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District-level multidimensional poverty and human development in the case of Pakistan: does institutional quality matter?

Kifayat Ullah · Muhammad Tariq Majeed

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Abstract This study explores the effect of institutional quality on district-level multidimensional poverty and human development by using the spatial autoregressive approach. The spatial autoregressive model also decomposes the direct and indirect effects of institutional quality on district-level multidimensional poverty and human development. Regarding multidimensional poverty, outcomes suggest that institutional quality, tertiary education, road length, and district level demographic factors have both direct and indirect impacts on district-level multidimensional poverty. Similarly, human development outcomes suggest that institutional quality, road length, health institutions, school infrastructure, urbanization, and population density are significant spatial factors to show both the direct and indirect impacts on district levels. These findings also imply that the spillover effects of institutional quality have a significant role in determining the wellbeing of neighboring districts as well. Although improvements in governance, rule of law, and political participation appear to decrease district-level multidimensional poverty and increase human development. A policy implication of the study may prove an innovative delivery strategy to achieve the target of sustainable development goal-1 (SDG-1) for Pakistan.

Keywords Institution quality · Multidimensional poverty · Human development · Pakistan

K. Ullah · M. T. Majeed (✉)
School of Economics, Quaid-i-Azam University, Islamabad, Pakistan
e-mail: m.tariq.majeed@gmail.com; tariq@qau.edu.pk

K. Ullah
e-mail: kifayat@eco.qau.edu.pk

Introduction

Differences in social capital, human capital, financial capital, and natural resources have generally occupied a central role in explaining poverty and human development. Lately, institutional quality and its effect on the economy have become important debates in the development of economics literature. Therefore, several studies have shown that the quality of institutions has played an important role in poverty reduction (Kakwani & Pernia, 2000; Perera & Lee, 2013; and Majeed, 2017). Institutional quality has reduced poverty among many nations by lowering income inequality (Lopez, 2004). However, corruption, political instability, ineffective governments, and weak governance will not only damage income levels through market inefficiencies but also increase the poverty rate via enlarged income inequality. For instance, the beneficiaries of tax exemptions and evasions are most likely to be the wealthy segment of the population, which implies that almost the complete tax burden falls on the poor (Andres & Ramlogan-Dobson, 2011).

However, poverty remains an unfinished problem in Pakistan because 24.5% of people are living below the poverty line whereas 12.5% and 30.5% of the population is estimated as poor in urban and rural areas, respectively. Provincial estimates for multidimensional poverty indicate that Baluchistan with 71% multi-dimensionally poor is the poorest province of Pakistan, while KPK, Sindh, and Punjab have 50%, 43%, and 32.5% multi-dimensionally poor, respectively. Similarly, district-level human development index estimates indicate that many districts of Balochistan have a low level of human development, for instance, Awaran (0.17), Jhal Magsi (0.18), and Chaghi (0.21). Furthermore, districts of Sindh such as Tharparkar (0.22), Umarkot (0.32), and Tando Mohammad Khan (0.37) also have a low level of human development, whereas districts of Punjab are containing the highest human development scores.

Literature suggests various determinants of poverty such as household-specific, institutional, macro-level, and environmental factors. Household specific factors such as age and gender composition, dependency ratio, household education, livelihood status of households, and asset ownership are significantly affecting regional poverty. Macro determinants of poverty including inflation, quality of human capital, unemployment, population density, and population growth rates are documented as important determinants of poverty. Institutional factors comprise multiple indicators such as institutional quality index, terrorism, rule of law, good governance, and public service delivery (Amarasinghe et al., 2005; Maalsen, 2019; Okwi et al, 2007; Owada et al., 2019; Tong & Kim, 2019). A notable number of studies on multidimensional poverty has been conducted in Pakistan and other nations (Sahn and Stifle, 2003; Gwatkin et al. 2007; Cheema et al., 2008; Schreiner, 2007; Jamal, 2009; Naveed and ul-Islam, 2012; Arif, 2015; Iqbal & Nawaz, 2015). But these studies are limited in their scope as they did not focus on multidimensional poverty at the district level. Poverty estimates calculated from these studies are not comparable because of differentials in methodologies, indicators, and data sets. We can have a glance at these studies with respect to their estimation techniques and data sets. A very limited number of studies are available on institutional quality and poverty around the globe.

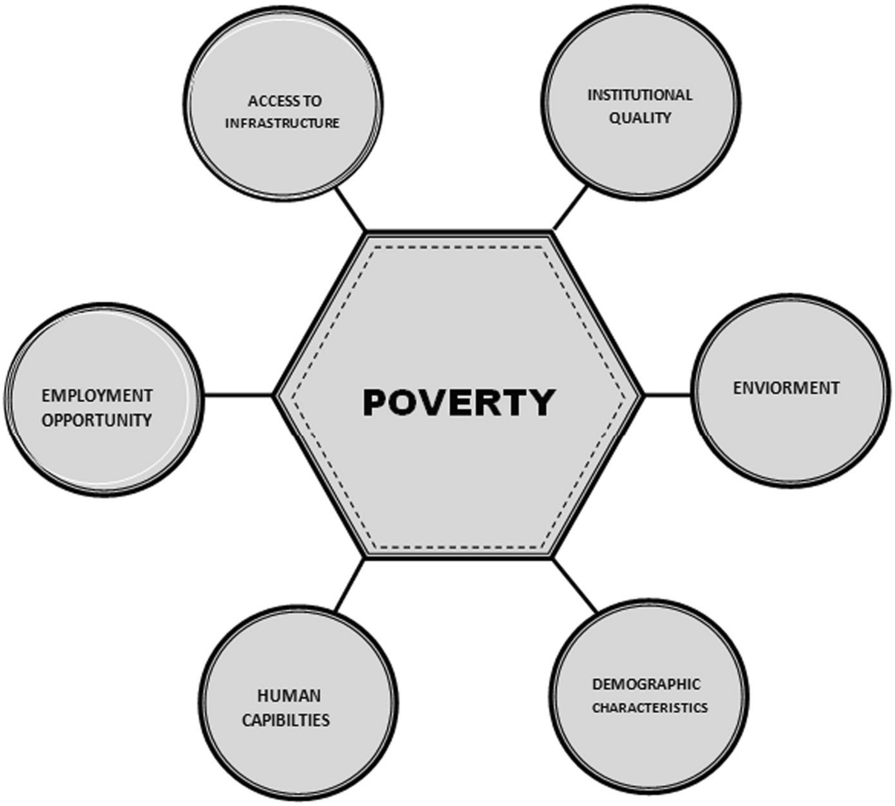
This study endeavors to explore the spatial determinants of multidimensional poverty and human development. Two sorts of spatial determinants such as those which have direct, and spillover impacts on district-level poverty. Figure 1 presents a framework of spatial determinants of spatial poverty. These determinants are estimated by capturing spatial variation and linkages across the locations. Literature regarding Pakistan is failed to capture spatial dependence across regions. Most of the documented studies (e.g., Arshed et al., 2018; Majeed & Malik, 2015; Yousaf & Ali, 2014) have usually estimated household level or macro-economic indicators of poverty. In the past, the majority of the above studies are failed to estimate spatial determinants of poverty. This study contributes by decomposing the total effect of spatial determinants into direct and spillover/indirect effects. However, these studies also neglect the spatial variation and dependence across regions which may also provide biased and inefficient parameters. This study attempts to overcome the deficiencies of previous studies regarding the spatial determinants of multidimensional poverty in Pakistan.

Since its inception, Pakistan is bearing the brunt of poverty. To alleviate poverty, detection of location-based determinants of poverty is also imperative to reduce poverty and enhance human development in Pakistan which are aligned with SDG-1, to reduce all forms of poverty, by 2030. This study contributes to the existing literature by computing the district-level institutional quality index which is one of the significant determinants of regional wellbeing. Besides, multiple new determinants of wellbeing indicators are included in this study such as overseas migration, district-level population density, urbanization, regional connectivity and health infrastructure, and climatic factors such as average temperature and rainfall of each district. These determinants are neglected by past studies in the context of Pakistan.

Study objectives

The study objectives are given as follows: Firstly, this study aims to compute the district-level institutional quality index which is one of the significant determinants of Pakistan's wellbeing. Secondly, this study evaluates the direct and indirect impacts of institutional quality on district-level multidimensional poverty and human development using a spatial autoregressive model. Lastly, this study also

Fig. 1 Determinants of district-level poverty



contributes by decomposing the total effect of spatial multidimensional poverty human development determinants into direct and indirect effects. To the best of our knowledge, this study is the first study of its kind that contributes to the existing literature by computing district-level poverty of 148 districts of Pakistan. Moreover, most of the past studies did not focus on spatial determinants of multidimensional poverty.

The rest of the study is organized as follows: the literature review is discussed in "Study objectives", "Literature review" sections encompasses the methodological framework, data, and variable description. The results and discussion are laid down in "Model specification and data" while concluding remarks are given in the last "Results and discussion" section.

Literature review

This section is furnished with unleash discussion on spatial determinants of poverty which are influencing spatial dependence between regions. Therefore, this section provides a review of literature on the evolution and importance of spatial regression analysis of determinants of Multidimensional poverty and Human development in the case of Pakistan.

Petrucci et al. (2004) have employed a spatial regression model to estimate the spatial determinants of poverty in Ecuador. The data was collected from three sources that have been prepared in a Geographic Information Systems (GIS) for managing the spatial dimension and all these data sets covering household level and geographical information. The findings of the study were indicating that some demographic variables (mortality rate, number of babies, population of geographical unit, and percentage of the adults' literacy) were found statistically significant. Similarly, some environmental and climatic factors (temperature and rainfall, slippery and landslide) were also having significant effects on poverty. Finally, distance from the main road, cereal production, county surface square kilometer, irrigated area, and arable lands were found having some significant impacts on poverty.

Another study that employed a spatial autoregressive model to trace out spatial determinants of poverty was conducted by Amarasinghe et al. (2005).

They explored the spatial patterns of food poverty at the administrative level in Sri Lanka. The findings of their study confirmed the statistically significant presence of spatial autocorrelation, demonstrating that spatial dependence was persisted in the model. The study estimated spatial determinants such as agriculture employment, better access to roads, water availability for irrigation, and average landholding size. Further results were showing that employment and poverty of adjacent regions were the prominent factors that could affect spatial dependence amongst the regions.

Contrary to the above study Farrow et al. (2005) had explored the spatial determinants of food poverty in Ecuador. This study also used a spatial regression model to estimate the unbiased factors. The results were showing that the mean value of conservative dry months, proportion of productive units with irrigations, land suitability, the labor force in agriculture, road infrastructure, and inequality of land ownership were the statistically significant factors of food poverty.

Similarly, Kam et al. (2005) estimated the spatial determinants of poverty in Bangladesh. The geographically weighted regression model showed that the percentage of landless households, percentage of agriculture area under tenancy, livestock holding, average years of schooling, modern irrigated facilities road infrastructure, access to amenities, and structure of the agricultural land were the factors that were affecting the rural poverty in Bangladesh.

The next study which was conducted by Palmer-Jones and Sen (2006) estimated the spatial determinants of rural poverty by using a spatial regression model. The results obtained from spatial regression demonstrated that irrigation facilities were the significant and important factor that caused poverty in adjacent areas as well. The road infrastructure, climatic factors, and demographic factors were the important variables that caused poverty in rural areas of India.

Evidence can be collected to observe the spatial determinants from African countries. Okwi (2007) checked the determinants of poverty in rural Kenya by using the spatial regression technique. This paper also highlighted the links between the occurrence of poverty and the geographical condition in the country. The results indicated that there is no homogenous relationship between poverty and income distribution. Demographic variables, livestock-related variables, quality of soil, use of land, agro-climatic variables, access to public resources have a significant effect on the pattern of poverty. Vasan et al. (2016) estimated the spatial correlation between educational attainment and regional poverty in Mexico. They employed a spatial regression technique to trace out the spatial dependence between regions. The results of the study were indicating that spatial correlation had been found significant. The main reason was the level of educational attainment and poverty of the adjacent region. Further findings showed that demographic and environmental variables are the significant determinants of poverty.

Saima and Naisr (2016) investigate spatial educational poverty by constructing the education poverty index (EPI) for Pakistan at the district level. They observed different trends of poverty across the provinces as well as across regions. The majority of households are deprived in terms of the cost of education. Empirical analysis shows that various socio-economic variables i.e., income, access to education facilities, infrastructure, and awareness cause spatial differentiation of education poverty. Alkire Foster methodology was employed to construct the EPI by using the PSLM survey data set. Regional variation of educational poverty has been captured by GIS analysis at the district level. The logistic model was employed to find out the socio-economic determinants of educational poverty.

The most recent studies on spatial determinants are conducted by Zhenbang et al. (2018) who detected the determinants of rural poverty in China. The study has applied an autoregressive spatial regression model to estimate spatial determinants. They found that climatic variables such as mean temperature and its square terms and patterns of rainfall, further distance to market, accessibility of roads, and other geographic factors were the significant determinants of rural poverty.

Saleem et al. (2021) estimated the multidimensional poverty level in the rural and urban areas of all four provinces of Pakistan. The results obtained based on Alkire–Foster methodology that poverty with its different shapes in terms of regional variation including four provinces, rural and urban regions of Pakistan showed an increasing trend between 2010/11 and 2012/2013. The results at the provincial level indicate that Baluchistan found a higher rate of poverty with all its dimensions, while Punjab has the lowest incidence during all selected time periods. The findings of the study also indicate the significant higher incidence of poverty in rural areas as compared to urban regions during all periods. Based on poverty estimates across all geographical regions the authors suggest that poverty can be removed from remote areas of Pakistan by providing subsidized inputs, easy access to credit for farmers, increasing health facilities in rural areas, and escalating the social protection program to the poor and most vulnerable segment of society on priority basis in order to achieve MDGs targets.

Awan et al. (2015) observed multidimensional poverty at the provincial level by using Alkire and Foster (2007) methodology. To measure poverty incidence, they used the PSLM data set for the year 2005–2006 following nine dimensions i.e. housing, electricity, water, asset, sanitation, education, expenditure, empowerment, and land. The empirical results showed that rural and urban areas of Baluchistan are mainly affected by poverty and lack of necessities followed by KPK, Sindh, and Punjab. The most pervasive dimensions are housing, sanitation, assets, land, and empowerment. Similarly, Ali et al. (2017) also estimated poverty at the regional level and found huge disparities in levels of poverty across regions in Pakistan. They observed empirically that urban poverty contravened with the rural portfolio of poverty. Their findings suggest the difference in poverty mechanism on a rural–urban basis.

Khan and Hafidi (2019) examined the association between poverty and forest degradation in rural areas of Pakistan using 420 randomly selected households. The study outcome suggests a significant correlation between multidimensional poverty and forest cover degradation. Sydunnaher et al. (2019) analyzed multidimensional poverty for Bangladesh. Their analysis reveals that the majority of the slum dwellers were multidimensionally poor, instead of income poor, and the spatial dimension had a considerable impact on urban poverty. Vaziri et al. (2019) provide evidence on the spatial distribution of poverty in the case of Malaysia. Salvacion (2020) investigated the spatial determinants of village-level poverty in the Philippines employing a geographical weight regression approach. The results suggested that spatial indicators such as distance to town centers, and distance to ports influence poverty. Besides annual rainfall and population growth rate are also significant determinants of poverty.

Quratulann and Mirza (2020) also investigate the determinants of multidimensional energy poverty incidence and severity for the case of Pakistan. They analyzed the demographic factors including household head characteristics, household characteristics, regional, economic and geographical factors that determine the multidimensional energy poverty status of households in Pakistan. These determinants of energy poverty provide an understanding of households and other characteristics that play a significant role in affecting the status of a household as a multidimensional energy poor. Moreover, geographical variations have also altered the need of energy services reacquired and increased the energy poverty severity. Lack of facilities in rural and distant areas of Pakistan make them more susceptible to natural and economic shocks. Finally, the study suggests that new and flexible approaches based on provincial and regional differences can help policymakers at all government levels to alleviate multidimensional energy poverty while addressing the energy access issue to achieve sustainable development goals target.

In another study, Quratulann and Mirza (2021) estimated the level of energy poverty in Pakistan by incorporating multiple dimensions at the provincial level as well as at the district level. Their study contributes to the literature by updating the new dimension of certain energy services deemed necessary for households to develop a multidimensional energy poverty index at the household level not only at the provincial level but also at the district level. This study also explains the deprivation level of energy across rural and urban differences in provinces and emphasized grass-root level targeting anti-poverty policy to overcome the energy deprivation issues in the case of Pakistan. The estimated results suggest that 59 percent of the households in Pakistan were experienced the severe intensity of multidimensional energy poverty in 2014–2015. The results also reflect the existence of a geographical pattern in the spread of energy poverty in Pakistan and this decomposition of the MEPI into districts of each province has provided significant insight into energy poverty in Pakistan at the grass-root level. Upon analysis of the results of rural–urban differences, within each district, the rural areas are affected the most by multidimensional energy poverty for the rural households the adjusted headcount was 59.7 percent as compared to the urban population which is only 33.4 percent in 2014–2015.

Chishti et al. (2021) examined the asymmetric influence of Trade openness, FDI, health expenditure, and population size on income poverty in the case of Pakistan by applying a non-linear Autoregressive approach. Their findings suggest the existence of long-run asymmetries among trade openness, FDI, and income poverty. Specifically, the empirical results revealed that positive shocks to FDI have a significant impact on income poverty (Gini Index) and population size in the short run demonstrates a positive and significant association with income poverty. Overall findings show the existence of interesting asymmetric nexus among FDI, trade openness, and income poverty.

Al-Tal et al. (2021) investigate the effects of energy efficiency gains and shocks to key macroeconomic factors on energy poverty. They explain in the case of developing countries the incidence of energy poverty is higher, therefore, energy efficiency gains initially aggravate the energy poverty but improve later on. in this case a U-shaped relationship is established between energy efficiency and access to clean cooking fuels and technologies. Empirically findings also portray that economic growth, FDI, IT, and CO2 emissions have a significant effect on reducing energy poverty contrary to financial development which is insignificant in influence on the incidence of energy poverty.

Adiqa and Usman (2020) observed the prevalence of multidimensional poverty on the basis of MPI and HDI indices which are generated from the PSLM data set by using PCA. They observed some provincial as well as regional differences in the level of poverty. Empirically, they estimate the factors which affect MPI and HDI by using two alternative models i.e., Probit model and OLS regression. Their results indicate that education has been observed as a strong factor to cope with poverty and sustaining household wellbeing. Nonetheless, landholding especially commercial land ownership has significant effects on the likelihood of wellbeing. Some demographic and infrastructure development-related indicators were found highly significant to aggravate the wellbeing of households and an important variable to poverty alleviation in Pakistan.

Nawab et.al (2022) has estimated provincial and district-wise MPI by incorporating the percentage contribution of each indicator and dimension. For the empirical purpose, they used four rounds of multiple indicators cluster survey data set to observe the change in MPI over the period from 2007 to 2018. They found that child mortality, nutrition, child school attendance, and cooking fuel are major determinants of poverty. They observed that southern Punjab is poorer than North-Central Punjab. They found that southern Punjab is badly affected by low nutrition. They identified Rawalpindi as the least poor whereas Rajanpur is the poorest.

This section provides us a comprehensive insight into literature regarding spatial determinants of poverty and findings are suggestive that an autoregressive spatial regression model has been employed to trace out unbiased and consistent estimates. Some socioeconomic, geographic, and climatic factors, and infrastructure-related elements are found determining spatial poverty. In nutshell, this section actually provides grounds and rationale to conduct this study which would cover the research gap regarding the impact of institutional quality on district-level Multidimensional Poverty and Human Development in the case of Pakistan.

Model specification and data

Spatial autoregressive model

This study follows the empirical strategy proposed by Acemoglu et al. (2001) to model the association between institutional quality and poverty. However, Aguilar and Sumner (2020) estimate the global profile of multidimensional poverty in 2015 using the Alkire–Foster measure. They revealed that the worlds multidimensionally poor are mainly young people, residing in rural areas though not necessarily working in agriculture. Poverty has been focused practically and academically for many years but remains a critical social and economic problem in developing economies despite improvements in standards of living (Padda & Hameed, 2018). However, there are many regression approaches to measure poverty.

The objective of this study is to explore the impact of institutional quality on district-level multidimensional poverty and human development by using the spatial autoregressive approach. This study is also followed by the direct and indirect spatial autoregressive approach of Golgher and Voss (2016). The spatial autoregressive (SAR) model provides two sorts of spatial determinants that may have both direct and indirect impacts on the regional poverty level. The direct impact captures the effects of poverty determinants from the same location, whereas indirect impact indicates spillover effect from neighboring locations (e.g. Owada et al., 2019; and Tong & Kim, 2019). In the case of SAR models, two types of coefficients i.e. direct and indirect effects are interpreted (Samreen & Majeed, 2020). The model is:

$$Y = \beta X + \varepsilon \tag{1}$$

In Eq. (1), Y is the outcome variable that is district-level multidimensional poverty and human development, X represents the vector of independent variables, β is also the vector of parameters, and whereas ε error terms of the respective district. Explanatory variables include institutional quality and household characteristics such as average family size, dependency ratio, female ratio, and different age groups of family members, and asset ownerships by households in respective districts. Similarly, district-level demographic variables such as literacy rate, population density, population growth, and level of urbanization are also employed as independent variables. Moreover, district-level infrastructure (roads, health, and educational institutions), and climatic variables (temperature and rainfall) are explanatory variables. The extended cross-sessional data model is

$$Y = \beta X + \lambda Wy + \varepsilon \tag{2}$$

Equation (2) has added the term λ which indicates lag of outcome variable, W stands for weighting matrix. Weights are created on the basis of the distance between specified locations. While, ⅄ indicates the spatial estimated value lag coefficient. Likewise, the spatial error lag model takes the following form.

$$Y = \beta X + \lambda Wy + (1 - \rho)^{-1}\varepsilon \tag{3}$$

In Eq. 3, ρ indicates the coefficient of spatial autocorrelation, whereas Eq. (3) encompasses both specifications; outcome lag and error lag model. However, spatial specification of fixed effect model of panel data can be written as follows:

$$Y_{nt} = \lambda WY_{nt} + X_{nt}\beta + c_n + u_{nt} \tag{4}$$

$$u_{nt} = \rho Mu_{nt} + v_{nt} \tag{5}$$

The above equations $Y_{nt} = (Y_{1t,} Y_{2t,\dots} Y_{nt})$ indicate an n × 1 vector. This vector contains observations for the outcome variable for period t, while n indicates the number of cross-sections that are districts in this study. Here, X_{nt} stands for the matrix of time-varying regression, whereas c_n indicates a vector of panel influences. Moreover, u_{nt} denotes spatial lagged error, and v_{nt} stands for a vector of error terms that are considered independent and identically distributed across both panels and the time along with variance σ^2. Similarly, W and M are denoted for spatially weighted matrices. To estimate fixed effects, SAR for panel data implements quasi-maximum likelihood estimator as suggested by Lee and Yu (2014). In this regard, a transformation is implemented to control fixed effects from the following equations.

$$\tilde{Y}_{nt} = \lambda W\tilde{Y}_{nt} + \tilde{X}_{nt}\beta + \tilde{u}_{nt} \tag{6}$$

$$\tilde{u}_{nt} = \rho M\tilde{u}_{nt} + \tilde{v}_{nt} \tag{7}$$

In the above equations, the fixed effect is helpful to remove panel effects from the estimation, whereas there is no requirement of distributional assumptions.

Data

The data of the district's social-economic and demographic features of Pakistan is collected from multiple sources such as provincial development statistics, population census, Pakistan Social and Living Standards Measurement (PSLM), and the World Bank data, which is a district-level data portal for Pakistan. All district information is collected from Punjab, Sindh, Baluchistan, and KPK along with four years 2008–2009, 2010–2011, 2012–2013, and 2014–2015. Household Integrated Economic Survey (HIES) is a national-level household survey that is conducted by the Pakistan Bureau of Statistics (PBS).

The data on multidimensional poverty, human development index, and institutional quality index is constructed by the author's own analysis. Multidimensional poverty is computed based on multiple deprivations of 16 indicators of health, education, and standard of living. The human development index is considered the indicator of human development at the macro level, covering life expectancy, mean enrollment level, and economic growth. A similar concept is disaggregated into the household level. District level human development is measured by health, education, and living standard indicators of households.

The institutional quality index is measured by using Principal Component Analysis (PCA) based on political participation, governance, and rule of law dimensions. Three dimensions include public service delivery, rule of law, and political participation. The institutional quality index is calculated for each district of Pakistan based on indicators covering three dimensions of institutional quality. The data of educational and health infrastructure, road length, population growth, and population density of Pakistan's districts are also collected from concerned provincial development statistics. The data of the urban population and the annual average temperature are collected from Pakistan Meteorological Department (PMD), respectively. The detailed summary statistics of each variable are provided in Table 1.

Results and discussion

District-level multidimensional poverty

Table 2 has two specifications of the estimated model: fixed effects model without time dummies and fixed effects model with time dummies. Estimated results show that institutional quality has a significant impact on multidimensional poverty with a negative sign, suggesting the beneficial impacts of institutional quality. The aforementioned impacts of institutional quality also remain similar in terms of significance, when time dummies are also included in the model. More precisely, Pakistan with better institutions measured by public service delivery, rule of law, and political participation has lower districts level multidimensional poverty rates. These results are consistent with Tebaldi and Mohan (2010) who noted that institutional quality reduces the intensity, severity, and occurrence of poverty. While our results are contradicted with the findings of Hasan et al. (2007). These findings also suggest that institutional quality is more favorable to reducing poverty rates at the district level because it suggests that regulatory quality, rule of law, government effectiveness, and voice and accountability ensure positive outcomes and reduce

Table 1 Descriptive statistics

Variable	2008		2010		2012		2014	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
	111		111		111		111	
Multidimensional poverty	63.08	22.17	58.47	22.41	55.12	24.32	53.68	23.87
HDI	0.49	0.18	0.49	0.18	0.54	0.19	0.56	0.18
Institutional Quality	0.54	0.06	0.54	0.06	0.56	0.07	0.55	0.06
Dependency Ratio	13.43	2.07	13.59	1.97	13.69	2.11	13.74	1.99
Literacy rate (tertiary)	1.36	1.32	2.48	0.95	3.51	2.52	2.85	1.98
Road length (Km)	1241.53	913.59	1366.46	934.81	1387.78	931.26	1414.17	937.18
Health infrastructure	170.47	353.55	179.69	373.49	205.67	446.56	194.98	429.86
Log employment	3.36	0.15	3.61	0.19	3.60	0.22	3.64	0.26
Population growth	2.27	0.90	2.32	0.87	2.37	0.85	2.47	0.86
Population density	614.57	3131.82	681.00	3374.13	747.42	3617.18	880.03	4105.01
Log migration (overseas)	6.45	2.73	6.29	2.60	6.83	2.74	7.20	2.62
Ratio of Irrigated area	89.32	72.31	80.90	40.29	86.85	61.85	79.12	33.89
Average rainfall	56.56	81.16	52.80	76.69	44.23	64.18	50.25	62.71
Rainfall square term	9726.56	59,621.65	8615.42	44,695.84	6038.45	30,995.90	6422.21	28,885.93
Average temperature	22.41	5.45	23.20	5.84	24.18	5.62	22.94	5.49
Temperature square term	531.62	219.74	572.17	241.28	615.96	238.65	555.96	220.60

Table 2 Institutional quality and multidimensional poverty (Direct effects)

	Specification-I		Specification-II	
	(1)	(2)	(1)	(2)
Institutional Quality	−0.4427*** (0.1693)	−0.4362*** (0.1652)	−0.2826* (0.1629)	−0.2704* (0.1605)
Dependency Ratio	0.1991*** (0.0711)	0.26070*** (0.0729)	0.2060*** (0.0687)	0.2319*** (0.0714)
Literacy rate (tertiary)	−0.0274*** (0.0051)	−0.0233*** (0.0052)	−0.0241*** (0.0048)	−0.0255*** (0.0049)
Road length (Km)	-9.6105*** (2.7505)	-8.4305*** 2.7405	-6.5905*** (2.8405)	-6.6905*** (2.8305)
Health infrastructure	−0.0009** (0.0004)	−0.0009*** (0.0003)	−0.0009** (0.0004)	−0.0009*** (0.0003)
Log employment	−0.0816* (0.0443)	0.0379 (0.0599)	0.0208 (0.0577)	0.03066 (0.0588)
Population growth	0.0307 (0.0269)	0.0478* (0.0270)	0.01020 (0.0244)	0.01680 (0.0245)
Population density	-5.5005*** (1.3306)	-5.3005*** (1.3206)	-5.7025*** (1.2006)	-5.5905*** (1.1506)
Log migration (overseas)	−0.0278*** (0.0070)	−0.0225*** (0.0070)	−0.0205*** (0.0065)	−0.0161** (0.0066)
Ratio of Irrigated area	0.0023 (0.0015)	0.0014 (0.0015)	0.0002 (0.0015)	0.0020 (0.0015)
Average rainfall	−0.0032*** (0.0006)	−0.0031*** (0.0006)	−0.0033*** (0.0005)	−0.0032*** (0.0005)
Rainfall square term	3.3906*** (1.3807)	3.1306*** (1.2207)	3.3206*** (1.0607)	3.1506*** (1.9007)
Average temperature	−0.0307** (0.0178)	−0.0303* (0.0176)	−0.0145 (0.0160)	−0.0110 (0.0157)
Temperature square term	0.0046*** (0.0003)	0.0047*** (0.0004)	0.0024*** (0.0003)	0.0016 (0.0003)
_cons	5.0720*** (0.3205)	4.5586*** (0.3361)	4.4812*** (0.3160)	−0.2604*** (0.1605)
Obs	444	444	444	444

Significance levels such as *p < 0.01, **p < 0.05, ***p < 0.001. () indicates standard errors, whereas Models (1)shows an estimated random effect model without time dummies, whereas (2) indicates when time dummies are included. Specification-1: Spatial error and outcome lag specification, and Specification-2: error, and outcome, covariates lag specification

poverty rates. The result also implies that institutional quality decreases district-level multidimensional poverty incidence by lowering income distribution in Pakistan. This finding is consistent with theoretical and empirical literature studies by Chong and Calderon (2000), Perera and Lee (2013) and Amin (2019) that examine the effects of institutional quality on multidimensional poverty.

The district-level dependency ratio appears to be a statistically significant determinant of multidimensional poverty with a positive sign. Positive sign implies adverse impacts on multidimensional poverty. While district-level tertiary education has significant and beneficial impacts on multidimensional poverty. These impacts have been revealed highly significant with a negative sign. Results of education imply that those districts wherein the tertiary literacy rate is higher may experience a reduction in multidimensional poverty of respective regions or districts. These results are consistent with Arshed et al. (2018) who empirically proved the effect of education enrollment level on income inequality and poverty. Specification-II is also showing a similar result.

Infrastructure related variables such as road length and health institutions are playing a significant role in reducing multidimensional poverty in districts of Pakistan. Van de Walle (1996) in his book describes the vital importance of road infrastructure which is indicative of regional connectivity to deal with multidimensional deprivations. As findings of this study indicate its direct impacts are estimated significant with a negative sign in both specifications. Similarly, the variable of health institutions also appears to be statistically significant with a negative sign which indicates advantageous effects as given by Khan et al. (2019). The district-level employment does not indicate significant impacts on multidimensional poverty. However, it contains negative signs and low significance in specification-1. We may conclude that district-level employment and overseas migration are exerting significant and advantageous influences on multidimensional poverty. Overseas migration is also an indicator of foreign remittances which are important determinants of the wellbeing of households in respective districts estimated results further indicate that demographic factors such as district-level population density have a significant influence on multidimensional poverty except for population growth. However, population growth becomes significant when time dummies are included. The negative sign of the coefficient of population density displays a beneficial impact on multidimensional deprivations. Similar to the above findings, these findings also appear to remain the same over time as well. Hence, we may conclude that population growth contains adverse impacts on multinational poverty with a low significance level. Nonetheless, population density encompasses a highly significant effect which is similarly noted in literature review studies about Determinants of poverty in Pakistan by Yousaf et al. (2014) and Arif (2000). The impact of irrigated areas on multidimensional poverty turns out to be statistically insignificant. It implies that the irrigated area does not have any significant impact on district-level multidimensional poverty, other things remaining constant (Table Institutional quality and multidimensional poverty (Period-wise)).

Furthermore, the findings of our study highlight the significant impacts of climatic factors such as average temperature and rainfall. The estimated results corroborate the presence of non-linear influences of climatic variables. The linear term for rainfall linear has negative signs whereas the rainfall square term encompasses positive signs, suggesting U-shaped impacts of climatic variables on multidimensional poverty. These impacts seem quite logical, because a higher degree of temperature and rainfall may have disastrous impacts on the well-being of people. In short, institutional quality, tertiary literacy rate, and road infrastructure, health institutions, and employment have direct impacts on multidimensional poverty. Moreover, demographic and climatic variables such as dependency ratio, population density, and average temperature and rainfall also have direct and significant impacts on multidimensional poverty which are similar significant determinants of poverty found by Saleem et al. (2019). These direct findings remain similar, consistent, and robust overtime when the sample is divided into following periods: 2008–2009, 2010–2011, 2012–2013, and 2014–2015 reported in Table 4.

Institutional quality comprises a significant indirect effect on multidimensional poverty of neighboring districts in Table 3. The estimated spillover impact of institutional quality implies that an increase in institutional quality for one district has significant effects on the outcome of the adjacent district. Spillover effects would remain similar to specification-II. The reason is the inclusion of covariates to let them correlate with the spatial matric of the adjacent district. The possible justification of spillover result is that institutional quality generates a positive wave in provincial and even at the district level that reduces the multidimensional poverty. One of the possible reasons is that institutional quality affects poverty alleviation indirectly through its effect on economic growth. There is a wealth of evidence showing similar results in developing and developed countries (Barro, 2000; Mauro, 1995). Another reason is that institutions indirectly affect government policies, which in turn affect distributional results, thereby increasing the speed of poverty reduction. This finding is consistent with ADB (2002) based on developing Asia nations. Furthermore, institutional quality affects the political behavior that further reduces the multidimensional poverty at the district level.

Road length also has slightly significant spillover effects on the multidimensional poverty of the adjacent district. Unlike road length, health infrastructure has strongly significant indirect effects on adjacent districts. Building health institutions such as basic health units and hospitals in one district comprises spillover impacts on the wellbeing of neighboring districts. Hence, health infrastructure indicates strongly significant spillover effects on multidimensional poverty. This finding is consistent with a theoretical and empirical literature study by Iqbal and Nawaz (2015) that examines the effects of spatial differences and socio-economic determinants of health poverty. Tertiary education also comprises significant

Table 3 Institutional quality and multidimensional poverty (Indirect effects)

	Specification-I		Specification-II	
	(1)	(2)	(1)	(2)
Institutional Quality	−0.0208 (0.0151)	−0.0188 (0.0139)	−0.6879* 0.3965)	−0.8254** (0.3790)
Dependency Ratio	0.0094 (0.0064)	0.0112 (0.0075)	0.0603*** (0.0276)	0.0585** (0.0269)
Literacy rate (tertiary)	−0.0013* (0.0008)	−0.0010 (0.0007)	−0.0367*** (0.0119)	−0.0455*** (0.0132)
Road length (Km)	−0.0005* (0.0003)	−0.0004 (0.0003)	−0.0002** (0.0001)	0.0001 (0.0001)
Health infrastructure	−0.0002* (0.0001)	−0.0002* (0.0001)	−0.0007*** (0.0002)	−0.0007*** (0.0002)
Log employment	−0.0038 (0.0035)	0.0016 (0.0027)	−0.0950 (0.0891)	0.0373 (0.0930)
Population growth	0.0014 (0.0016)	0.0021 (0.0018)	0.0030 (0.0072)	0.0042 (0.0062)
Population density	−0.0004** (0.0002)	−0.0002* (0.0001)	−0.0002*** (0.0001)	0.0004*** (0.0001)
Log migration (overseas)	−0.0013* (0.0008)	−0.0010 (0.0007)	−0.0060** (0.0025)	−0.0043** (0.0022)
Ratio of Irrigated area	0.0001 (0.0001)	0.00001 (0.00001)	0.0007 (0.0005)	0.0001 (0.0004)
Average rainfall	−0.0002* (0.0001)	−0.0002* (0.0001)	−0.0010*** (0.0003)	−0.0008*** (0.0003)
Rainfall square term	0.0002* (0.0001)	0.0001 (0.0001)	0.0010*** (0.0004)	0.0006** (0.0003)
Average temperature	−0.0014 (0.0012)	−0.0013 (0.0011)	−0.0166 (0.0096)	−0.0235** (0.0093)
Temperature square term	0.0002 (0.0002)	0.0002 (0.0021)	0.0001 (0.0001)	0.0004 (0.0011)
Obs	444	444	444	444

Significance levels such as *p < 0.01, **p < 0.05, ***p < 0.001. () indicates standard errors, models (1) shows estimated random effect model without time dummies, whereas (2) indicates when time dummies are included. Specification-1: Spatial error and outcome lag specification, and Specification-2: error, and outcome, covariates lag specification

impacts on the multidimensional poverty of neighboring districts. Those districts where tertiary education is higher leave significant and beneficial effects on their neighboring districts as well. Similarly, population density is revealing significant spillover effects on the multidimensional poverty of the adjacent district. This finding implies that population density has an indirect impact on reducing the multidimensional poverty of the adjacent district. These results are found consistent over time in terms of the sign, statistical significance, and magnitude of the coefficients with Arif et al. (2000).

Further results of our study show that overseas migration is also having significant effects on neighboring districts. Overseas migration has advantageous influences on determining the multidimensional poverty of neighboring locations. Climatic factors such as average temperature and precipitation also have some spillover impacts on adjacent districts. Estimated impacts of climatic variables are implying that adverse events of weather may cause harmful events like floods and temperature intensity. The occurrence of such events may hurt the well-being of households living in neighboring districts. Hence, climate change indicators have adverse spillover impacts on multidimensional poverty. These results are consistent with the institutional environment for economic growth found by Henisz (2000). These indirect findings remain similar, consistent, and robust overtime when the sample is divided into the following periods: 2008–2009, 2010–2011, 2012–2013, and 2014–2015, reported in Table 4.

Table 4 Institutional quality and multidimensional poverty (Period-wise)

	2008			2010			2012			2014		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Institutional Quality	−0.2811* (0.1636)	−0.6879* (0.3965)	−0.9690** (0.4476)	−0.2811* (0.1636)	−0.6879* (0.3965)	−0.9690** (0.4476)	−0.2811* (0.1636)	−0.6879* (0.3965)	−0.9690** (0.4476)	−0.2811* (0.1636)	−0.6879* (0.3965)	−0.9690** (0.4476)
Dependency Ratio	0.2086*** (0.0696)	0.0603* (0.0276)	0.2689*** (0.0921)	0.2086*** (0.0696)	0.0603* (0.0276)	0.2689*** (0.0921)	0.2086*** (0.0696)	0.0603* (0.0276)	0.2689*** (0.0921)	0.2086*** (0.0696)	0.0603* (0.0276)	0.2689*** (0.0921)
Education	−0.0256*** (0.0048)	−0.0367*** (0.0119)	−0.0623*** (0.0125)	−0.0256*** (0.0048)	−0.0367*** (0.0119)	−0.0623*** (0.0125)	−0.0256*** (0.0048)	−0.0367*** (0.0119)	−0.0623*** (0.0125)	−0.0256*** (0.0048)	−0.0367*** (0.0119)	−0.0623*** (0.0125)
Road Length	−0.0001** (0.0003)	0.0002** (0.0001)	−0.0001 (0.0001)	−0.0002** (0.0001)	0.0002 (0.0001)	−0.0001 (0.0001)	−0.0002** (0.0001)	0.0002** (0.0001)	−0.0001 (0.0001)	−0.0002** (0.0001)	0.0002** (0.0001)	−0.0001 (0.0001)
Health Index	−0.0005*** (0.0001)	−0.0007*** (0.0002)	−0.0012*** (0.0002)	−0.0005*** (0.0001)	−0.0007*** (0.0002)	−0.0012*** (0.0002)	−0.0005*** (0.0001)	−0.0007*** (0.0002)	−0.0012*** (0.0002)	−0.0005*** (0.0001)	−0.0007*** (0.0002)	−0.0012*** (0.0002)
Employment	0.0170 (0.0562)	−0.0950 (0.0891)	−0.0781 (0.0891)	0.0170 (0.0562)	−0.0950 (0.0891)	−0.0781 (0.0891)	0.0170 (0.0562)	−0.0950 (0.0891)	−0.0781 (0.0891)	0.0170 (0.0562)	−0.0950 (0.0891)	−0.0781 (0.0891)
Population Growth	0.0103 (0.0248)	0.0030 (0.0072)	0.0133 (0.0320)	0.0103 (0.0248)	0.0030 (0.0072)	0.0133 (0.0320)	0.0103 (0.0248)	0.0030 (0.0072)	0.0133 (0.0320)	0.0103 (0.0248)	0.0030 (0.0072)	0.0133 (0.0320)
Population Density	−0.0003*** (0.0001)	0.0004*** (0.0001)	−0.0004*** (0.0001)	−0.0001*** (0.0000)	0.0005*** (0.0001)	−0.0006*** (0.0001)	−0.0003*** (0.0001)	0.0004*** (0.0001)	−0.0004*** (0.0001)	−0.0005*** (0.0001)	0.0005*** (0.0001)	−0.0005*** (0.0001)
Average Rainfall	−0.0034*** (0.0006)	−0.0010*** (0.0003)	−0.0044*** (0.0008)	−0.0034*** (0.0006)	−0.0010*** (0.0003)	−0.0044*** (0.0008)	−0.0034*** (0.0006)	−0.0010*** (0.0003)	−0.0044*** (0.0008)	−0.0034*** (0.0006)	−0.0010*** (0.0003)	−0.0044*** (0.0008)
Square Rainfall	0.0003** (0.0001)	0.0004** (0.0002)	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0002)	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0002)	0.0004*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0002)	0.0004*** (0.0001)
Average Temperature	−0.0148 (0.0161)	−0.0166* (0.0096)	−0.0314 (0.0209)	−0.0148 (0.0161)	−0.0166* (0.0096)	−0.0314 (0.0209)	−0.0148 (0.0161)	−0.0166* (0.0096)	−0.0314 (0.0209)	−0.0148 (0.0161)	−0.0166* (0.0096)	−0.0314 (0.0209)
Square Temperature	0.0003 (0.0004)	0.0001 (0.0001)	0.0003 (0.0005)	0.0003 (0.0004)	0.0001 (0.0001)	0.0003 (0.0005)	0.0003 (0.0004)	0.0001 (0.0001)	0.0003 (0.0005)	0.0003 (0.0004)	0.0001 (0.0001)	0.0003 (0.0005)
Overseas Migration	−0.0207*** (0.0066)	−0.0060** (0.0025)	−0.0267*** (0.0086)	−0.0207*** (0.0066)	−0.0060** (0.0025)	−0.0267*** (0.0086)	−0.0207*** (0.0066)	−0.0060** (0.0025)	−0.0267*** (0.0086)	−0.0207*** (0.0066)	−0.0060** (0.0025)	−0.0267*** (0.0086)
Irrigated Area ratio	0.0002 (0.0002)	0.0001 (0.0005)	0.0003 (0.0002)	0.0002 (0.0002)	0.0001 (0.0005)	0.0003 (0.0002)	0.0002 (0.0002)	0.0001 (0.0005)	0.0003 (0.0002)	0.0002 (0.0002)	0.0001 (0.0005)	0.0003 (0.0002)

Significance levels such as *$p < 0.01$, **$p < 0.05$, ***$p < 0.001$

() indicates standard errors

District-level human development

In Table 5, estimated results show that institutional quality has positive and significant impacts on human development. The finding implies that the score of institutional quality increases the human development rank. Resultantly, a positive sign of institutional quality presents helpful impacts. Statistical significance of the impacts of institutional quality remains the same in all specifications. The positive and significant direct impact of institutional quality also remains similar in terms of significance and sign of coefficients when time dummies are included in the model. These results are consistent with the transition economies found by Tridico (2007). This result implies that institutional quality improves the social and human capital at the district level in Pakistan. However, the institutional quality has completely changed the education and health infrastructure that is the basic cause of human development. This also infers that institutional quality stimulated human development in many developed countries.

Similarly, the impact of dependency ratio on human development appears to be statistically significant and negative implying that dependency ratio exerts adverse direct impacts on district-level human development as estimated by Sinnathurai (2013) in the case of developing countries. The direct impacts of the dependency ratio are found similar in the case of separately estimated results for each sampled period. These results indicate that there is no time effect in the model. The study explores the effects of physical infrastructure (education, health, and roads) on district-level human development. The total number of schools signifies educational infrastructure, which has significant and positive influences

Table 5 Institutional quality and human development (Direct effects)

	Specification-I		Specification-II	
	(1)	(2)	(1)	(2)
Institutional Quality	0.2593*** (0.0611)	0.2191*** (0.0580)	0.2580*** (0.0600)	0.2070*** (0.0580)
Dependency Ratio	−0.1241*** (0.0260)	−0.1430*** (0.0263)	−0.1044*** (0.0248)	−0.1326*** (0.0259)
School Infrastructure	0.0197 (0.0126)	0.0294** (0.0120)	0.0235** (0.0109)	0.0379*** (0.0110)
Road length (Km)	6.9406 (9.1506)	6.7606 (8.8406)	5.2806 (1.0105)	3.7406 (9.7706)
Health infrastructure	8.4605*** (2.1305)	8.6605*** (2.1405)	8.4105*** (1.9205)	8.2505*** (1.9305)
Log employment	0.0001 (0.0201)	0.0535*** (0.0204)	0.0221 (0.0178)	0.0378* (0.0208)
Population growth	−0.0111 (0.0090)	−0.0181** (0.0087)	−0.0054 (0.0079)	−0.0141* (0.0080)
Population density	7.4806*** (2.5206)	6.2806** (2.5306)	7.4606*** (2.2506)	5.8806*** (2.2406)
Log migration (overseas)	0.0084*** (0.0026)	0.0039 (0.0026)	0.0077*** (0.0024)	0.0034 (0.0025)
Agriculture Productivity	0.0037 (0.0026)	0.0033 (0.0025)	0.0023 (0.0024)	0.0030 (0.0023)
Average rainfall	0.0008*** (0.0001)	0.0007*** (0.0001)	0.0007*** (0.0001)	0.0006*** (0.0001)
Rainfall square term	−6.0707*** (2.5907)	−3.9807 (2.4507)	−5.0107** (2.5407)	−3.2407 (2.4907)
Urbanization	0.0302*** (0.0071)	0.0211*** (0.0068)	0.0296*** (0.0065)	0.0251*** (0.0063)
_cons	0.0501 (0.1151)	0.2607** (0.1149)	−0.0107 (0.0992)	0.2133** (0.1075)
Obs	444	444	444	444

Significance levels such as *$p < 0.01$, **$p < 0.05$, ***$p < 0.001$. () indicates standard errors, models (1)shows an estimated random effect model without time dummies, whereas (2) indicates when time dummies are included. Specification-1: Spatial error and outcome lag specification, and Specification-2: error, and outcome, covariates lag specification on district-level human development. Similarly, the variable of health institutions also appears to be statistically significant with the positive signs which indicate advantageous effects. Road infrastructure is an indicator of regional connectivity which is considered to be the main driver of human development. Our results are consistent with Munir et al. (2018), Jan et al. (2012) and Candland (2001); who explored the effects of physical infrastructure on human development.

District level employment does not indicate strongly significant impacts on human development without time dummies, but after the inclusion of time times, it seems to be statistically significant. Similarly, overseas migration has statistically significant and positive impacts on district-level human development. International migration is also an important determinant of the well-being of households (Majeed, 2015). Estimated results indicate that district-level demographic factors such as population density, population growth, and urbanization have significant and direct influences on human development. It is witnessed that population growth becomes significant when time dummies are included; otherwise, it is having insignificant impacts. Negative effects imply that rising population growth contains adverse impacts on determining district-level human development. Unlike this, population density and urbanization demonstrate positive and significant direct influences on establishing district-level human development.

The impact of agriculture productivity on human development turns out to be statistically insignificant. It implies that agriculture productivity does not have any significant impact on district-level human development, other things remaining constant. Findings pertaining to climatic factors highlight significant impacts of average rainfall and rainfall square term to see through non-linear impacts. Estimated results substantiate the presence of non-linear effects of rainfall. Finding demonstrates that rainfall linear terms have positive signs whereas rainfall square terms encompass negative signs which mean inverse U-shaped impacts of climatic variables. These impacts seem quite logical, because a higher degree of rainfall may have beneficial, however, after a certain level it may be harmful. These factors include institutional quality, school infrastructure, and road infrastructure, health institutions, and employment have direct impacts on human development. Moreover, demographic and climatic variables such as dependency ratio, population density, and average rainfall have also significant and direct impacts on human development. The findings are consistent with Umer et al. (2019).

Table 6 contains the estimated indirect impact of determinants of human development on neighboring districts. The influences of institutional quality remain to unleash significant spillover effects on the human development of the neighboring district. The spillover impact of institutional quality implies that an increase in institutional quality for one district has significant effects on the outcome of the adjacent district. The district-level dependency ratio also has significant spillover effects on the human development of the adjacent district. While a negative sign of coefficient implies adverse impacts that are insignificant. This result also suggests that institutions indirectly impact long-run human development.

Health and school infrastructures have strongly significant indirect effects son adjacent districts. Building health, as well as school institutions such as basic health units, hospitals, and schools in one district, comprise spillover impacts on the wellbeing of neighboring districts, other things remaining the same. Hence, health and school infrastructure indicate strongly significant spillover effects on human development as explained by Ahmed (2016). Unlike health and school infrastructure, the road length has very small coefficients with lesser significance level but no one can ignore the importance of regional connectivity to improve the level of human development at the district level.

The employment level also comprises significant impacts on the human development of neighboring districts. Those districts where employment opportunities are higher it leaves significant and beneficial effects on its contiguous districts as well. The results of specification-II with time dummies show the high-level significant spillover effect of employment on human development of adjacent districts. Similarly, overseas migration is also having significant effects on neighboring districts, which implies that overseas migration has advantageous indirect influences. Similarly, district-level demographic variables such as population growth, population density, and level of urbanization are showing significant indirect impacts on the human development of contiguous districts. The results related to demographic variables are consistent with the findings of Sathar (2011).

Table 6 Institutional quality and human development (Indirect effects)

	Specification-I		Specification-II	
	(1)	(2)	(1)	(2)
Institutional Quality	0.0817*** (0.0286)	0.0674*** (0.0228)	−0.2291 (0.2075)	0.0038 (0.1609)
Dependency Ratio	−0.0391*** (0.0123)	−0.0440*** (0.0122)	−0.1152*** (0.0407)	−0.0875*** (0.0302)
School Infrastructure	0.0062* (0.0038)	0.0091** (0.0038)	0.0259* (0.0138)	0.0250** (0.0102)
Road length (Km)	0.0002 (0.0003)	0.0002 (0.0003)	−0.0002 (0.0003)	0.0000 (0.0002)
Health infrastructure	0.0003*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0003*** (0.0001)
Log employment	−0.0005 (0.0063)	−0.0165 (0.0072)	−0.0175 (0.0317)	−0.0906*** (0.0328)
Population growth	−0.0035 (0.0028)	−0.0056** (0.0028)	−0.0060 (0.0088)	−0.0094* (0.0057)
Population density	0.0002** (0.0001)	0.0002** (0.0001)	0.0003*** (0.0001)	0.0004* (0.0002)
Log migration (overseas)	0.0027** (0.0010)	0.0012 (0.0008)	0.0085** (0.0033)	0.0023 (0.0017)
Agricultural productivity	0.0012 (0.0008)	0.0010 (0.0008)	0.0026 (0.0027)	0.0020 (0.0016)
Average rainfall	0.0003*** (0.0001)	0.0002*** (0.0001)	0.0002 (0.0003)	0.0003 (0.0003)
Rainfall square term	−0.0002** (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0003)	−0.0002 (0.0002)
Urbanization	0.0095*** (0.0032)	0.0065** (0.0025)	0.0327*** (0.0109)	0.0166*** (0.0063)
Obs	444	444	444	444

Significance levels such as *p < 0.01, **p < 0.05, ***p < 0.001. () indicates standard errors, whereas models (1)shows estimated random effect model without time dummies, whereas (2) indicates when time dummies are included. Specification-1: Spatial error and outcome lag specification, and Specification-2: error, and outcome, covariates lag specification

Furthermore, the results show that climatic factor such as rainfall also has some spillover impacts on the human development of adjacent districts. Furthermore, the direct and indirect impact of institutional quality on the human development index reliable and robust for each period (2008–2009, 2010–2011, 2012–2013, and 2014–2015) separately. Other control variables' findings remain the same over time as well in Table 7.

Conclusion and policy implications

The objective of this study is to explore the impacts of institutional quality on district-level multidimensional poverty and human development by using the spatial autoregressive approach. This study used cross-section and panel data of Pakistan's districts for multidimensional poverty and human development. The findings obtained from spatial autoregressive suggest that institutional quality, tertiary education, road length, and district level demographic factors have both direct and indirect (spillover) impacts on district-level multidimensional poverty. Similarly, institutional quality, road length, health institutions, school infrastructure, urbanization, and population density also have both direct and indirect impacts on district-level human development. The results also suggest that the quality of the public service delivery, rule of law, and political participation are inversely related to district-level poverty and positively related to human development.

The estimated findings of the study may help policymakers in achieving the sub-targets of SDG-1 for Pakistan. Few important policy implications are recommended for poverty at districts and tehsils levels of Pakistan. District-level institutional quality also appears as an important determinant of poverty

Table 7 Institutional quality and human development (Period-wise)

	2008			2012			2012			2014		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Institutional quality	0.2419*** (0.0600)	−0.229 (0.2075)	0.0127 (0.2311)	0.2419*** (0.0600)	−0.2291 (0.2075)	0.0127 (0.2311)	0.2419*** (0.0620)	−0.229 (0.2075)	0.0127 (0.2311)	0.2419*** (0.0610)	−0.2291 (0.2075)	0.0127 (0.2311)
Dependency Ratio	−0.1128*** (0.0260)	−0.1152*** (0.0407)	−0.2271*** (0.0587)	−0.1221*** (0.0250)	−0.1151*** (0.0407)	−0.2271*** (0.0587)	−0.1210*** (0.0270)	−0.1151*** (0.0407)	−0.2271*** (0.0587)	−0.1321*** (0.0260)	−0.1151*** (0.0407)	−0.2271*** (0.0587)
Road Length	3.7006 (9.7996)	-2.2105 (2.7505)	-1.9005 (2.8515)	3.7006 (9.7926)	-2.2105 (2.7505)	-1.9105 (2.8515)	3.70E-06 (9.79E-6)	-2.2105 (2.7505)	-1.9105 (2.8515)	3.7006 (9.796)	-2.2105 (2.7505)	-1.9105 (2.8515)
Health infrastructure	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)	0.0003*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)
Employment	0.0209 (0.0180)	−0.0175 (0.0316)	0.0034 (0.0394)	0.0209 (0.0180)	−0.0175 (0.0316)	0.0034 (0.0394)	0.0209 (0.0180)	−0.0175 (0.0316)	0.0034 (0.0394)	0.0209 (0.0180)	−0.0175 (0.0316)	0.0034 (0.0394)
Population growth	−0.0058 (0.0085)	−0.0059 (0.0087)	−0.0118 (0.0172)	−0.0058 (0.0085)	−0.0059 (0.0087)	−0.0118 (0.0172)	−0.0058 (0.0085)	−0.0059 (0.0087)	−0.0118 (0.0172)	−0.0058 (0.0085)	−0.0059 (0.0087)	−0.0118 (0.0172)
Population density	8.0506*** (2.4696)	8.2306** (3.9316)	1.6305*** (6.0606)	8.0506*** (2.4616)	8.2306** (3.9316)	1.6305*** (6.0606)	8.0506*** (2.4655)	8.2306** (3.936)	1.6305*** (6.0606)	8.0506*** (2.4616)	8.2306** (3.9316)	1.6305*** (6.0606)
Rainfall	0.0007*** (0.0001)	0.0002 (0.0003)	0.0009** (0.0004)	0.0007*** (0.0001)	0.0002 (0.0003)	0.0009** (0.0004)	0.0007*** (0.0001)	0.0002 (0.0003)	0.0009** (0.0004)	0.0007*** (0.0001)	0.0002 (0.0003)	0.0009** (0.0004)
Rainfall square term	-5.4007** (2.7307)	-5.5207* (3.2017)	-4.0906* (2.7007)	-5.0007** (2.6317)	-5.5207* (3.2017)	-1.0906* (5.7007)	-5.4007** (2.7117)	-5.5207* (3.2017)	-1.0906* (5.7007)	-5.3007** (2.5317)	-5.5207* (3.2017)	-1.0906* (5.7007)
Overseas migration	0.0083*** (0.0026)	0.0085** (0.0033)	0.0168*** (0.0053)	0.0083*** (0.0026)	0.0085** (0.0033)	0.0168*** (0.0053)	0.0083*** (0.0026)	0.0085** (0.0033)	0.0168*** (0.0053)	0.0083*** (0.0026)	0.0085** (0.0033)	0.0168*** (0.0053)
Agricultural productivity	0.0025 (0.0025)	0.0025 (0.0026)	0.0051 (0.0051)	0.0025 (0.0025)	0.0025 (0.0026)	0.0051 (0.0051)	0.0025 (0.0025)	0.0025 (0.0026)	0.0051 (0.0051)	0.0025 (0.0025)	0.0025 (0.0026)	0.0051 (0.0051)
School infrastructure	0.0253** (0.0117)	0.0259* (0.0138)	0.0513** (0.0243)	0.0253** (0.0117)	0.0259* (0.0138)	0.0513** (0.0243)	0.0253** (0.0117)	0.0259* (0.0138)	0.0513** (0.0243)	0.0253** (0.0117)	0.0259* (0.0138)	0.0513** (0.0243)
Urbanization	0.0319*** (0.0068)	0.0326*** (0.0109)	0.0645*** (0.0153)	0.0319*** (0.0068)	0.0326*** (0.0109)	0.0645*** (0.0153)	0.0319*** (0.0068)	0.0326*** (0.0109)	0.0645*** (0.0153)	0.0319*** (0.0068)	0.0326*** (0.0109)	0.0645*** (0.0153)

Significance levels such as *$p < 0.01$, **$p < 0.05$, ***$p < 0.001$

() indicates standard errors

reduction. This study suggests the establishment of inclusive institutional quality to have significant and advantageous impacts on dealing with regional poverty to end it. The government should improve the quality of public administration and public services. A strong legal framework can reduce poverty and improve human development. Social assistance schemes are one such policy that targets the poor and can improve human development. Therefore, governments should create suitable social, legal, and political environments that foster sustainable human development, jobs, and business opportunities. Hence, in terms of the policy, this study suggests that policies designed at reducing regional poverty should first consider improving institutions at the district level in Pakistan as a pre-requisite for human development and poverty eradication because district level institutional quality appears as an important determinant of poverty reduction.

This study provides vital implications for the regularization of institutional quality and poverty reduction in developing economies. Overall, the study calls for a multidimensional policy approach that targets poverty reduction and human development at the regional and district level in developing economies. Our study strongly recommends that authorities need to stimulate institutional quality at the local level in developing economies. This study also suggests that authorities and policymakers should re-examine the link between institutional quality and human development. Governments should create social, legal, and political environments at local levels that reduce poverty. As this study explains the spatial determinants of MPI and HDI in the case of Pakistan, future research studies can contribute to the literature by studying the other dimensions of poverty such as health poverty, energy poverty, and educational poverty by focusing on spatial determinates of the poverty.

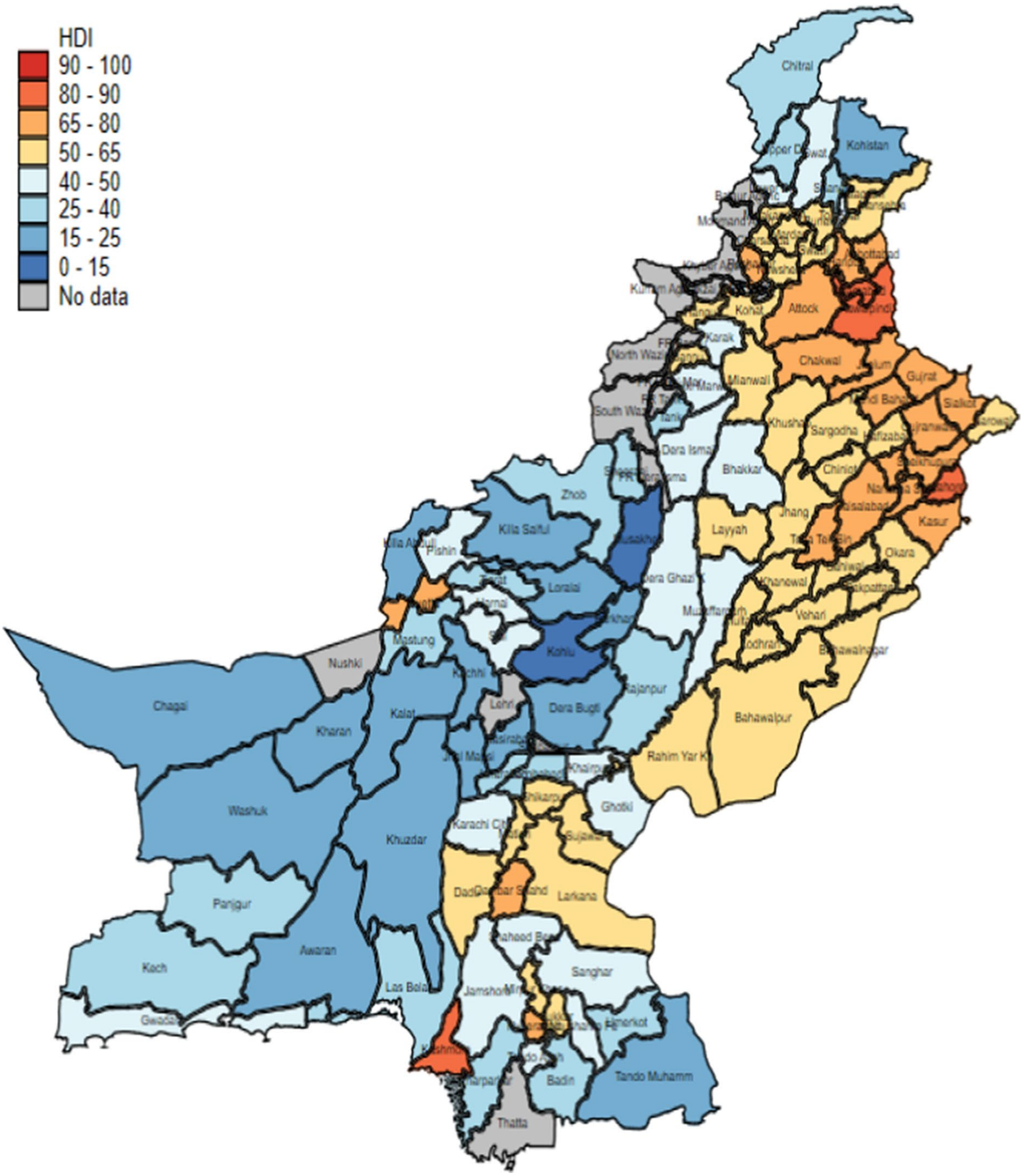
Declarations

Conflict of interest It is to state that “we do not have any conflict of interest and this research is not sponsored by any organization”

Human Participants and/or Animals The authors declare that their research does not involve Human Participants and/or Animals

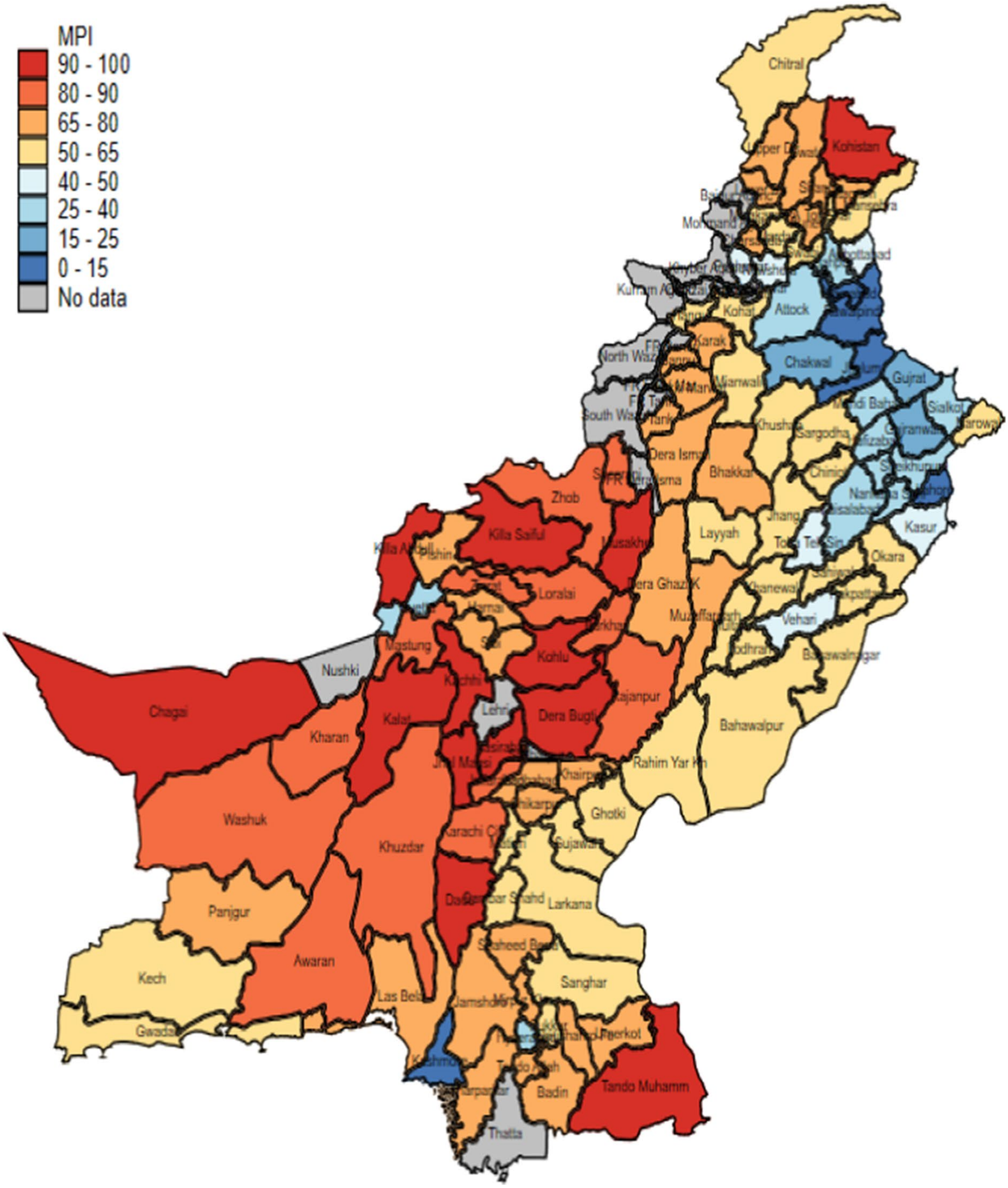
Appendix I

District Level Human Development Index (HDI) Ranking



Appendix II

District Level Multidimensional Poverty Index (MPI)



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