see Table 1).

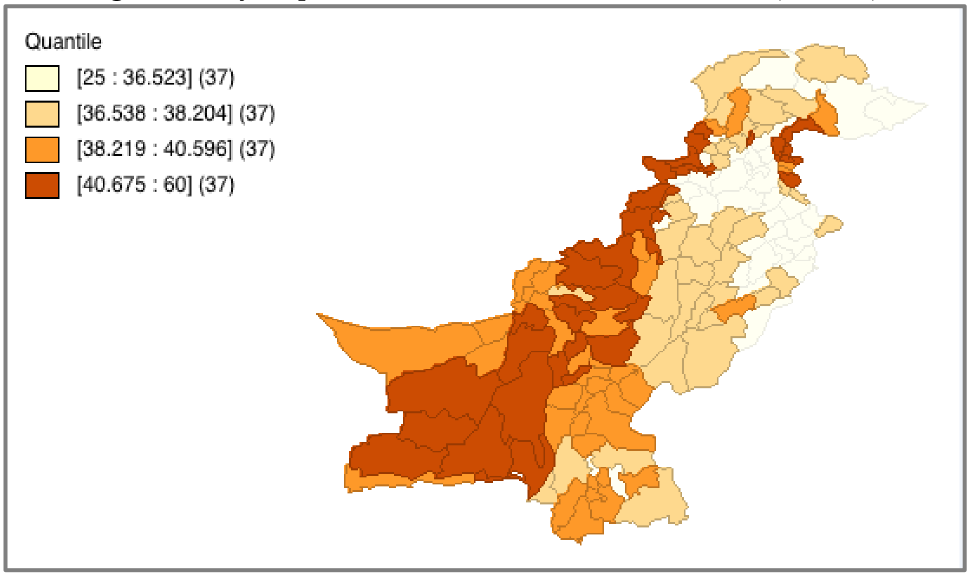
Fig. 1. Provincial Poverty (%) Predicted by SAE



Source: Authors' own calculation.
Poverty line: PKR 3030 per adult equivalent monthly consumption.

Figure 2 depicts district level poverty maps, which illustrate that the poorest districts lie in quintile-IV across all provinces. Most of the districts of Baluchistan are located in said quintile. These districts of Baluchistan include Barkhan, JhalMagsi, Harani, Lasbela, Awaran and Dera Bugti. Likewise, Sukhar, Mitiari, Umerkot are the poorest districts of Sindh while Lower Dir, Swat, and Bannu districts of KPK are at the same level of poverty. As far as districts of Punjab are concerned, Rahim Yar Khan, Dera Ghazi Khan, Rajan Pur and Vehari are seen to be the poorest districts of Punjab. Finally, district level analysis also reveals Baluchistan and Sindh are much poorer as compared to Punjab. The least poverty stricken districts are Lahore, Sialkot, and Rawalpindi, which can be seen in quintile-I.

Fig. 2. Poverty Map of 148 Districts of Pakistan from NSER (2010-11)



Source: Author's own Mapping.

5. RESULTS ESTIMATED FROM SPATIAL AUTOREGRESSIVE (SAR) MODEL

5.1. Diagnostic Test for Spatial Dependence

To diagnose spatial dependence, Moran I test has been applied.[4] Three specifications of Moran 1 test are used by creating weighting matrices: contiguity weighting matrix, distance weighting matrix, and a combination of both contiguity and distance matrix.

Findings demonstrate the presence of spatial dependence which means application of OLS estimator would give biased and inefficient parameters (see Table 2). The statistical significance of Moran I test implies justification of using SAR model owing to presence of spatial dependence. Similarly, estimations of SAR also suggests that an error term of one district is also found to have a significant correlation with nearby districts which highlights that spatial autorotation is significantly measured in models (see Table 4).

Table 2

Estimated Results of Moran I Test

Test Name	Chi^2 Statistic	p-value	Conclusion
Moran I Test: Contiguity Weight Matrix	4.25	0.039	Spatial Dependence
Moran I Test: Distance Weight Matrix	2.83	0.076	Spatial Dependence
Moran I Test: Both Contiguity & Distance	4.42	0.096	Spatial Dependence

Note: Null hypotheses in Moran I and Wald tests are no presence of spatial dependence.

[4]Moran I test is a post estimation test. To apply it, we have to estimate model through OLS. This test hypothesises whether spatial dependence exists or not. In this regard, Null Hypothesis is no spatial dependence against Alternative Hypothesis: spatial dependence exists.

5.2. Discussion on Spatial Determinants of Poverty in Pakistan: Direct Effects

This section discusses factors that have direct impact on district level poverty. Three specifications of SAR model are employed: Model-1, Model-2 and Model-3.[5] Primarily the whole discussion is based on Model-1, because it contains outcome and error lag effects as well. Nonetheless, results estimated from the other two specifications are also reported for comparison with Model-1 (see Table 3). Estimated results suggest that by and large, the findings of aforesaid specifications look similar as per sign and statistical significance of variables.

Direct effects of determinants of district level poverty are estimated by using OLS as well but a significant presence of spatial dependence in the model hinders us from continuing to apply OLS because it would provide inefficient parameters. Appendix-A encompasses estimated previously mentioned model. We will detail those findings. However, when results of OLS are compared with SAR, they seem quite different in terms of sign and statistical significance. This study only discusses direct effects of determinants of poverty estimated by SAR in this section.

Estimated factors, which have direct impact on district level poverty, indicate average family size has been found positive and highly significant. A positive impact implies that an increase in average family size would increase poverty in a particular district, other things remaining the same. Similarly, female to male ratio also shows a significant direct impact on district level poverty, whereas dependency ratio has no direct significant effects (see Table 3).

The study categorises age of households into five groups to show the impact of each age group separately while below 15 years age group has been kept as a reference category. Estimated results indicate that age composition has significant and direct impacts on district level poverty. Four variables of district level age groups (16-25, 26-35, 36-50, and above 50 years) show negative impacts on poverty. The negative sign of these variables means that with the increase of population of abovementioned age groups, compared to below 15-year age group, poverty will decrease, other things remaining the same.

Estimated results of district level educational variables show a mixed impact on poverty. Metric and Intermediate levels of education show significant influences whereas middle and above metric level education do not show any statistically significant impact. Likewise, primary level of education does not demonstrate any significant effects on district level poverty. These results are consistent with the previous studies (Amarasinghe, et al. 2005).

District level employment suggests that government jobs have statistically significant impacts on poverty while private employment and pension indicate insignificant effects. The negative sign implies a significant role of government jobs in reducing district level poverty.

[5]Three specifications are: (1) **Model-1** allows outcome variable to be associated with covariates of neighboring districts and other two specification as well. (2) **Model-2** is estimated by allowing only outcome variable to be correlated with poverty of adjacent districts, and (3) **Model-3** allows the outcome variable to be correlated with the error of nearby districts along with outcome variable itself.

The study includes three types of assets in the model: capital, household durable, and livestock.[6] In Model-1, household assets have no significant influence on poverty. However, capital and durable assets demonstrate significant impacts in Model-2 and Model-3.

Urbanisation has direct and significant effects on determining district level poverty. Similarly, the population growth rate of the sampled district shows significant impacts as well.

Further findings demonstrate that road length, which indicates road infrastructure and regional connectivity, is found highly significant with negative sign. It implies that road infrastructure has beneficial impacts on determining district level poverty.

Unlike road infrastructure, provision of health and education facilities has insignificant influences on district level poverty. These insignificant effects of education and health infrastructure may imply that most of the districts in Pakistan lack well-established education and health infrastructure. One of the reasons for the insignificant effects of infrastructure may be due to the 148 sampled districts of FATA, AJK, and Gilgit Baltistan (GB). Inclusion of districts of these regions may bring about insignificant impacts of health and education infrastructure.

The study also attempts to show the direct influence of climate variables on district level poverty. In this respect, the SAR model provides statistically significant impacts of climatic norms such as average temperature and precipitation. Empirical findings exhibit significant non-linear effects of 20-year averages of monthly temperature and rainfall. Square terms of both temperature and rainfall suggest non-linear impacts while linear terms portray linear effects. Temperature has no linear effect whereas average rainfall indicates a significant impact, which means significant linear effects of average rainfall on poverty. In addition, the interactive term of both temperature and rainfall is also introduced to see their joint impact. The interactive term also provides the direct significance on district level poverty. Summing up the total impact of climate variables, one sees that extreme events of weather reflect climate change, which is threatening the wellbeing of households as well.

Finally, dummy variables of provinces and agro-climate zones are introduced in the models to control their impacts. Results obtained from SAR demonstrate that cotton and wheat growing areas, and arid Punjab zones have significant impacts. Additionally, provincial dummies of KPK and Baluchistan are also estimated as statistically significant. These findings conclude that provincial and agro-climate zones are showing their impacts (see Table 3).

It is important to mention that the problem of endogeneity is not supported by literature and diagnostic test. Literature regarding spatial determinants of poverty does not indicate which variable is causing the above problem. Moreover, we apply Hausman-Wu test[7] to diagnose whether explanatory variables correlate with error terms or not. Results of diagnostic test suggest that the problem of endogeneity does not exist in the model (see Appendix-B).

[6]Capital assets comprise the percentage of households in district which possess car, tractor, motorcycle, and threshers etc. and, livestock assets consists of percentage of households in district which own small and large animal species while household durable assets comprise tv, fridge, freezer, and air cooler etc.

[7]To apply Hausman-Wu test, we apply OLS to estimate determinants and computed residual of model. Estimated residual is used as independent variable in original model. This model is again estimated and if this additional variable is not found statistically significant, then there is no problem of endogenity, vice versa. See Appendix B where "y11" is not significant.

Table 3

Spatial Determinants of District Level Poverty: Direct Effects from SAR Models

	Model-1		Model-2		Model-3	
Variables	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Family Size	0.762***	0.267	0.929***	0.250	0.782***	0.265
Female Ratio	–1.832***	0.534	–1.789***	0.560	–1.695***	0.583
Depend Ratio	–0.094	0.221	–0.1429	0.232	–0.194	0.233
Age 16–25 years	–0.042	0.037	–0.053	0.037	–0.085**	0.039
Age 26–35 years	–0.122*	0.066	–0.107*	0.065	–0.069	0.071
Age 36–50 years	–0.090	0.070	–0.059	0.067	0.012	0.074
Age >50 years	–0.113**	0.055	–0.124**	0.054	–0.121*	0.064
Primary Education	0.065*	0.038	0.063*	0.038	0.061*	0.035
Middle Education	–0.048	0.050	–0.042	0.051	–0.021	0.046
Metric Education	0.165***	0.051	0.153***	0.052	0.143***	0.044
Inter Education	–0.151***	0.036	–0.142***	0.036	–0.172***	0.035
Above Inter (>12)	–0.026	0.046	–0.0327	0.050	–0.024	0.048
Government Job	–0.103**	0.049	–0.096*	0.051	–0.100**	0.049
Private Job	0.019	0.027	0.010	0.026	–0.006	0.026
Pension HH	0.019	0.018	0.020	0.017	0.024	0.017
Livestock Asset	–0.007	0.015	–0.004	0.015	–0.009	0.015
Capital Asset	–0.062	0.049	–0.086*	0.050	–0.077	0.050
HH Assets	–0.010	0.007	–0.008	0.008	–0.014*	0.008
Rooms availability	–6.095**	3.029	–5.562**	3.011	–7.649***	2.665
Road Length	–0.001***	0.0001	–0.001***	0.0001	–0.009***	0.0002
Health Institution	4.06412	39.87	5.154.8	39.89	2.14493	40.26
Number of Schools	–4.5782	18.57	–11.884	18.40	–41.869	19.54
Urbanisation	–0.028*	0.017	–0.026	0.017	–0.0169	0.017
Population Growth Rate	–0.348**	0.147	–0.315**	0.151	–0.34**	0.171
Average Temperature	–0.081	0.163	–0.058	0.162	–0.173	0.166
Temperature square	0.002	0.004	0.002	0.004	0.003	0.004
Average Rainfall	–0.003***	0.001	–0.003***	0.001	–0.004***	0.001
Rainfall square	3.9E-07*	2.0E-07	3.95E-07*	0.000	3.44E-07	0.000
Interaction Temp*Rainfall	8.1E-05	0.000	8.5E-05*	0.000	0.0002**	0.000
Rice-wheat Zone	0.345	0.783	0.357	0.771	–0.541	0.712
Cotton-wheat Zone	1.533*	0.834	1.640*	0.842	0.595	0.730
Arid Punjab	2.093**	1.050	2.037*	1.058	0.229	1.103
KP	–3.252***	0.545	–3.112***	0.537	–2.537***	0.578
Baluchistan	1.842**	0.881	1.893**	0.899	2.228***	0.658
Constant	50.327***	5.024	48.846***	4.925	53.087***	4.536
			Models Specification Test			
Chi^2 Statistic	186.27***		170.16***		154.76***	

Significance level *** p<0.01, ** p<0.05, * p<0.1.

5.3. Factors That Have Spillover Effect on Poverty of Neighbouring Districts

This section discusses the spillover effect of covariates, which are estimated by SAR models. Liu (2017) has suggested that SAR also decomposes total effect into direct and indirect effect. This study has discussed direct effects in the previous section, whereas spillover effects of determinants of district poverty are given in Table 4.

Table 4

Factors that have Spillover Effects on Poverty of Neighbouring Districts

	Variables	Coefficients	S.E	Z-stat.
Spatial Errors	Spatial Autocorrelation	–1.059***	0.246	–4.29
	Spatial Factors Having Spillover Effect on Poverty			
Outcome Variable	Outcome Variable (Poverty)	0.095*	0.051	1.88
Spatial Covariates	Rice-wheat zones	–3.339**	1.429	–2.34
	Cotton-wheat zones	–3.588**	1.414	–2.54
	Primary Education	0.234**	0.098	2.37
	Secondary Education	–0.264***	0.086	–3.05
	Private Sector Employment	–0.044*	0.024	–1.83
	HH Capital Asset	–0.233**	0.108	–2.15
	HH Animal Asset	–0.215*	0.129	–1.66
	Road Lengths	–0.002***	0.0004	–3.85
	Average Temperature	0.267***	0.085	3.13
	Average Rainfall	–0.002*	0.0009	–1.79

Significance level; *** p<0.01, ** p<0.05, * p<0.1.

Estimated findings show that the poverty levels of one district significantly affects the poverty levels in its adjacent districts. The coefficient of the outcome variable is positive which implies that the increase in poverty of one district may cause an increase in poverty of neighbouring districts.

Further findings reveal that primary and secondary levels of education cause significant spillover effects on the poverty levels of neighbouring districts. The sign of primary education is estimated as positive whereas secondary level of education contains negative signs. Overall impacts of education imply that higher levels of education in one district would cause reduction in poverty of its neighbouring districts, and vice versa.

District level employment in the private sector indicates a statistically significant spillover influence on poverty levels of the adjacent district. The result posits that any district where most people are working in the private sector may have significant effects on the poverty of its nearby districts. Private employment is an indicator of business and entrepreneurial activities, which generate employment opportunities. It provides employment to people of neighbouring districts. Ultimately, it is conducive to reducing poverty in neighbouring districts as well. Similarly, livestock and capital assets release beneficial spillover effects. Findings are significant with negative sign of both asset variables. It implies that asset ownership overall in one district, will be helpful in reducing poverty in adjacent districts (see Table 4).

Likewise, assets such as road length also reveal significant indirect impacts on poverty levels of neighbouring districts. Road length determines the regional integration through road connectivity and has a profound impact on regional wellbeing. For Pakistan, this result may have significant implications in the context of China Pakistan Economic Corridor (CPEC).

Climatic norms (temperature and rainfall) also extract spillover effects on bordering districts. The previous section makes it clear that climate changes have adverse impacts on district level poverty. Here, average temperatures in particular contain an adverse spillover effect on determining the outcome of adjacent districts. Finally, controlling agro-climate zones have significant influences on neighbouring locations (see Table 4).

6. CONCLUSION AND POLICY IMPLICATIONS

The primary objective is to explore spatial determinants, which have direct and spillover effects on poverty levels of 148 districts. Simulated poverty estimates indicate that districts of FATA and Baluchistan are the poorest whereas Punjab has the lowest levels of poverty as compared to other provinces. The application of Moran I test validates the presence of spatial dependence in the model, which means OLS would yield biased and inefficient estimates. Therefore, Spatial Autoregressive (SAR) model is employed to tackle spatial dependence.

Estimated findings reveal that determinants of district level poverty such as urbanisation, population growth rate, and road length, tertiary education, government job, and average family size, show significant and direct effects. Similarly, climatic factors such as average temperature and rainfall also indicate significant direct impacts on district level poverty.

Furthermore, the study explores those factors that have spillover effects on poverty levels of neighbouring districts. These factors include poverty itself, employment, education, road length, and climatic norms such as temperature and rainfall as the determinants that demonstrate indirect or spillover effects on poverty levels of neighbouring districts.

The key implications of these findings demonstrate that building a road infrastructure in one district would reduce poverty in neighbouring districts because road length is an indicator of connectivity among districts. Similarly, literacy rate and generating private employment opportunities indicate spillover effect on adjacent districts. These stylised implications can provide new insights to government to combat regional poverty in Pakistan

This study offers three main recommendations. Firstly, health and education infrastructures need to be enhanced on a priority basis in all underdeveloped districts. Secondly, regional connectivity needs to be extended from developed to the deprived districts. Thirdly, private employment opportunities should be promoted through establishing industry in districts, which would generate employment prospects for people of the closest districts.

APPENDIX: A

poverty_district	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Family Size	–0.0367	0.02841	–1.29	0.199	–0.09297	0.019567
Female Ratio	–1.02957	0.599946	–1.72	0.089	–2.21784	0.1587
Depend Ratio	–0.12343	0.255386	–0.48	0.63	–0.62925	0.382394
Age 16–25 years	–0.03349	0.037242	–0.9	0.37	–0.10726	0.04027
Age 26–35 years	–0.01264	0.059791	–0.21	0.833	–0.13106	0.105781
Age 36–50 years	0.049855	0.079191	0.63	0.53	–0.10699	0.206703
Age >50 years	–0.08865	0.064505	–1.37	0.172	–0.21641	0.039107
Primary Education	0.066283	0.040697	1.63	0.106	–0.01432	0.146889
Middle Education	–0.05638	0.052433	–1.08	0.284	–0.16023	0.047471
Metric Education	0.193879	0.054978	3.53	0.001	0.084989	0.302769
Inter Education	–0.17064	0.038674	–4.41	0	–0.24724	–0.09404
Above Inter (>12)	0.000464	0.051923	0.01	0.993	–0.10238	0.103303
Government Job	–0.17627	0.05381	–3.28	0.001	–0.28285	–0.0697
Private Job	–0.02057	0.020942	–0.98	0.328	–0.06205	0.020908
Pension HH	–0.03829	0.011279	–3.4	0.001	–0.06063	–0.01595
Livestock Asset	0.001962	0.017368	0.11	0.91	–0.03244	0.036361
Capital Asset	–0.03692	0.051485	–0.72	0.475	–0.1389	0.06505
HH Assets	–0.01955	0.00898	–2.18	0.032	–0.03733	–0.00176
Rooms availability	–5.9529	2.730453	–2.18	0.031	–11.3609	–0.5449
Road Length	–0.00096	0.000305	–3.15	0.002	–0.00156	–0.00036
Health Institution	0.00395	0.011869	0.33	0.74	–0.01956	0.027459
Number of Schools	–0.0039	0.005424	–0.72	0.474	–0.01464	0.006847
Urbanisation	–0.00351	0.018583	–0.19	0.851	–0.04031	0.0333
Population Growth Rate	–0.45219	0.190109	–2.38	0.019	–0.82873	–0.07566
Average Temperature	0.047895	0.040158	1.19	0.235	–0.03164	0.127432
Average Rainfall	–0.00059	0.00037	–1.59	0.114	–0.00132	0.000144
Rice-wheat Zone	–1.44578	0.728785	–1.98	0.05	–2.88923	–0.00233
Cotton-wheat Zone	–0.36006	0.652018	–0.55	0.582	–1.65147	0.931342
Arid Punjab	1.311883	1.286285	1.02	0.31	–1.23577	3.859532
KP	–2.27252	0.767758	–2.96	0.004	–3.79316	–0.75187
Baluchistan	2.156895	0.697	3.09	0.002	0.776399	3.537391
Constant	53.72838	3.843929	13.98	0	46.115	61.34176

Appendix: B

poverty_district	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Family Size	–0.0367	0.028534	–1.29	0.201	–0.09322	0.019816
Female Ratio	–1.02957	0.602549	–1.71	0.09	–2.2231	0.163964
Depend Ratio	–0.12343	0.256494	–0.48	0.631	–0.63149	0.384635
Age 16–25 years	–0.03349	0.037403	–0.9	0.372	–0.10758	0.040596
Age 26–35 years	–0.01264	0.06005	–0.21	0.834	–0.13159	0.106305
Age 36–50 years	0.049855	0.079534	0.63	0.532	–0.10769	0.207397
Age >50 years	–0.08865	0.064784	–1.37	0.174	–0.21698	0.039673
Primary Education	0.066283	0.040874	1.62	0.108	–0.01468	0.147246
Middle Education	–0.05638	0.052661	–1.07	0.287	–0.16069	0.047931
Metric Education	0.193879	0.055216	3.51	0.001	0.084507	0.303251
Inter Education	–0.17064	0.038842	–4.39	0	–0.24758	–0.0937
Above Inter (>12)	0.000464	0.052148	0.01	0.993	–0.10283	0.103759
Government Job	–0.17627	0.054044	–3.26	0.001	–0.28332	–0.06922
Private Job	–0.02057	0.021032	–0.98	0.33	–0.06223	0.021092
Pension HH	–0.03829	0.011328	–3.38	0.001	–0.06073	–0.01585
Livestock Asset	0.001962	0.017443	0.11	0.911	–0.03259	0.036513
Capital Asset	–0.03692	0.051708	–0.71	0.477	–0.13935	0.065501
HH Assets	–0.01955	0.009019	–2.17	0.032	–0.03741	–0.00168
Rooms availability	–5.9529	2.742299	–2.17	0.032	–11.3849	–0.52094
Road Length	–0.00096	0.000307	–3.13	0.002	–0.00157	–0.00035
Health Institution	0.00395	0.011921	0.33	0.741	–0.01966	0.027563
Number of Schools	–0.0039	0.005448	–0.72	0.476	–0.01469	0.006895
Urbanisation	–0.00351	0.018664	–0.19	0.851	–0.04048	0.033463
Population Growth Rate	–0.45219	0.190934	–2.37	0.02	–0.83039	–0.07399
Average Temperature	0.047895	0.040332	1.19	0.237	–0.03199	0.127785
Average Rainfall	–0.00059	0.000371	–1.58	0.116	–0.00132	0.000147
Rice-wheat Zone	–1.44578	0.731947	–1.98	0.051	–2.89563	0.004062
Cotton-wheat Zone	–0.36006	0.654847	–0.55	0.583	–1.65719	0.937064
Arid Punjab	1.311883	1.291865	1.02	0.312	–1.24705	3.87082
KP	–2.27252	0.771089	–2.95	0.004	–3.79989	–0.74514
Baluchistan	2.156895	0.700024	3.08	0.003	0.770283	3.543507
YY	1.978806	4476779	0	1	–8867637	8867641
Constant	53.72838	3.860605	13.92	0	46.08126	61.3755

APPENDIX: C

Variables	Obs	Mean	Std. Dev.	Min	Max
Family Size	148	5.96516	1.173162	4.112527	11.322
Female Ratio	148	0.799016	0.470479	0.278743	4.322
Depend Ratio	148	6.349761	1.680483	2.5433	12.432
Age 16–25 years	148	52.18351	12.34364	5.120372	74.45319
Age 26–35 years	148	37.68074	9.662385	3.913012	58.32
Age 36–50 years	148	14.9922	6.77094	1.403738	40.47619
Age >50 years	148	11.36353	5.743753	1.168831	30.49155
Primary Education	148	33.19765	18.25089	0	69.92481
Middle Education	148	32.14418	18.44558	0	75
Metric Education	148	20.44654	14.39391	0	56.37681
Inter Education	148	20.91282	14.76894	0	100
Above Inter (>12)	148	12.31326	8.310088	0	38.24405
Government Job	148	8.553131	6.420144	0.6784	34.332
Private Job	148	90.36203	16.34173	9	100
Pension HH	148	3.438996	5.9697	0	50
Livestock Asset	148	42.43405	17.99705	0.709322	87.89626
Capital Asset	148	6.86838	5.466271	0.400534	29.36321
HH Assets	148	53.13047	30.43479	2.333	99.48795
Rooms availability	148	0.343845	0.111964	0.024717	0.984332
Road Length	148	966.6302	958.5573	0	4132.83
Health Institution	148	32.95946	23.9361	3	126
Number of Schools	148	958.1757	882.0678	19	4151
Urbanisation	148	18.79284	14.91972	1.7	100
Population Growth Rate	148	2.307961	1.322583	–4.81	7.38
Average Temperature	148	21.52148	6.902419	–0.03905	33.3457
Average Rainfall	148	620.0881	711.7694	92.245	4876.245
Interaction Temp*Rainfall	148	10812.3	11344.17	–20.371	100695.9
Rice-wheat Zone	148	0.114865	0.319942	0	1
Cotton-wheat Zone	148	0.128378	0.335647	0	1
Arid Punjab	148	0.033784	0.181286	0	1

APPENDIX: D

"STATA do-file for poverty estimation at district level using SAE

cd "C:\Users\kifayat\Desktop\kifayat\files\"

use sheet.dta //file including all covariates and log of adult equivalent consumption expenditure svyset psu [pweight = weight], strata(prov) // declaring survey data forval i=1/4 {

svy: reg y x if prov ==`i'

mat beta`i' = e(b)

predict e`i', residual // predicting residuals for each prov to standard error calculation replace e`i' = (e`i')^2}

gen se`i'=r(sum)}

replace se1=se1/6915 //the number of obs for punjab is adjusted for degree of freedoms.

replace se`i'=(se`i')^0.5

gen lpren`i' = beta`i'a*X if prov==`i' replace lpren`i' = 0 if lpren`i'==.

replace lpreg = lpreg + lpren`i'}

gen probabilities=normal(z) //estimating of probabilities using cumulative normal distribution mean probabilities, over(district) //calculation of poverty as average of probabilities over each district."

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