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Does within-country poverty convergence depend on spatial spillovers and the type of poverty measure? Evidence from Pakistan

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Abstract

Knowing whether poverty rates converge within a country matters for regional development policy and for understanding growth processes. In this paper we use five poverty measures, calculated biennially from 2004 to 2014 for 100 districts in Pakistan, to test for poverty convergence. Spatial autoregressive models are used to capture spatial spillovers. Conventional money-metric poverty measures, such as the headcount index and poverty gap index, show unconditional convergence, and the convergence is more apparent if indirect impacts from spillovers are accounted for. In contrast, two multidimensional poverty indexes show no convergence and no indirect effects coming from spatial spillovers. Catch-up growth in initially poorer areas is apparent with the money-metric poverty measures traditionally used in Pakistan but not with the types of multidimensional poverty measures used officially since 2015. This difference in apparent poverty convergence may affect regional development policy choices.

Keywords

convergence

multidimensional

poverty

spatial spillovers

Pakistan

JEL Codes

I32

R12

1. Introduction

Living standards widely differ over space in many countries. If poor people are clustered in certain areas, then targeting regional development programs to these areas may be an effective way to alleviate poverty, even if there is insufficient capacity to target individuals or households. Yet unequal treatment of areas may be politically contentious so having firm evidence to underpin regional policy is important. For example, in Pakistan—the setting for the current study—the perception that regional developments spurred by the China-Pakistan Economic Corridor were favoring some areas saw one provincial government take the central government to court (Shah, 2018). While spatial patterns of poverty matter, regional development policy should also be informed by evidence on changes in poverty over time. If areas with high poverty rates in the past experience slower rates of poverty reduction than other areas, it suggests that the fruits of economic development may not be spreading very widely within a country (Gibson et al, 2005).

In light of these concerns, the question of whether poverty rates converge over time is increasingly studied by economists. A theoretical underpinning for these studies is the Solow-Swan growth model, where falling marginal productivity of capital as more capital accumulates sets an economy on a path towards a steady state (Solow, 1956; Swan, 1956). A key implication of this model is that poor places that are further from their steady state, where capital is less abundant, should have a higher growth rate. In addition to this source of convergence, the so-called *advantage of backwardness* (Gerschenkron, 1962) comes from the possibility of poorer areas adopting technologies developed in richer areas. Poverty rates are lower if mean income is higher, holding inequality constant, so the faster rate of growth for poorer areas implied by convergence should see poverty rates fall fastest in places with higher initial poverty rates.

Yet despite a convergence in average living standards amongst developing countries a seminal paper found no poverty convergence; countries with initially higher poverty rates did not see faster rates of poverty reduction (Ravallion, 2012). This finding spurred other studies, that find poverty convergence between countries if attention is restricted to certain regions such as Sub-Saharan Africa (Ouyang et al, 2019), if attention is paid to convergence clubs (Marrero et al, 2017), or if different functional forms for the relationship between initial levels of poverty and poverty changes are used (Cuaresma et al, 2017). Convergence within a country should be faster than between countries, due to freer movement of capital and labour, and to fiscal transfer systems that supra-national groupings cannot match. Hence, several studies find within-country poverty convergence. For example, by grouping all provinces in Turkey into 26 regions and then looking at the 19 regions outside the largely rural East, Azevedo et al (2016) find that regions with higher initial poverty rates in 2006 had greater reductions in poverty from 2006 to 2013. More compelling evidence comes from Lopez-Calva et al (2020), who find convergence when studying poverty changes for 2400 municipalities (the second sub-national level) in Mexico between 1992 and 2014.

Despite these extant studies, there are at least two reasons why the evidence on within-country poverty convergence is insufficient. First, the evidence is for traditional, money-metric poverty measures, such as the *headcount index* (the share of the population living in households whose consumption or income is below the poverty line) and the *poverty gap index* (the average proportionate shortfall from the poverty line). Yet many developing countries are switching to multidimensional poverty measures (Alkire et al, 2015; UNDP, 2016) to either supplement or replace the traditional money-metric ones. While Amaghouss and Ibourk (2020) study poverty convergence (in Morocco) using the Alkire and Foster (2011) Multidimensional Poverty Index (MPI), no studies compare convergence in multidimensional measures versus in money-metric measures.[1] Other aspects of poverty analysis for Pakistan, such as spatial patterns and temporal changes, appear to be sensitive to using multidimensional versus money-metric poverty measures (Najam, 2020) and so it is worth testing whether evidence for poverty convergence also depends on the type of poverty measure used.

The second reason the existing evidence is insufficient is that studies use the traditional econometric assumption that each cross-sectional unit—districts in our setting—is independent of every other unit. In reality, it can be hard to make much progress in reducing poverty in a particular district if it is surrounded by other districts that are doing poorly, while conversely, having neighbours who are doing well can help with more rapid poverty reduction because of the economic linkages between nearby areas. For example, in neighbouring India, the elasticity of own-region poverty with respect to the poverty rate of neighbouring regions is 0.3 and the rate for neighbours always significantly predicts own-region poverty (Gibson et al, 2017).

Given these gaps in the evidence, this paper reports on tests for poverty convergence within Pakistan. Our database consists of 100 districts, observed six times (biennially from 2004 to 2014). We use five different poverty measures; two multidimensional and three money-metric. One measure from each of these groups is distributionally sensitive. With this multitude of measures we can assess whether evidence for convergence, that to date is mostly for money-metric poverty, is sensitive to the type of poverty measure used. To allow for spatial spillovers we use spatial autoregressive models, where poverty changes in nearby districts may affect the rate of poverty change in the district under consideration. These models recognize the economic inter-connections between nearby districts.

We find that all three money-metric measures show unconditional convergence and the rate of convergence is faster when indirect impacts from other districts are accounted for. In contrast, there is no convergence for either of the two multidimensional poverty measures, irrespective of whether we allow for spatial spillovers or not. There are at least two implications of these results. First, the catch-up growth for initially poorer areas that is apparent with the money-metric poverty measures traditionally used in Pakistan is not seen in multidimensional measures. Thus, an apparent policy failure, of the districts with high initial multidimensional

[1] Moreover, the MPI is not distributionally sensitive, and therefore it violates a desirable property (the strong transfer axiom) for a poverty measure (Datt, 2019).

poverty rates not showing much decline in poverty, may just reflect what is being measured, given that there is a decline in poverty and unconditional convergence when the money-metric measures are used. The architects of regional policy should be made aware of this fragility in the evidence, in terms of the dependence on the type of poverty measure used. Second, the evidence for spillovers suggests data requirements for spatial targeting need not be too onerous; even if it is not possible to target individual districts, poverty-alleviation programs for groups of nearby districts may be sufficient, given the inter-district spillovers.

The rest of the paper is set as follows: Section 2 provides details on poverty in Pakistan and on the data that we use. Section 3 discusses methods of testing for convergence and of testing for, and allowing, spatial spillovers. Section 4 has the results and Section 5 concludes.

2. Poverty in Pakistan: Background and Data

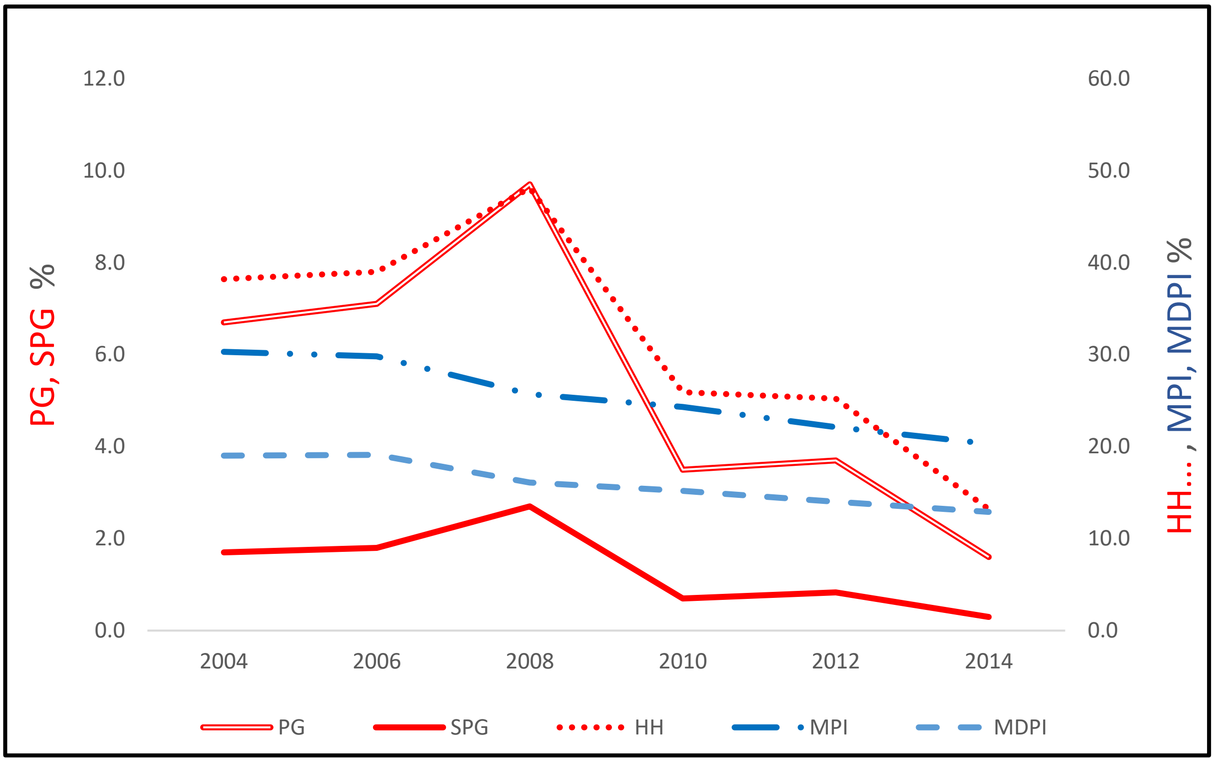
Traditionally the Government of Pakistan (GoP) used money-metric poverty estimates derived from detailed household consumption surveys to target social safety net programmes. This system was put under considerable stress in 2008 when Pakistan's annual inflation rate briefly hit 21% (up from 12% the year before) as world food prices surged. The money-metric measures of poverty showed a sharp increase in 2008 from their previous values in 2006 (the surveys are biennial), especially for poverty depth (the average shortfall from the poverty line). Hence, the GoP then switched from Community Based Targeting to the Benazir Income Support Programme (BISP) that uses Proxy Mean Testing (PMT) to identify poor households. With PMT, money-metric measures based on detailed consumption surveys were no longer needed, as poor households are identified by using indicators such as health and education. These non-monetary measures were further developed into multidimensional poverty estimates, in line with a switch away from relying on money-metric poverty measures in several other countries.

The evolution of average poverty rates over the six waves of surveys that we use from 2004 to 2014 is shown in Figure 1. The three money-metric measures shown in the figure are the headcount index (HH), the poverty gap index (PG) and the squared poverty gap index (SPG). The SPG is a distributionally sensitive measure, that puts more weight on the people furthest below the poverty line, while HH and PG are not distributionally sensitive. The other two measures are the MPI, which is based on Alkire and Foster (2011) and Alkire et al (2015), and the multidimensional distribution-sensitive poverty index (MDPI) developed by Datt (2019). As the name implies, the MDPI is distributionally sensitive while the MPI is not. The detailed formulae for these five indices are provided in Appendix A, with full details on the survey data used to construct them in Najam (2020). For our purposes here, it is sufficient to note that we have estimates at district level for every second year, from 2004 to 2014.[2] We

[2] For money-metric poverty measures, this involves an Elbers et al (2003) approach to project consumption data from the Household Income and Expenditure Surveys (HIES) onto the sample of the Pakistan Social and Living

control for the occasional splitting of districts by using the administrative geography from 2004.

Figure 1: The Average Poverty Estimates (District Level) for Six Alternative Years (2004 – 2014)



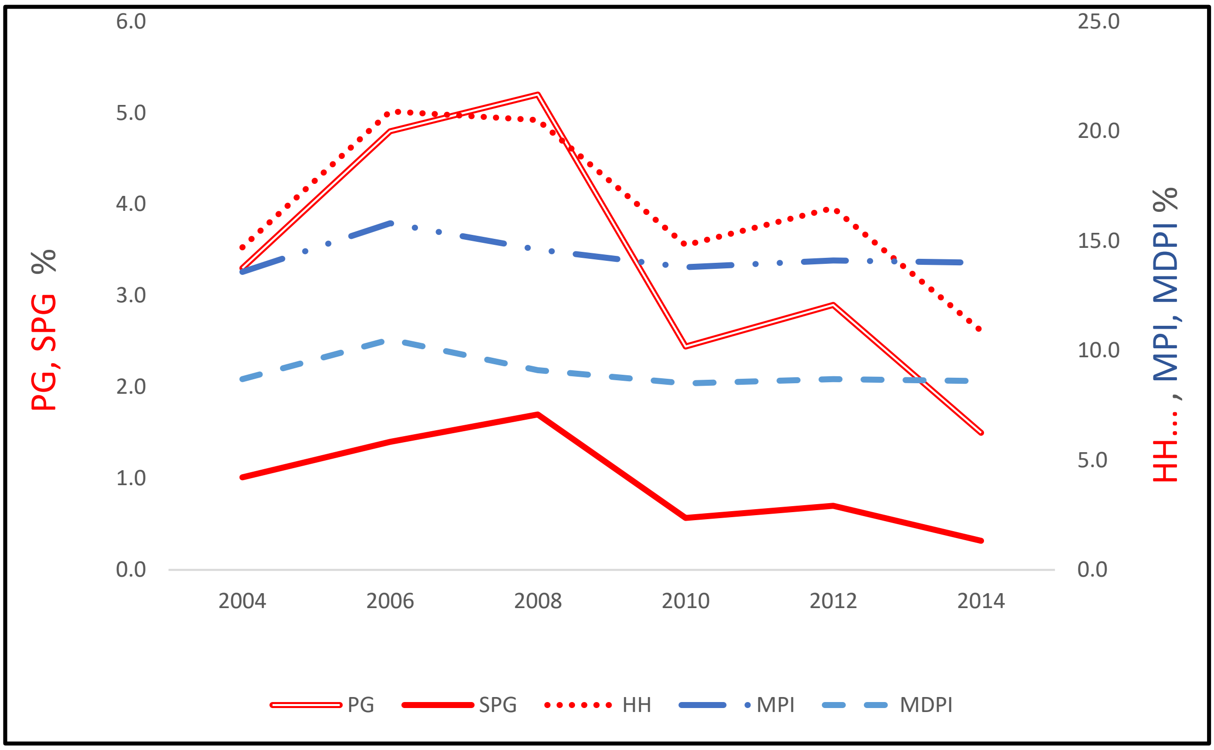
The headcount poverty rate was around 40% in 2004 and 2006 but rose to almost 50% in 2008 (Figure 1). These increases were followed by an even sharper fall, to about 25% in 2010, with a slight decline in 2012 and then a further sharp decline to below 15% by 2014. The movements of the poverty gap index (which uses the left-hand axis, while the headcount index and the multidimensional measures use the right-hand axis) was even more pronounced, rising faster from 2006 to 2008 and then declining even faster than what the movements in HH show. The patterns for SPG are similar but with less sharp movements, so the overall patterns revealed by the money-metric measures is that poverty rates in 2014 were substantially lower than in 2004, albeit with an initial period of rising poverty, especially in 2008.

The multidimensional poverty measures present quite a different picture. There was a slow decline in the MPI, with an average index value of about 30% in 2004 declining to be just above 20% by 2014. The average level of the MDPI starts lower but does not decline quite as fast and neither measure shows any jump in 2008, unlike the fluctuations seen with the money-

Standards Measurement Surveys (PSLM) that lacks consumption data, using sets of predictor variables from the two surveys that overlap (see Dang et al, 2019 for a review of these methods). PSLM surveys are representative at district level, and are used to directly calculate the multidimensional poverty measures. This survey-to-survey imputation approach provides district-level money-metric poverty estimates. Full details are available in Najam (2020). This approach to generating spatially disaggregated poverty estimates is also used in the convergence study of Azevedo et al (2016).

metric measures. The trends shown in Figure 1 relate to averages over all 100 districts (and years) but a disaggregated analysis by Najam (2020) also shows that the time trends in poverty in Pakistan depend on what sort of measures are used; over two-thirds of the districts show opposite trends in poverty rates, if using multidimensional measures rather than money-metric ones, for at least two of the five spells between the six survey waves.

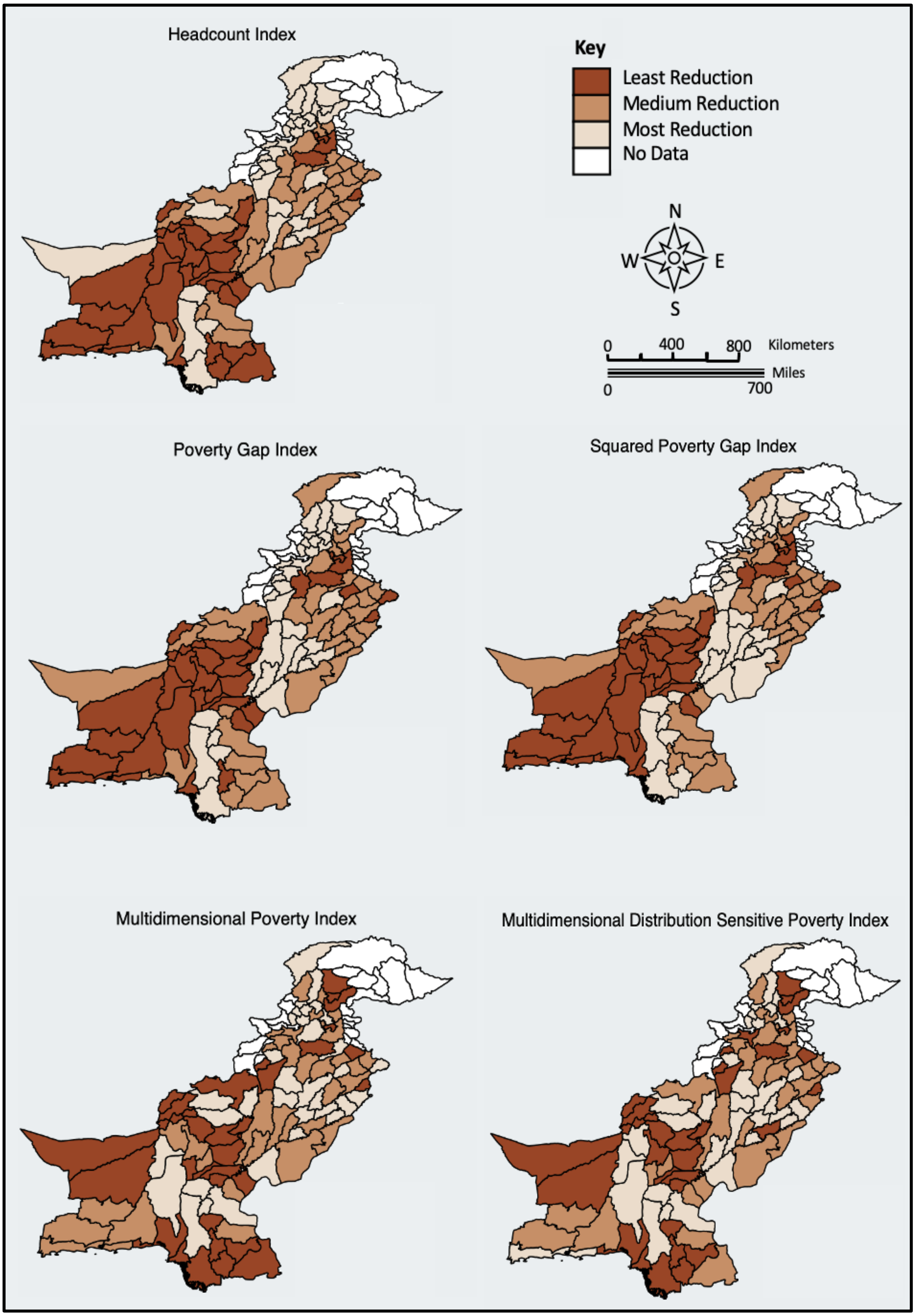
Figure 2: The Standard Deviations of District Poverty Estimates for Six Alternative Years (2004 – 2014)



Another way to show how the differences across districts in their poverty rates evolved is to chart the movements in the standard deviation of the district-level poverty rates. All five poverty measures show increases in the standard deviation of the poverty rates between 2004 and 2006, so there was an initial tendency for the districts to become more dissimilar in their poverty rates (Figure 2). This increased inter-district variance was observed also in 2008 for PG and SPG but the other three poverty measures showed slight falls in the variance that year. There were sharp falls in the standard deviations for money-metric poverty measures in 2010 that slightly reversed in 2012 and then fell further in 2014. In contrast, the standard deviation of the multidimensional measures was largely unchanged after 2010. Overall, the districts have become more alike in their money-metric poverty rates over time, but the multidimensional measures show that the inter-district differences in multidimensional poverty rates have not changed much across the six surveys that we examine.[3]

[3] The evidence in Figures 1 and 2 weights districts by their population, but similar time patterns would show up if unweighted averages and standard deviations were shown.

Figure 3: Spatial Depiction of the Change in Poverty Estimates for the Districts between 2004 – 2014



The last pattern we examine before discussing the methods of testing for convergence is the question of where in Pakistan have the declines in poverty rates been most apparent. In Figure 3 we present district-level maps of the change in the poverty rates over the 2004 to 2014 period for the five poverty measures that are our focus. For clarity of presentation, we group districts into terciles, in terms of those that saw the smallest rate of poverty reduction, those with medium rates of poverty reduction, and those with the fastest rates of poverty reduction (so the thresholds for inclusion in these groups differs between the poverty measures). The darker colours on the map denote districts that had the slowest rates of poverty reduction. There are also some districts with no data, mainly in the Federally Administered Tribal Areas (FATA), where the PSLM surveys were not fielded due to the security situation.

A group of neighbouring districts in Balochistan province (in the southwest) are amongst those with the least reduction in money-metric poverty measures over 2004-2014 (Figure 3). The larger physical size of some of these districts draws attention to them but it is also the case that the majority of districts in the tercile with the least poverty reduction are in Balochistan. This spatial clustering of districts that were less successful in achieving poverty reduction implies that spillovers may be important in the Pakistan context. Indeed, a Moran *I* statistic strongly rejects the null hypothesis of spatial randomness (with a χ^2 statistic of 65.4 which is statistically significant at $p<0.01$) in the pattern of changes in the headcount index.

In contrast to the maps for money-metric poverty measures, where the tercile with the slowest rates of poverty reduction is mostly in Balochistan and a few scattered parts of northern Punjab, the multidimensional poverty measures show patterns that are more spatially random. The tercile with the slowest rates of reduction in multidimensional poverty includes parts of Sindh and Khyber Pakhtunkhwa provinces, plus districts from Balochistan and Punjab. With this scatter, it is unsurprising that the Moran *I* statistic for changes in either multidimensional poverty measure less strongly rejects spatial randomness, with χ^2 values of just 3.6 and 3.3. This closer to random pattern, for changes in the multidimensional poverty measures, suggests that any spillovers may be less important for them than for the money-metric poverty measures.

3. Methods of Testing for Convergence and Spatial Spillovers

The regression model for the test of unconditional convergence, adapted to our setting, is:

$$\Delta PI_{it=0-it=1} = \alpha + \beta(PI_{it=0}) + \varepsilon_i \quad (1)$$

where ΔPI is the annualised change in the poverty rate (for a particular poverty measure like HH or MPI) for district *i* from $T_0 = 2004$ to $T_1 = 2014$. This is simply the change in the poverty index ($P_0 - P_1$) from time T_0 to T_1 averaged over time T ($T = T_o - T_1$). This outcome variable is regressed on the initial poverty rate: $PI_{it=0}$ in our case is for the year 2004 for the i^{th} district. Unconditional convergence holds when β is statistically significant with a negative sign. In that case, the districts with a higher initial rate of poverty have larger changes (falls) in poverty. Some prior studies use percentage rates of change (e.g. Ravallion, 2012) while a majority use the absolute change (e.g. Azevedo et al, 2017; Cuaresma et al, 2017; Marrero et al, 2017; Lopez et al, 2020) when calculating the time-averaged rate of change. We follow the approach that is used in the majority of studies.

The regression error, ε_i from equation (1) is typically treated as independent of errors for the other cross-sectional observations (that is, for $i \neq j$). Yet the maps shown in Figure 3, and the Moran *I* statistics for spatial randomness, suggest that there is cross-sectional dependency where the change in poverty for one district is related to the change in poverty for the nearby districts. This lack of independence in the outcome variable is likely to transmit through into the regression errors, and so the traditional testing approach that assumes independence for ε_i may be mis-specified. Also, the right-hand side variable in equation (1) may exhibit dependence on poverty rates of the nearby districts; the baseline poverty rates (in 2004) also showed some spatial clustering, where poor districts were near to other poor districts and richer districts were near other richer districts.

A more general model than equation (1), that lets the change in poverty and the initial level of poverty in a district influence poverty changes of nearby districts, is a spatial regression model. The key aspect of this model is that spillovers can be allowed for with a spatial weights matrix, *W*. Several types of weights matrix can be used, ranging from a simple 0/1 matrix where a district is defined as a neighbour (typically based on contiguity) or not, through to more complex distance-based matrices where closer districts have more influence and further away ones have less influence (LeSage and Pace, 2009). We use Euclidean distance to form a weights matrix, as this allows for the variation in population density in Pakistan. Specifically, we find the geographic centroid of each district in Pakistan and then the inverse of the distance from that centroid to the centroid of any other district is the weight we put on the observations from the other districts. These weights let us form spatial lags; the weighted averages over the other districts of the dependent variable, of the independent variable(s) and (potentially) of the errors. These lags allow estimation of a more general model:

$$\Delta PI_{it=0-it=1} = \alpha + \beta PI_{t=0} + \delta W \Delta PI_{it=o-it=1} + \lambda WPI_{it=0} + \mu_i \qquad (2a)$$

$$\mu_i = \gamma W \nu_i + \varepsilon_i \qquad (2b)$$

There are three additions in equation (2a) compared to equation (1). The $W\Delta PI$ term is the weighted average of the change in poverty rates in all 100 districts, with higher weights on nearby districts. If the δ coefficient is statistically significantly different from zero it implies the presence of global spillovers, where the change in poverty in one district will propagate through all the districts (including feedback effects to the district under consideration). The $WPI_{it=0}$ term is the weighted average of the initial poverty rates; if the λ coefficient on this term is statistically significant it implies local spillovers, where a higher or lower initial poverty rate of a neighbour affects poverty changes in a district, without the effect spreading globally through all 100 districts. The third addition is that the error term now has a potential correlation, shown by the γ coefficient, with the error terms for nearby districts. This spatial autocorrelation may affect inferences if information in the spatial pattern of the regression errors is ignored.

The model set out in equations (2a) and (2b) is a very general one that nests several other commonly used models. If $\gamma = 0$ the resulting model is a spatial Durbin model that has lags of the outcome variable and of the right-hand side variable. The spatial auto-regressive model (*aka* the spatial lag model) results if $\lambda = \gamma = 0$, where only the dependent variable is spatially lagged. A spatial error model results if just errors are spatially lagged (so $\lambda = \delta = 0$). An ordinary least squares model without any spatial lags results if: $\lambda = \delta = \gamma = 0$. Neither the spatial error model nor the OLS model generate any spillovers where shocks to the right-hand side variable in one location may propagate through other observations and cause a total impact that may exceed the initial direct impact given by the $\hat{\beta}$ coefficient. The general nesting model is known as a spatial autoregressive model with autoregressive errors (SARAR), and using it as a starting point should give unbiased coefficient estimates even if the true data-generation process is one of the nested models.[4] Notably, the reverse is not true given that estimating one of the nested models if the true model is SARAR involves omitting relevant variables.

With either local or global spillovers, the changes in a right-hand side variable—in this case a different initial poverty rate—will produce both direct and indirect effects. The indirect ones are not just from nearby districts, if $\lambda \neq 0$, but also from (potentially) all areas through the spatial autoregressive effect when $\delta \neq 0$. Specifically, a local change in the initial poverty rate may affect how quickly poverty declines in the own-district and also in nearby districts. This spillover to nearby districts may, in turn, affect the change in poverty of their neighbours, including the original district. In order to allow for these spillover and feedback effects, we use an estimator with (separately for each poverty measure) a 100×100 matrix of cross-partial effects (given our sample has 100 districts). Each cell in this matrix shows the relationship between poverty in district i and the change in poverty in the j^{th} district. The average direct effect is the effect of a change in a right-side variable *in district i* on the outcome variable in district i averaged over all districts (in other words, this average effect is based on cells along the diagonal of the matrix). The total effect is the effect of the same change in the right-hand side variable *in all districts* on the outcome variable in district i averaged over all districts. The indirect effect is the difference between the total effect and the direct effect (and is based on the row-sums of the off-diagonal elements of the matrix). This decomposition, which is due to LeSage and Pace (2009), is also used to study poverty spillovers in India (Gibson et al, 2017).

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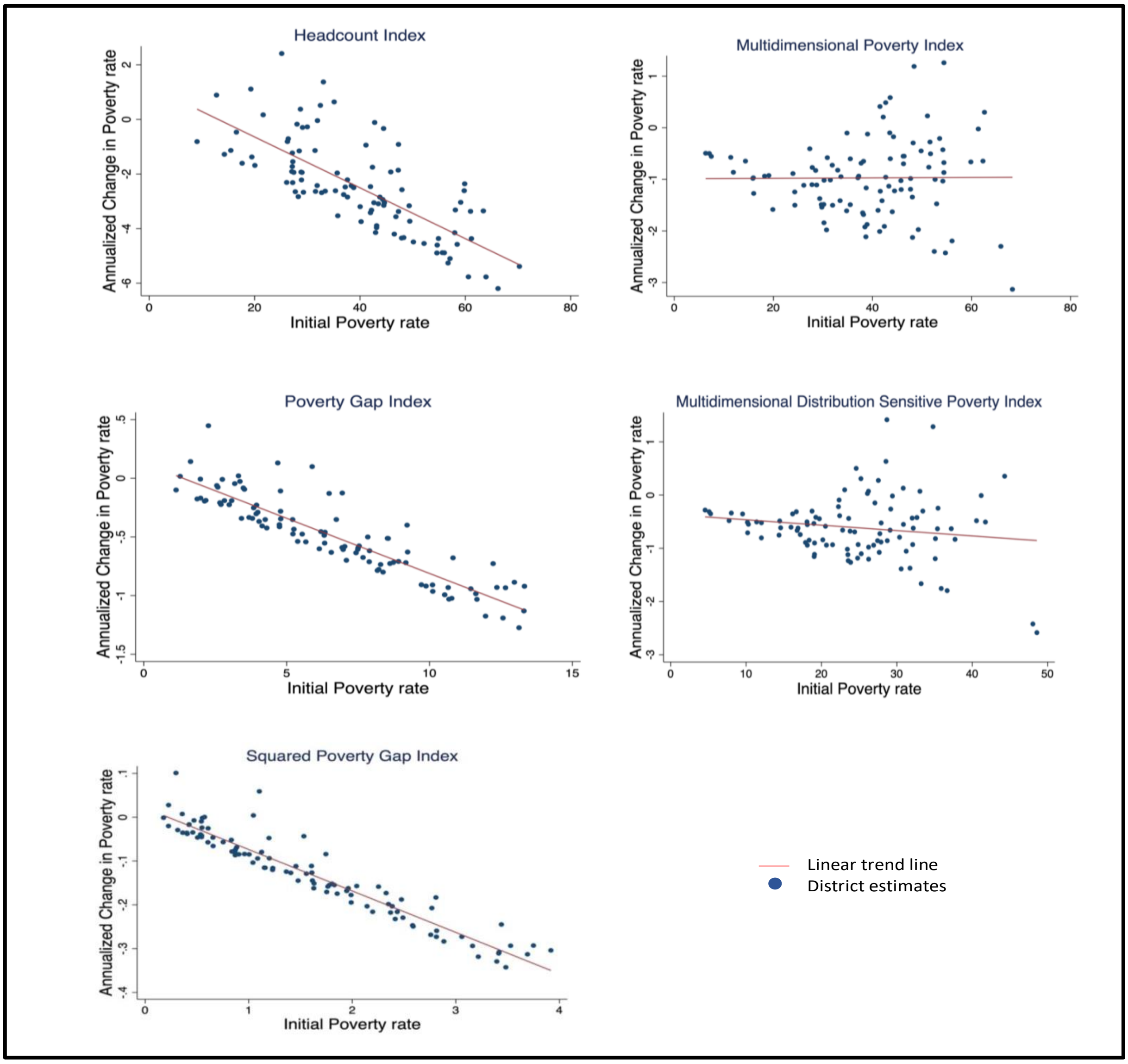
[4] The SARAR model is estimated using a recently implemented procedure in *Stata* (Drukker et al, 2013). Given that any particular district is it's neighbours' neighbour, there is simultaneity that must be accounted for when estimating equation (2a), which is dealt with by spatial two-stage least squares (Kelejian and Prucha, 1998).

4. Results

We begin by presenting scatterplots of the annualized change in the poverty rate against the initial poverty rate, for each of the five poverty measures (Figure 4). There is a clear negative relationship for the three money-metric poverty measures; the higher the initial poverty rate (in 2004) in a district, the greater the annual average reduction in the poverty rate in that district over the following 10 years through to 2014. The spread of the points around the linear trend line falls when moving from HH to PG to SPG, that is, as attention switches from the simple indicator of poor/not-poor, to also considering how poor (the depth of poverty shown with the PG index), and then further considering differences amongst the poor by putting more weight on those furthest below the poverty line (the severity of poverty shown with the SPG index) the evidence in favour of the unconditional convergence in poverty rates seems to get stronger.

Figure 4: Scatterplots for Districts' Initial Poverty Rates and Annualized Change in Poverty Estimates between 2004 – 2014



In contrast to the situation with money-metric poverty measures, there is no apparent convergence in the two multidimensional poverty measures. Rather than a downward sloping relationship the scatter of points seems to be more of a fan-shape as moving from a lower to a higher initial poverty rate sees the gap between the lowest and highest districts—in terms of their annualized change in the poverty rate—get bigger. Thus, the districts that had the highest initial values of the multidimensional poverty indexes might have some of the largest annual average falls in the poverty index, or some of the largest annual average rises. Consequently, the trend line is either completely flat, for the MPI, or only slightly downward sloping for the MDPI, compared with the much more steeply downward sloping trend lines for the money-metric poverty measures.

The scatterplots shown in Figure 4 provide a visual counterpart to equation (1), which is the basic equation for testing for unconditional convergence. The regression results that correspond to the linear trend lines in Figure 4 are reported in Table 1. We note that these OLS regressions are special cases of the more general SARAR model, but we present the OLS results before turning to the results from either the SARAR models or the models nested within them because the OLS results link to the scatterplots and also because of the widespread intuition that exists around OLS results (as lines of best fit). Table 1 includes the convergence coefficients, $\hat{\beta}$, which are the slopes of the trend lines in Figure 4.

Table 1: **OLS Estimation Results for Equation (1), to Test for Unconditional Convergence**

	Money-metric			Multidimensional	
Poverty Measures	HH	PG	SPG	MPI	MDPI
Convergence, β	-0.092***	-0.098***	-0.100***	-0.0004	-0.010
	(0.009)	(0.006)	(0.005)	(0.006)	(0.008)
R^2	0.5398	0.8018	0.9045	0.0001	0.0251

Notes: The dependent variable is the annualized change in the poverty rate (estimated separately for each of the five poverty measures), and the independent variable is the initial poverty rate. *N*=100 districts. Standard errors in ( ), with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

For all three of the money-metric poverty measures, a one-point higher initial poverty rate leads to a subsequent annualized rate of change in the poverty rate that is between -0.09 and -0.10. An example may help with the interpretation of these coefficients. Consider a district where the initial headcount poverty rate was ten percentage points higher than in another district; the district with the higher initial poverty rate would have experienced, on average over 2004-14, an annual decline in the headcount poverty rate that was 0.9 percentage points greater than the decline in poverty experienced in the initially lower poverty rate district. These coefficients of unconditional convergence are all statistically significant at the $p<0.01$ level. In keeping with the tighter spread around the trend line in Figure 4, when moving from HH to PG to SPG, the R-squared values for the regressions rise, from 0.54 for HH to 0.80 for PG and to 0.90 for the regression for the SPG poverty measure.

In contrast to the clear evidence of unconditional convergence for the money-metric poverty measures, neither of the two multidimensional poverty measures show any relationship between the initial level of poverty and the average change in poverty. For these measures we cannot rule out the hypothesis that there is zero effect of the initial poverty rate on the change in poverty, and so there is no evidence for unconditional convergence in multidimensional poverty measures for Pakistan.

Table 2: **GS2SLS Estimation Results for Poverty Measures at District Level of Pakistan**

		Money-metric			Multidimensional	
Poverty Measures		HH	PG	SPG	MPI	MDPI
Convergence[a] β		-0.075*** (0.007)	-0.084*** (0.004)	-0.089*** (0.003)	-0.017** (0.007)	-0.027*** (0.008)
Spatial Lags	Change in Poverty, δ	0.021*** (0.003)	0.012*** (0.004)	0.007** (0.004)	0.051*** (0.011)	0.065*** (0.019)
	Initial Poverty, λ	-	-	-	0.002*** (0.0006)	0.002** (0.0006)
	Error, γ	0.067*** (0.023)	0.044*** (0.007)	0.043*** (0.007)	0.411*** (0.058)	-
Impacts	Direct	-0.077*** (0.007)	-0.085*** (0.004)	-0.098*** (0.003)	-0.016*** (0.522)	-0.027*** (0.007)
	Indirect	-0.196* (0.121)	-0.060* (0.033)	-0.030 (0.020)	-0.027 (0.031)	0.005 (0.017)
	Total	-0.273** (0.122)	-0.144*** (0.032)	-0.119*** (0.019)	-0.043 (0.026)	0.022 (0.138)
Pseudo R^2		0.6680	0.8438	0.9179	0.0627	0.0549
Wald (spatial lags)	Chi square	49.18***	77.81***	55.47***	76.74***	12.20***
Spatial Correlation	Moran's *I*	0.012***	-0.002***	-0.008***	-0.008***	-0.011***

Notes: The dependent variable is the annualized change in the poverty rate (estimated separately for each of the five poverty measures). Independent variables are the initial poverty rate and the spatial lags of the dependent and independent variables and the errors. The general to specific selection criteria is used for the model specification. The Wald test is reported for the final model, after dropping insignificant spatial lags. The results are estimated using Generalised Spatial 2 Stage Least Squares (GS2SLS) estimation. N=100 districts. Standard errors in ( ), with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

[a] With spatial regression models, the total impact, that accounts for direct and indirect effects, provides a more complete account of the convergence effect than what is shown by the direct impact estimate, β.

As noted above, the results in Table 1 are from a model that is a special case of the more general SARAR model that allows spatial lags of the dependent variable, the independent variable, and the errors. In Table 2 we report the results of a general-to-specific model selection approach, where we started with the SARAR model and then removed spatial lags that were statistically insignificant. For the model with the MPI poverty measure, all three spatial lags were statistically significant, while for the MDPI measure, the lags of the error term were not significant, so the resulting model was a Spatial Durbin model with lags of the outcome and of the independent variables. For the three money-metric poverty measures (HH, PG, and SPG) the lags of the independent variable were not statistically significant, so the resulting model was a spatial autoregressive model, with spatially autoregressive errors. A common feature of the selected models for all five poverty measures is that the spatial lag of the outcome measure, has a coefficient, δ, that is always statistically significant. Consequently, there will be global spillovers, where a change in the poverty rate in one district will affect the change in the poverty rates of nearby districts (these autoregressive coefficients range from 0.01 to 0.07), and the change in poverty rates of those nearby districts will, in turn, affect the changes in poverty rates of other areas (including the original district).

Given the importance of the spatial lag of the dependent variable, the counterpart to the β coefficient reported in Table 1 is no longer a sufficient measure of convergence. Instead, we focus on the total impacts, which have direct and indirect components, that account for the spillovers. For the money-metric poverty measures, the total impacts are larger than the direct impacts, especially for the headcount index, and are larger than the Table 1 results that ruled out any possible spillovers. In other words, there is firmer evidence for convergence in money-metric poverty in Pakistan once spillovers from nearby districts are taken into account. Thus, the poverty reduction in a district will influence poverty reduction in nearby districts, which reflects the spatial clustering seen in Figure 3.

For the multidimensional poverty measures, even though there are significant spatial lags for the dependent variable and the independent variable, total impacts remain statistically insignificant. Thus, even allowing for spillovers, there is no evidence of convergence in the multidimensional poverty measures for Pakistan. This implies that the districts surrounded by districts with high initial poverty rates (calculated through multidimensional indicators) are failing to converge, as their rate of poverty reduction was relatively low.

5. Discussion and Conclusions

The question of whether sub-national poverty rates converge matters for the design of regional development policy. In Pakistan, regional development polices have been politically criticised for their apparent biases in favour of some regions and cities. It is therefore important to have an evidence base to underpin these policies. The research reported in this paper attempts to contribute to that evidence base, by examining patterns of poverty changes in Pakistan over the

2004 to 2014 period. We find that districts that started off with higher rates of poverty in 2004 experienced larger reductions in poverty over the subsequent decade, if we use the traditional money-metric poverty measures. In contrast to this pattern, the recently introduced and now widely used multidimensional poverty measures do not exhibit convergence. Hence, these results concur with a finding of Najam (2020), that some inferences about poverty changes in Pakistan depend on whether newer multidimensional or older money-metric measures are used.

In addition to this finding about convergence in money-metric poverty but not in the multidimensional poverty measures, another key finding from our study is that the change in poverty in one location is affected by the change in poverty in nearby districts. These spillovers are sufficiently strong that for the headcount index and the poverty gap index, indirect effects coming from other districts (as distinct from the direct effects for the own-district) significantly amplify the convergence pattern. However, multidimensional poverty measures do not exhibit significant indirect effects, and so the pattern of non-convergence in these poverty measures still holds when the more general spatial regression models are used instead of OLS regression. These spatial spillovers in the money-metric poverty measures also imply that even if the authorities in Pakistan lack capacity to target individual districts (due to either insufficient information or to political factors), poverty alleviation interventions targeted at groups of nearby districts may be sufficient, given the inter-district spillovers in money-metric poverty.

The profound difference in results if using money-metric poverty measures instead of multidimensional measures requires some explanation. One factor is a differing role for private sector goods and services compared to government-provided services. The multidimensional measures are based on access to services such as health and education, and also depend on local infrastructure, and these are largely within the domain of government. It has been noted before that public sector development initiatives in Pakistan may be concentrated on specific districts (Sandilah & Yasin, 2011). Relatedly, Mohammad et al (2017) highlight various disparities in infrastructure development between the provinces; for the road network, over two-fifths is concentrated in Punjab, almost one-third is in Sindh, while just 16% is in Khyber Pakhtunkhwa and 11% in Balochistan. To put things in perspective, Balochistan has the largest area of any province and the highest incidence of poverty. To the extent that access to health, education and infrastructure is mediated by either political factors or state capacity, there may be no mechanism with an inherent propensity for worse-served areas to converge with other areas.

In contrast, money-metric poverty is largely determined by household consumption, which is heavily influenced by private sector activity such as own-account agriculture, wage earning, entrepreneurial earnings and so forth. Labour intensive firms might locate in poorer areas because of low wages. Also, either wage income or remittances might provide a possibility for catch-up growth. Moreover, a rise in income and consumption in one district can have ripple effects through supply and demand channels. For example, if incomes in a district rises due to increased economic activity people there will demand more goods and services and this should also generate demand for goods, services and labour from nearby districts. This is the phenomenon studied by Gibson et al (2017) for neighbouring India, where poverty in rural areas fell by more where and when there was stronger growth in nearby towns and cities. Our results for Pakistan suggest that these spillovers may also occur between districts without big cities. However, these effects may be less likely for infrastructure development and access to public facilities because the spread of those things is managed externally by the government.

Beyond Pakistan, it would be useful for future research to examine whether evidence of within-country poverty convergence varies with whether money-metric or multidimensional poverty measures are used. As more countries switch to using the multidimensional measures, finding which patterns change, due to a switch in what is measured rather than in what actually changes on the ground, will be important for enhancing our understanding of poverty and of progress towards meeting the Sustainable Development Goals.

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Appendix A

Table A1: Description of the Five Poverty Measures Used in the Study

Poverty Measures	Description
Money-Metric	
Distribution Insensitive	
Headcount Index $HH= \left(h/n\right) \times 100$	where *h* is the number of poor people living below the poverty line and n is the total number of people. HH is the proportion of people living below the poverty line.
Poverty Gap Index , $PG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right) \times 100\right)}{n}$	where Z stands for Poverty Line and Y_i is individuals i's consumption. (if consumption is greater than poverty line then it is set equal to zero)
Distribution Sensitive	
Squared Poverty Gap , $SPG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z-Y_i}{Z}\right)^2 \times 100\right)}{n}$	where Z stands for Poverty Line and Y_i is individuals i's consumption. (if consumption is greater than poverty line then it is set equal to zero)
Multidimensional	
Distribution Insensitive	
Multidimensional Poverty Index $MPI = M(\alpha, k; y) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right) I_i^k \times 100$	For *n* individuals and *d* total dimensions, $g_{ij}^{\alpha}=(1-y_{ij}/z_j)^{\alpha}\ I_{ij}$ for $\alpha \geq 0$ is the indicator for deprivation for an individual *i* in dimension *j*. z_j is the cut-off point for the dimension *j*. $I_i^k = I(C_i \geq k)$ is the poverty indicator in which *k* is the cut-off number of dimensions in which an individual has to be deprived to be poor and C_i is the total dimensions in which an individual *i* is deprived. $C_i = \sum_{j=1}^{d} I_{ij}$
Distribution Sensitive	
Multidimensional Distribution-Sensitive Poverty Index $MDPI = M(\alpha, \beta; y) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right)^{\beta} \times 100$ for $\alpha \geq 0$ and $\beta \geq 1$	For β > 1, the measure M(α, β; y) satisfies a cross-dimensional convexity axiom Where; $g_{ij}^{\alpha} = (1-\frac{y_{ij}}{z_j})^{\alpha} I_{ij}\quad for\ \alpha \geq 0$ $I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function. and y_{ij} is the individual *i's* score in dimension *j* and z_j is the cutoff point for deprivation *j*. I_{ij} is zero when $y_{ij} > z_j$ and 1 when $y_{ij} \leq z_j$