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Abstract

Using the 2011 South African population census, we provide income and multidimensional poverty and inequality estimates at the municipal level. We go on to estimate a spatial econometric model to identify the correlates of poverty across municipalities in South Africa. Our results show that both income and multidimensional poverty and inequality vary significantly across municipalities in South Africa. In general, areas that are historically characterized by low economic and welfare outcomes still experience significantly higher poverty and deprivation levels. Using both global and local spatial autocorrelation measures we find significant and positive spatial dependence and clustering of regional development indicators. The situation of poverty is both spatially unequal and autocorrelated.

Results from our spatial econometric analysis indicate negative and significant relations between the municipal poverty levels and local levels of education and economic activity (GDP per capita). Significant and positive relations are found between municipal poverty levels and local inequality levels, suggesting that municipalities with higher levels of inequality also have higher incidences of poverty. In contrast, natural geographic factors such as rainfall and temperature are not significantly related to municipal poverty. Accounting for both direct, intra-municipality effects as well as spillover effects of neighbouring municipalities is important. These spillover effects notably reduce the coefficient sizes suggested by non-spatial, OLS regressions. Most striking, the large negative coefficient that OLS attributes to residing within a historical homeland area is greatly reduced and even loses statistical significance in some spatial models. Clearly municipalities in homeland areas are particularly likely to be surrounded by very poor municipal neighbours and therefore subject to strong negative spillovers. That said, when interactions between this historical geographical variable and contemporary socio-economic deprivations are included, then homeland becomes statistically significant once more. This makes the important point that while, it is these socio-economic deprivations that are particularly important in explaining contemporary income poverty across the county, those who reside in these homeland areas remain especially badly off in terms of these deprivations.

1. Introduction

Spatial inequality as a key dimension of inequity has drawn renewed interest from scholars and policymakers (Kanbur & Venables, 2005; Ezcurra & Rodríguez-Pose, 2017). The spatial distribution of economic activities has significant implications for the performance of a given economy, as well as, on the welfare of individuals (Martin, 1999). Although the clustering of economic activities in some regions is not a problem if lagging regions are catching up, large and persistence spatial inequalities in economic activities may result in self-reinforcing disparities in welfare outcomes. Recent evidence suggests that spatial inequalities in economic and welfare outcomes are high and rising in most developing and transition economies (Kanbur & Venables, 2005).

In this paper, we examine the spatial distribution of poverty and inequality in contemporary South Africa. Both the pre- and post-1994 periods in the South African economy are characterized by high regional disparities in terms of economic activities, as well as welfare outcomes (Fedderke & Wollnik, 2007; Wilson, 2011; NDP, 2012). Significant progress has been made since 1994 in reducing overall poverty and deprivation levels in the country. Public spending on social grants and the provision of basic goods and services played an important role in reducing poverty and vulnerability in historically disadvantaged areas. However, high and persistent inequalities, including spatial inequalities, are still among the main challenges that need to be addressed in order to create an inclusive society in South Africa (NDP, 2012).

With some exceptions (Rossouw & Naudé, 2008; Noble & Wright, 2013; Nobel et al., 2013; Krugell, 2014; Statistics South Africa, 2014; Frame et al., 2016; Sartorius & Sartorius, 2016), spatial analysis of poverty and inequality in South Africa is limited to national, province, and rural/urban levels. Research is limited in analysing the extent of inequality at disaggregate geographical units (Sartorius & Sartorius, 2016), and especially in linking local-level inequality, poverty, and other factors. Yet, understanding the extent of inequalities at local levels is important for poverty reduction and other social policies. For instance, previous international research finds that a high level of inequality in a given region is associated with worse anti-poverty targeting performance (see Galasso & Ravallion, 2005; Araujo et al., 2008), higher crime rates (Demombynes & Özler, 2005), lower income growth of the poor (Van der Weide & Milanovic, 2014), and lower intergenerational mobility (Chetty et al., 2014).

In this paper, we provide estimates of both poverty and inequality at the municipal level. We consider estimates of both income and non-income dimensions of well-being. Using the two approaches together provides a better picture of the spatial distribution of well-being across South Africa. Thereafter we use some spatial correlation indices to explore the extent to which poorer and more unequal municipalities cluster together. We then employ a spatial econometric model to identify the correlates of poverty and explain why poverty levels in some municipalities in South

Africa are higher than others? Using municipal-level data from the 2011 South African census and other data sources we give particular attention to exploring the importance of levels of economic activity and inequality within municipalities in driving municipal poverty levels. These municipalities are relevant units of local area analysis because, following the decentralization of fiscal power to local administrative units in 2000, local municipalities are expected to play a key role in delivery of social services and in promoting local economic development in South Africa (Edoun & Jahed, 2009). South Africa is divided into nine provinces which are divided into 52 districts. At the time of the 2011 census, the 52 districts were divided into 234 municipalities.

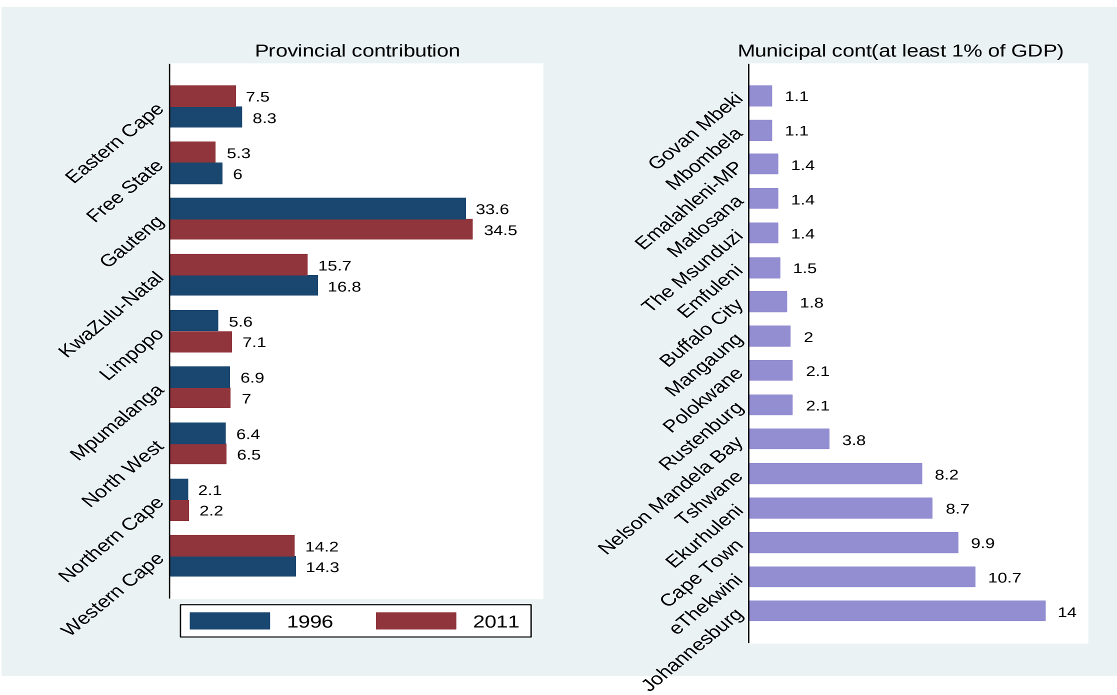
The remainder of the paper is organized as follows. Section 2 provides an overview of the literature on the factors that are associated with the spatial distribution of development, and discusses the approach used to estimate our model. Section 3 provides a description of the dataset used, approaches used in measuring poverty and inequality, and results from exploratory spatial data analysis. In section 4, we present the results of our empirical analysis. The final section offers the main conclusions of the paper.

1. Background and conceptual framework

Across a range of theoretical perspectives, the existence and persistence of spatial inequalities in economic development have been explained by a combination of various factors including, initial conditions, history, endowments, institutions, trade, increasing returns to scale, imperfect information, and transaction costs (Krugman, 1991; Martin & Sunley, 1996; Boschma & Frenken, 2006). For instance, once firms and people find it advantageous to cluster in a particular location, this leads to a reduction in transport costs and an increase in profits, and further agglomeration. However, there are differences among these approaches regarding the role each factor plays in facilitating a particular spatial pattern of economic development (Martin & Sunley, 1996). For example, according to the new economic geography model, increasing returns to scale and reduced transaction costs drive agglomeration and the concentration of firms in some locations (Krugman, 1991). In contrast, an institutional approach stresses the role played by place-specific factors such as culture and institutions in facilitating or constraining the process of local economic development (Boschma & Frenken, 2006). The role of history is one common factor stressed by the different approaches in explaining regional development patterns. History matters, "both in terms of the initial conditions and accidental events that set-in motion particular patterns of industrial development over time and space and in terms of the subsequent "locking in" of those patterns via self-reinforcing effects" (Martin & Sunley, 1996: P.286). Such cumulative causations mean that shocks or adjustments are expensive and difficult to reverse and may have long-term effects, and thus, economic activities and population tend to concentrate more in few locations. (Martin & Sunley, 1996).

The South African economy is characterised by high and persistence spatial inequalities in economic activities. As Figure 1 illustrates economic activities have been historically concentrated in few regions of the country. In both 1996 and 2011, three of the nine provinces, Gauteng, Kwazulu-Natal, and Western Cape, contributed about 65% to the South African economy, with the contribution of Gauteng increasing slightly over time. Out of 234 municipalities, only three of them (Johannesburg, Ethekwini, and Cape Town) contributed about 35% to the South African economy in 2011.[1] Population settlement patterns also tend to concentrate more in these locations. For instance, the Western Cape and Gauteng experienced high net in-migration after 1996, while other provinces experienced negative net migration (e.g. Eastern Cape) or very small positive net migration (i.e North West) (Harrion, 2013). By 2011, Western Cape and Gauteng provinces constituted about 35% of the country's population (Stats SA). Such patterns of concertation of the population and economic activities in these locations are expected to continue in the near future NDP (2012).

Figure 1: Provincial and municipal contributions to GDP in South Africa (1996 and 2011)



Source: Own calculations using data from Stats SA.

The dominance of few locations in terms of economic activities can be attributed to a combination of various factors. The role of history and initial conditions are vital in explaining the spatial distribution of population, economic activities, and well-being in South Africa (Wilson, 2011). The initial development of economically advanced cities such as Cape Town and Durban

[1] We do not have comparable municipality level estimates for 1996.

was associated with their function as trading ports, while the discovery of minerals (diamonds and gold) was related to the initial development of inner cities such as Johannesburg and Pretoria (Krugell & Naudé, 2005; Wilson, 2011). Continued urbanization together with globalization played a role in driving the post-apartheid agglomeration around initially well-developed cities with little convergence (Naudé & Krugell, 2003; Krugell & Naudé, 2005; Krugell; 2014).

Although factor mobility is expected to promote convergence and reduce spatial inequalities in economic and social developments, the initial divergent development patterns in South Africa were further exacerbated and sustained by various Colonial and Apartheid segregation policies (Wilson, 2011; NDP, 2012; Todes & Turok, 2017). For instance, the Native Land Act of 1913 led to the deprivation of black Africans' right to own land and they were confined only to 13% of the land (Todes & Turok, 2017). Furthermore, following the Group Area Act of 1950, which made residential segregation compulsory, individuals were segregated based on their racial identity and Blacks were forcibly moved to mainly rural areas known as 'homelands', and to townships within urban centres. Although the pass laws were repealed in 1987 a century of such policies and restrictions on migration has led to dense settlements in rural areas, mainly homelands, and circular migration between urban and rural areas that endures as a legacy to the present day (NDP, 2012). In effect, the majority of Blacks have been and still are restricted to living in areas which are far from urban centres and jobs.[2]

The removal of restrictions on labour movements from the late 1980s onwards and especially after 1994 increased migration of people to areas where there are more jobs, which led to the better alignment of jobs and people (Harrison, 2013). In addition, public spending on the provision of basic goods and services, and social grants have been intensified in an effort to reduce poverty and vulnerability in historically disadvantage areas. Such policies and migration to urban areas led to significant declines in overall poverty and deprivation levels in recent years[3]. However, high and persistence spatial disparity in economic activities and welfare outcomes are still significant challenges in South Africa (NDP, 2012). Despite the increased urbanisation, an estimated 40% of the South African population still lives in rural areas where economic activities remain limited and many households experienced persistent deprivations (NDP, 2012).

[2] Although the Apartheid regime had started to implement an industrial decentralization policy as a regional strategy aiming to disperse industries towards Bantustan (homeland) areas since the late 1960s, such policy "had very little impact on the "development" of the Bantustan sub-economies either in terms of the creation of employment opportunities or through local multiplier effects", (Wellings & Black, 1986). Todes and Turok (2017) provide a detailed review of the various spatial initiatives and policies implemented in the past in South Africa.

[3] A number of studies find that social spending reduced poverty levels in South Africa (See e.g. Leibbrandt et al., 2010; Leibbrandt et al., 2012; Gomersall, 2013; Coetzee, 2013; Bhorat. et al, 2014). Social spending is also associated with reduction in income inequality (Bhorat et al, 2014; Hundenborn, Woolard & Leibbrandt, 2016). In contrast, the study by Leibbrandt et al (2012) uses static income decomposition techniques and finds no significant impact of social grants in reducing overall inequality levels.

In this paper, we examine the spatial distribution of poverty and inequality, and the link between poverty, inequality, and other factors in South Africa. There is a fair amount of research in South Africa that uses national survey data to analyse poverty and inequality at the national, provincial, and rural/urban levels (see e.g. le R Booysen et al., 2003; Leibbrandt et al., 2010; Van der Berg et al., 2008; Ozler, 2007; Van der Berg, 2014; Finn et al., 2013; Adams et al., 2015; Burger et al., 2017). The findings from these studies suggest significant progress has been made since 1994 in reducing overall poverty and deprivation levels in the country. With few exceptions (Rossouw & Naudé, 2008; Noble & Wright, 2013; Nobel et al., 2013; Krugell, 2014; Statistics South Africa, 2014; Frame et al., 2016; Sartorius & Sartorius, 2016) the analysis has not been at the local level.

These studies indicate that the more disaggregated analysis of spatial poverty indicate that there are significant variations in the level of poverty and deprivation levels across space in South Africa. For instance, using province level estimates, Burger et al (2017) find that a significant fall in deprivation levels across all provinces and evidence of catching up by some areas. However, provinces with high initial deprivation levels remain still the most deprived areas. Likewise, using indicators of multiple deprivations, Noble and Wright (2013) find that the most deprived areas in 2001 in the country were located in the rural former homeland areas and these areas remain among the most deprived. However, they also find large variations in deprivation levels across the former homelands and variation within these areas. Such a fine-grained analysis of poverty at lower geographical units is expected to be helpful for policymakers to identify pockets of poverty.

However, there is limited work analysing the extent of inequality at disaggregate geographical units (Sartorius & Sartorius, 2016), and the link between inequality, poverty, and other factors. Sartorius and Sartorius (2016) use the 2007 South African Community Survey to estimate service delivery inequality across districts and municipalities in South. They consider an individual's education status, and access to water, sanitation, electricity, and refuse removal. Using these indicators, they constructed an index to measure the extent of service delivery for each district and local municipality. The index measures service non-delivery, with the estimate varying between 0 indicating the best level of service delivery and 1 reflecting the poorest level of service delivery. They also use a Theil inequality index to estimate service delivery inequality levels. They find a large disparity in the extent of service delivery and the level of service delivery inequality across regions. Comparing the two measures at a district level, they find an inverted U shape relationship. This suggests that the level of service delivery inequality is higher both in poor and well-performing districts in terms of absolute service delivery, and districts with an intermediate level of service delivery sore have the highest level of service delivery inequality.

Understanding the extent of inequalities at local (or neighbourhood) levels are important for poverty reduction and other social policies. Previous research indicates that the extent of local level inequality is related to the effectiveness of anti-poverty targeting policies in developing countries. For example, Galasso and Ravallion (2005: p.727) find that intra-village inequality in land distribution in Bangladesh is associated with poor targeting of anti-poverty programs in that country. One potential channel through which local level inequality affects anti-poverty targeting is that inequality affects the relative power of the poor in the local decision-making process (Galasso & Ravallion, 2005; Araujo et al., 2008). Higher inequality at the local level can lead to the exclusion of the poor and minority groups. This exclusion can be consequential. A recent literature suggests that high level of inequality is associated with lower income growth rates among the poor (Van der Weide & Milanovic, 2014). Chetty, et al. (2014) find that areas characterised by high racial and income segregations, and high-income inequality levels are associated with lower- intergenerational income mobility in the United States.

It is not only income well-being that is impacted. There is a large literature showing that persistently high levels of inequality can be associated with high crime rates, and may lead to conflict and less political and social stability (Alesina, Baqir & Easterly,1999; Stewart, 2000; Demombynes & Özler, 2005). Using disaggregated data from South Africa, Demombynes and Özler (2005) find that high local level inequality is significantly correlated with high crime rates. Such findings suggest that high levels of initial inequality at the local level may undermine efforts to reduce poverty and other social developments. Such issues are important in the context of South Africa given that historically disparities in economic development and welfare outcomes are aligned with both race and space. Thus, policies aiming to reduce poverty also should focus on reducing local level inequalities.

This paper aims to add such a contribution to the existing literate. First, we provide estimates of both poverty and inequality at the municipal level. We provide income and non-income dimensions of well-being. Using these two approaches together provides a more nuanced picture of the distribution of well-being across regions as a ranking of places based on an economic and non-economic dimension of quality of life is not necessarily the same in South Africa (Rossouw & Naudé, 2008). Importantly, it allows our analysis to be more sensitive to the impact of post-apartheid social policies. Second, we test whether there are significant spatial correlations of regional development patterns in South Africa using national (global) and local spatial correlation measures (Moran's I statistics). These statistics allow us to test whether or not municipalities with high or low levels of poverty and inequality are clustered spatially. Third, we further explore this descriptive picture by estimating a spatial econometric model to identify the factors that are associated with local level poverty in South Africa and with due consideration of spatial autocorrelation of poverty rates and spatial spillover effects on poverty rates across municipalities.

There is limited analysis of the correlates of poverty across space in South Africa (Naudé & Krugell, 2003; Naudé et al, 2009; Gnade et al., 2017). Using data from 1996–2005 Naudé et al (2009) constructed a local level vulnerability index for 354 magisterial districts from South Africa.[4] The results of their analysis show that vulnerability is higher in areas which are remote

[4]The local vulnerability index is constructed using various indicators: the size of the local economy, structure of the local economy, international trade capacity, remoteness, human development (poverty, unemployment human development index), governance etc.

and isolated from economic hubs. Likewise, Naude´ and Krugell (2003) show that cities with better human capital, and areas closer to large urban centres grow faster than others.

There are some technical issues that need to be confronted in such spatial estimations. Conventional estimation methods such as OLS assume geographical units are independent, which is unrealistic. This is especially problematic for us as the presence or absence of these dependencies is part of what we are exploring. Spatial econometric approaches allow us to account for interdependences among spatial units. We can estimate spatial spillover effects, which arise when an outcome of a given location is affected/related to characteristics of other locations. In our context, for example, change in economic development in a neighbouring or nearby municipality may affect the extent of poverty in a given municipality. On channel could be through migration. People migrate from one location to another in search of jobs and this may reduce poverty levels in the migrants' origin, other things held constant. We therefore use spatial econometrics models in order to understand the relationship between local-level poverty, inequality and other factors.

2. Data and Descriptive Analyses

2.1. Data description

The data for this paper is derived from various sources. Information on individual income and other socioeconomic characteristics such as, education level, and population size by race for each municipality are obtained from the 2011 South African census. To measure economic activities at municipality level, we use GDP per capita estimates at municipality levels from Stats SA's recent report (Morudu, 2016). Other variables such as information on climate and topography (mean temperature and mean rainfall and ground slope) are obtained from Aid watch. Google maps is used to calculate distance in time and kilometers by road between municipal capitals. In the next sub-sections, we discuss the approaches used to measure poverty and inequality at municipal levels and provide results from exploratory spatial data analysis of poverty and inequality.

2.1.1. Income poverty and inequality

We use income data from the 2011 South African Census to estimate income poverty and inequality at the local municipality level. In the 2011 South African census, information on personal income (annual gross income from all sources) was collected for all individuals living in a household (excluding those living in institutions).[5] There are some challenges in using income data from the Census for analysing inequality and poverty. First, a large proportion of households have zero income (14 %) and a large proportion of individuals have missing information (7.6 %). Households with zero incomes could truly have zero income. However, this figure is expected to be low given that income includes all income sources. The zero income could be due to the fact that some income types are not included (e.g. may be in-kind income is not included). To minimize the fraction of households with zero income, we replaced individuals who were employed but received zero income into missing. Then, we used imputation procedures to impute income levels for those with missing incomes. Although this procedure minimizes the fraction of household with zero income, still 10.5 % the households have zero income. [6]

Second, the income data were collected only in bands and the top bin has no upper bound. The common approach to deal with such bands is to use Pareto midpoint imputation (PME). Following this procedure, we imputed the midpoint of each income band to each individual in the band, except for the top bin (which is unbounded). Assuming the top two bins follow a Pareto distribution with a shape parameter of 2, the midpoint for the top bin is twice the value of the top bin's lower bound. Then, we summed incomes for each individual in a household and divided it by household size to get per capita income levels. We use Stats SA's upper and lower poverty lines in our income poverty analysis. The estimated upper poverty line is R779 per month per capita, while the lower poverty line is R501 per month per capita.

2.1.2. Multidimensional poverty estimates

The 2011 South African census is also used to calculate a multidimensional poverty index (MPI) for each municipality. The MPI is calculated using four dimensions and 10 indicators. The selection of dimensions and indicators is in line with the recent literature in measuring multidimensional poverty in South Africa (Statistics South Africa, 2014; Frame et al., 2016). We use the Alkire and Foster's (2011) counting approach to aggregate the various dimensions into a single MPI. Each dimension is equally weighted and each indicator within a dimension is equally weighted. Table 1A in the appendix presents dimensions, indicators, deprivation thresholds, and weights used to calculate the MPI. The four dimensions considered are education, health, living standards, and employment. We use individuals as the unit of analysis to determine deprivation cut-offs for education and health indicators. This is in line with the approach used by Frame et al (2016) in calculating MPI for youth in South Africa.

[5] The income question was also asked for small children since they could have an income in the form of child maintenance grants (census metadata, 2011).

[6] Given the ordered nature of the income variable, we impute the missing individual level income values using ordered logistic regression imputation method. The following variables are used in the regression: education level, employment status (for pay), province, rural/ urban dummy, race, age categories, sex, and access to basic services and assets (dwelling type, water, sanitation, electricity, car, and TV). In the case of estimating Gini coefficient for income inequality, we replaced households with zero income with a very small number(one).

Regarding inequality estimates, we use Gini coefficients to measure income inequality at a municipal level. Following Seth and Alkire's (2014) approach, we use the variance of multiple deprivations as our measure of deprivation inequality. Appendix A provides the formulas used to estimate multidimensional poverty and deprivation inequality measures.

Table 1 provides income and poverty estimates for South Africa by region, gender and population groups. The percentage of individuals considered income poor and multidimensional poor in South Africa are 55% and 25% respectively. These estimates are significantly higher in rural areas compared to urban areas. Comparing poverty across provinces, the incidence of both income and multidimensional poverty are the highest in the Eastern Cape and Limpopo provinces, while it is relatively lower in the Western Cape and Gauteng provinces. There is a gender poverty gap with households headed by females having relatively higher levels of income and multidimensional poverty compared to their male counterparts. Also, the poverty estimates in Table 1 show significant disparities in poverty levels by race. Both income and multidimensional poverty estimates are significantly higher for Black and Coloured population groups compared to Whites and Indians/Asians. While the incidence of income poverty is 63% and 40% for the Black and Coloured population groups respectively, the corresponding estimates for Whites and Indians are about 6% and 16% respectively.

Table 1: Income and multidimensional poverty estimates for South Africa (2011)

	Income poverty (PL=R779)			Multidimensional poverty (Poverty cut-off=1/3 of the weighted deprivation scores)		
	P_0	P_1	P_2	MPI	H	A
South Africa	**54.5**	**0.34**	**0.25**	**0.129**	**25.2**	**51.2**
Rural/urban						
Rural	73.8	0.47	0.34	0.197	39.1	50.3
Urban	42.7	0.26	0.20	0.088	16.8	52.3
Province						
Western cape	37.3	0.21	0.15	0.074	14.4	51
Eastern cape	68.7	0.43	0.32	0.196	37.6	52.3
Northern cape	55.3	0.32	0.22	0.134	25.7	52.1
Free state	59.4	0.35	0.25	0.126	23.7	53.3
Kwazulu-Natal	62.3	0.39	0.29	0.151	29.2	51.6
North west	58.5	0.36	0.27	0.146	28.2	51.8
Gauteng	37.2	0.23	0.18	0.080	15.2	52.4
Mpumalanga	58.8	0.37	0.27	0.124	24.7	50.0
Limpopo	69.9	0.45	0.34	0.162	34.2	47.3
Gender						
Female	56.4	0.35	0.26	0.138	26.7	51.6
Male	52.4	0.33	0.25	0.119	23.6	50.5
Household head gender						
Male	44.5	0.27	0.20	0.118	23.0	51.1
Female	66.9	0.43	0.32	0.143	27.9	51.2
Population group						
Black African	62.8	0.40	0.30	0.148	28.9	51.1
Coloured	40.4	0.21	0.14	0.073	14.2	51.3
Indian or Asian	15.6	0.09	0.06	0.048	9.5	50.8
White	6.4	0.04	0.04	0.027	5.3	51.2

Source: Own estimates using data from the South African Census, 2011.

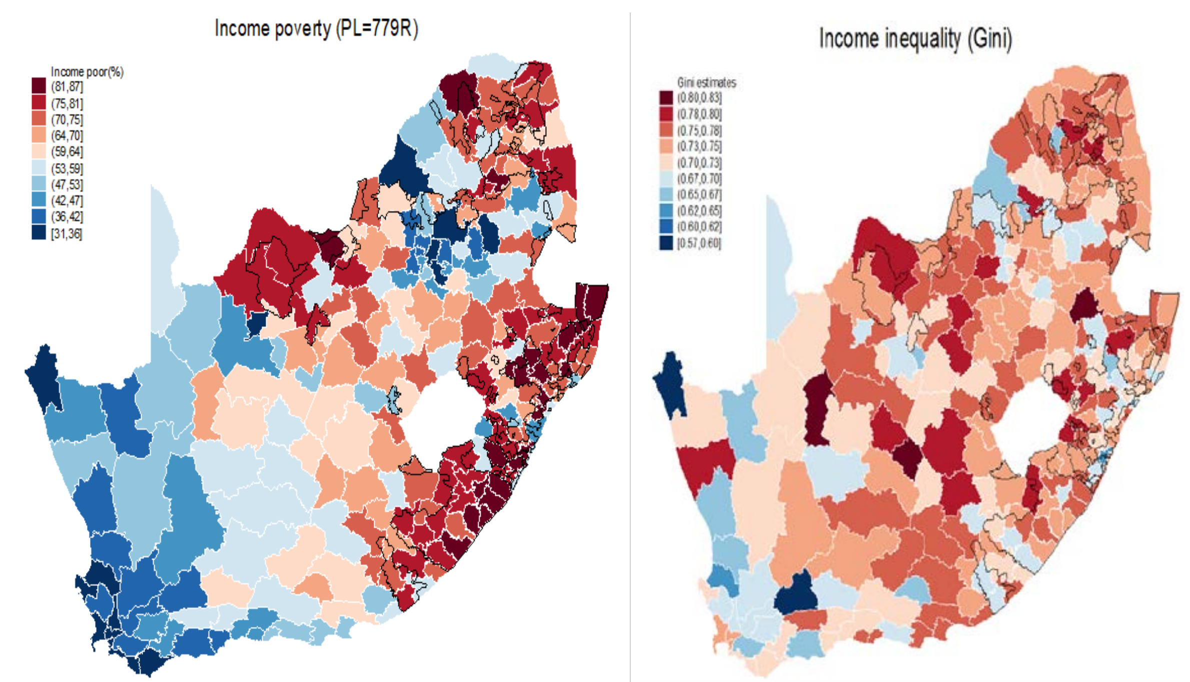
3.2. Exploratory spatial data analysis

In this section, we present the distribution of poverty and inequality levels across municipalities using exploratory spatial data analysis. Then, we test for global and local spatial autocorrelation using Moran's I statistic (Moran, 1950; Cliff and Ord, 1981; Anselin, 1995).

3.2.1. Patterns of inequality and poverty across municipalities

Figure 2 presents the spatial distribution of income poverty[7] and inequality in South Africa. As found in other studies (Noble et al, 2013;), the level of income poverty is much higher for municipalities found in the Eastern Cape and KwaZulu-Natal provinces. In contrast, poverty is relatively lower for municipalities located in the Western Cape and near Johannesburg metropolitan areas in Gauteng province. The level of income poverty is lower than 35 % in the richest nine municipalities (Gamagara, Thabazimbi, Steve Tshwete, Bergrivier, Midvaal, Richtersveld, Stellenbosch, Cape Agulhas, and Saldanha Bay), while the figure ranges between 83%-87% in the poorest 12 municipalities (Mbhashe, Ngquza Hill, Nyandeni, Mbizana, Maphumulo, Ratlou, Nkandla, Ntabankulu, Indaka,Nqutu, Msinga, and Port St Johns). The figure also indicates that most of the former homeland areas are among the poorest locations.

Figure 2: Patterns of income inequality and poverty across municipalities



Source: Own estimates using data from the South African Census, 2011.

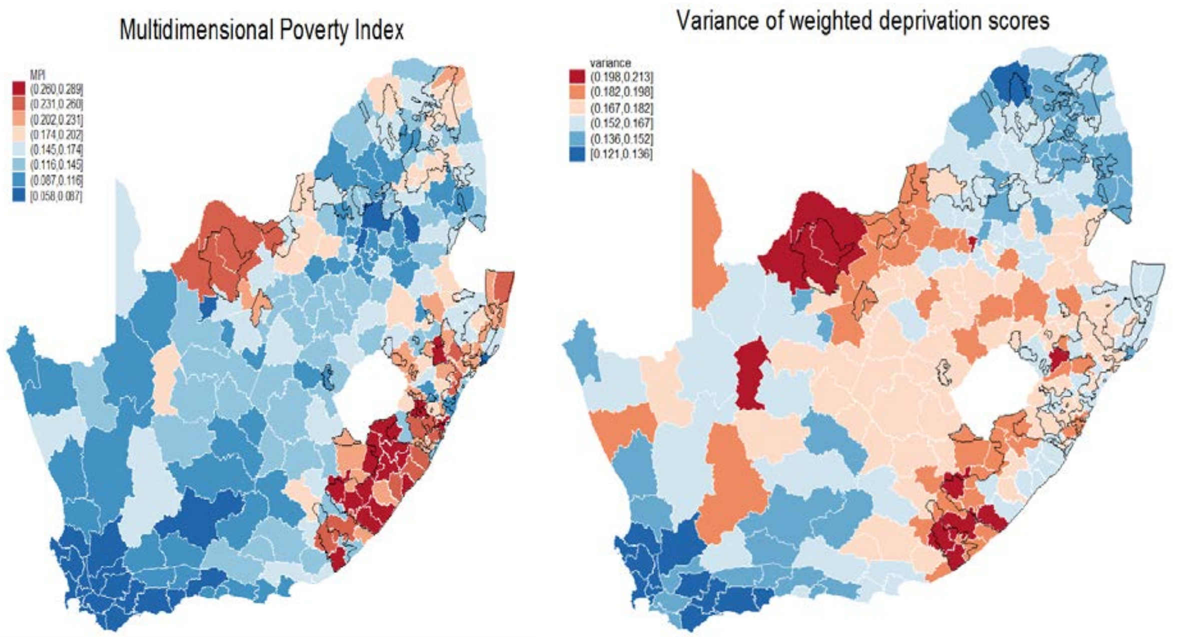
[7] We present results based only on the upper income poverty line (PL=R779).

Among the largest metropolitan cities (Ekurhuleni, City of Johannesburg, City of Tshwane, eThekwini, Mangaung, Nelson Mandela Bay, City of Cape Town, and Buffalo City), the level of income poverty is relatively lower in the City of Cape Town, City of Tshwane, and City of Johannesburg (about 35%-36%), while the figure is about 52%-54% in Buffalo city and Nelson Mandela Bay.

The Gini coefficient estimates indicates that the level of income inequality is at least 0.57 in all municipalities. Thus, there is significant inequality in all municipalities. Against this picture, there are significant variations across municipalities. The large metropolitan areas are characterised by high-income inequality with the Gini coefficient ranging between 0.73-0.76. The Gini coefficient for income inequality ranges between 0.80-0.83 in five municipalities (Abaqulusi, Maquassi Hills, Renosterberg, Kheis, Pixley Ka Seme). The level of income poverty in these municipalities ranges from 63% in Renosterberg to 72% in Abaqulusi. The Gini coefficient of income inequality is relatively lower in seven municipalities with the figure ranging between 0.57-0.65 (Laingsburg, Richtersveld, Vulamehlo, Bergrivier, Cederberg, Nqutu, Hessequa). The poverty estimates in these municipalities, however, vary significantly. While the incidence of poverty reaches 81% and 86% in Vulamehlo and Nqutu respectively, the figure is 40% and less in other municipalities. Income inequality in the poorest 10 municipalities ranges from 0.65 in Nqutu and 0.68 Maphumulo to 0.77 in Mbizana and Ngquza Hill. These figures suggest that income inequality is high both in poor and rich municipalities.

The patterns of regional disparities in income poverty described above are also reflected in Figure 3, which maps the values of the MPI and variance of deprivation scores across municipalities. The MPI estimates range between 0.058 and 0.074 in the ten riches municipalities (Swartland, Drakenstein, Saldanha Bay, Bergrivier, City of Johannesburg, Langeberg, Witzenberg, City of Cape Town, Stellenbosch, Mossel Bay, City of Tshwane) and between 0.266-0.289 in the poorest ten municipalities (Matatiele, Vulamehlo, Msinga, Ngqushwa, Umzimvubu, Mbhashe, Engcobo, Elundini, Intsika Yethu, Ntabankulu). The proportion of people who are considered multidimensional poor is 14 % and less the riches ten municipalities, the figure ranges between 50%-54% in the poorest ten municipalities. Deprivation level inequality estimates are higher in municipalities with higher MPI estimates, while these figures are relatively lower in richer municipalities. Among the largest metropolitan cities inequalities in deprivation levels are relatively lower in City of Cape Town and Johannesburg, while the figure is higher in Buffalo and Mangaung Cities.

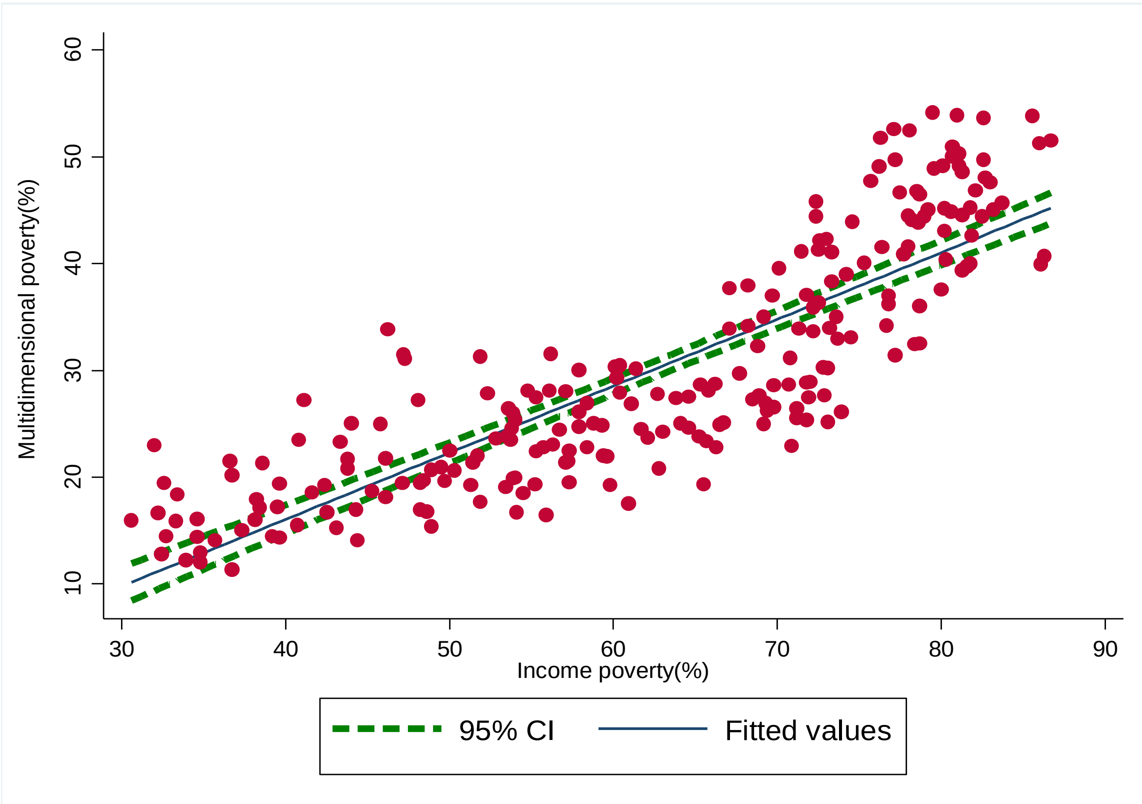
Figure 3: Patterns of multidimensional poverty and inequality across municipalities



Source: Own estimates using data from the South African Census, 2011.

Figure 4 shows a strong positive relationship between the level of income poverty and multidimensional poverty estimates, with Spearman's rank correlation coefficient being 0.88. This indicates that areas that are deprived of access to education and other basic services are also characterized by lack of income generating opportunities. Overall, the figures above indicate that both income and multidimensional poverty and inequality estimates vary significantly across municipalities in South Africa. We also find that within municipality inequalities in multidimensional deprivation scores seems higher in poor municipalities. These results are in line with a recent finding by Sartorius and Sartorius (2016) who show that although there are large disparities in service delivery between richer and poorer districts, within district inequality is higher in both richer urban districts and poorer rural districts.

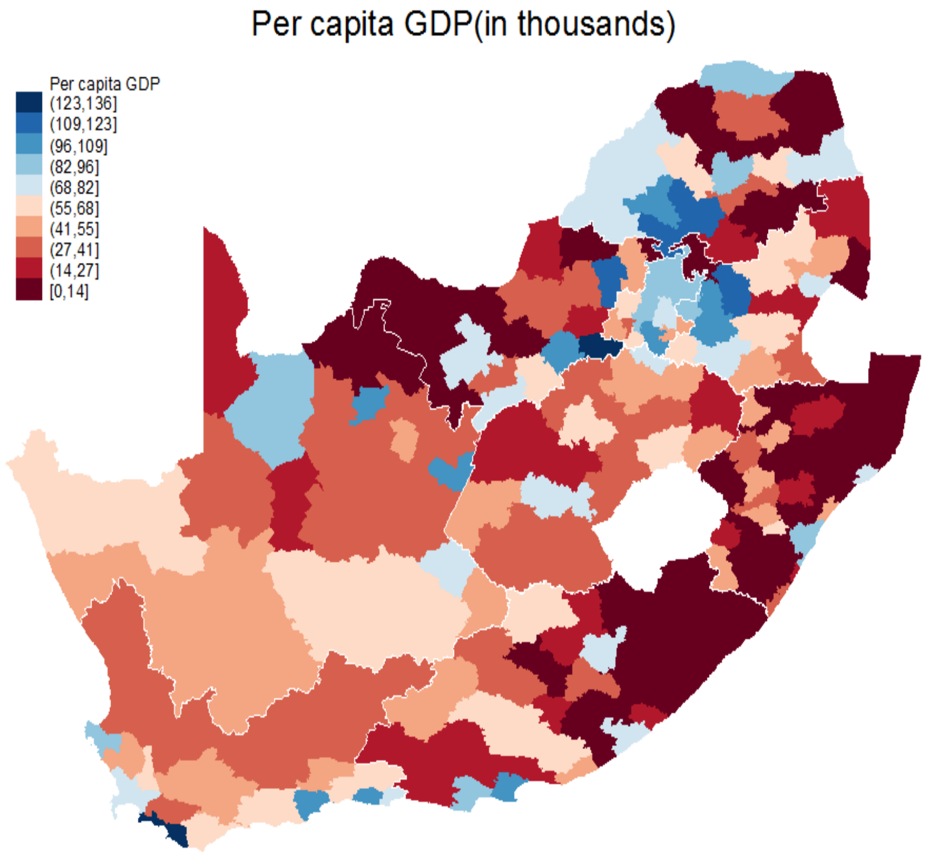
Figure 4: Income and multidimensional poverty estimates by municipality



Source: Own estimates using data from the South African Census, 2011.

Municipalities characterized with a high level of poverty estimates have very low level of per capita GDP estimates. Figure 5 maps the distribution of GDP per capita for 2011 (in Rands). The figure shows large disparities in the level of economic activities across municipalities in South Africa. For example, GDP per capita in the richest municipality was close to 100% of that in the poorest. The figure shows that the top 10 richest municipalities include (Tlokwe city council, Overstrand, Bela-Bela, Mookgopong, Steve Tshwete, Rustenburg, Modimolle, Knysna, Govan Mbeki, and the city of Matlosana). The City of Johannesburg and eThekwini rank 18 and 19 respectively in per capita terms, while Cape Town ranks 37. The poorest municipalities include Nongom, Ndwedwe, Umhlabuyalingana, Ezingoleni, Vulamehlo, Msinga, Umzumbe, Joe Morolong, Ntambanana, Indaka.

Figure 5: Patterns of GDP per capita across municipalities



Source: Own calculations using data from Morudu (2016)

3.2.2. Spatial autocorrelation

Next, we test whether there are significant spatial autocorrelations of regional development in South Africa using both global and local spatial autocorrelation measures. Global spatial autocorrelation measures such as the global Moran's I test whether there is an overall spatial dependency in regional development (Moran, 1950; Cliff & Ord, 1981). The estimated value takes positive (negative) if there is positive (negative) spatial autocorrelation in spatial dependency in regional development; namely, the trend of regional development between neighbouring municipalities is similar (different). In addition, a value of zero indicates random spatial pattern. The formula for calculating the global Moran's I statistics is given as follows:

$$I = \frac{N}{\sum_i^N \sum_j^N w_{i,j}} \frac{\sum_i^N \sum_j^N w_{i,j}(x_i - \overline{X})(x_j - \overline{X})}{\sum_i^N (x_i - \overline{X})^2}$$

Where x_i is an attribute for municipality i, x_j is an attribute for municipality j, $\overline{X}$ is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between municipality i and j. For statistical significance test, we utilize standarlized form of global Moran's I, which is assumed to follow asymptotically standard normal distribution. Then, we conduct a Z-test, for which the null hypothesis is that of a random distribution in regional development. Table 2 presents global Moran's I estimate for the various indicators of development in South Africa. The coefficient estimates are all positive and statistically significant. These results suggest there is significant and positive spatial dependence in the distribution of regional development.

Table 2: Measures of global spatial autocorrelation, Moran's I

Variables	I	E(I)	sd(I)	Z	p-value*
GDP_per capita	0.318	-0.004	0.041	7.881	0.000
Income Poverty (LPL)	0.643	-0.004	0.041	15.784	0.000
Income Poverty _(UPL)	0.591	-0.004	0.041	14.529	0.000
Income Gini	0.150	-0.004	0.041	3.785	0.000
Multidimensional poverty	0.614	-0.004	0.041	15.077	0.000
Deprivation inequalities	0.594	-0.004	0.041	14.605	0.000

Source: Own estimates using data from the South African Census, 2011 and GDP from Stats SA.
1-tail test

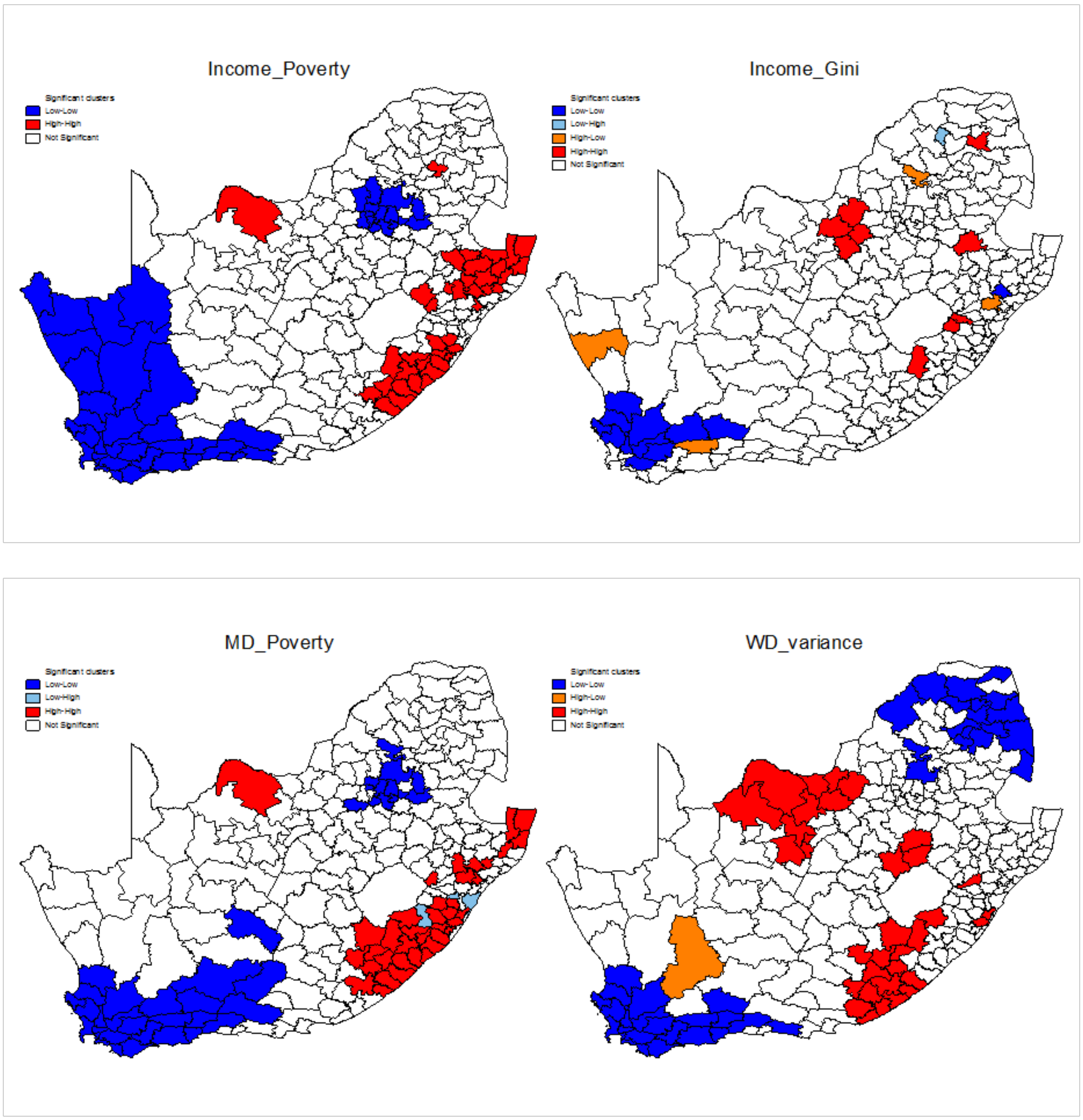
Although the global Moran's I suggests significant positive spatial autocorrelation, the approach does not tell us whether there are regional heterogeneities in patterns of developments. For this purpose, we use the local Moran's I statistics, which allow us to identify whether high or low values are clustered spatially (Anselin, 1995). The formula of local Moran's I is given by:

$$I_i = \frac{x_i - \overline{X}}{N^{-1}\sum_i^N \left(x_i - \overline{X}\right)^2} \sum_j^N w_{i,j}\left(x_j - \overline{X}\right)$$

A positive value for the local Moran I statistic indicates that a given municipality has neighbouring municipalities with similarly high or low poverty or inequality estimates (identifying clustering), while a negative value indicates that a municipality has neighbouring municipalities with dissimilar poverty or inequality estimates (identifying an outlier). The Z-score of the local Moran's I index, and its p-value are used to test whether either the clustering or the outlier features are statistically significant.

Figure 6 maps the local Moran's I estimates for poverty and inequality indicators. Figure 1B and 2B in the appendix present the corresponding scatter plots for the local Moran's I estimates. We find that there are significant clusters of high-income poverty and multidimensional poverty measures (hotspots) mainly around KwaZulu-Natal and Eastern Cape provinces. In contrast, coldspots are found in municipalities located in Western Cape (for all measures) as well as for poverty around Gauteng's agglomerated areas. In the case of multidimensional estimates, we find some areas with clusters of Low-High poverty estimates. Three municipalities with relatively lower multidimensional estimates (Greater Kokstad, The Msunduzi, eThekwini) are surrounded by municipalities with higher poverty levels.

Figure 6: Mapping local Moran's I



Source: Own estimates using data from the South African Census, 2011.

3. Estimation results for the correlates of poverty

Our analysis in the previous section indicates that both income and multidimensional poverty and inequality estimates vary significantly across municipalities in South Africa. In addition, using both global and local spatial autocorrelation measures we find significant, positive spatial dependence and clustering in the distribution of regional development indicators. These observations show that the situation of poverty is both spatially unequal and autocorrelated. In this section, using the municipality-level data from the 2011 Census and other data sources, we conduct a spatial econometric analysis in order to understand the relationship between local-level poverty, inequality and their determinants. In this section of the paper, we will restrict our analysis to income poverty in order to avoid the endogeneity problems that arise when dealing with the MPI and with inequality as outcomes. In order to estimate these relationships, we estimate the following spatial econometric models:

The spatial autoregressive model, SAR:

$$y = \rho \mathbf{W} y + \mathbf{X\beta} + \varepsilon$$

and the spatial Durbin model, SDM

$$y = \rho \mathbf{W} y + \mathbf{X\beta} + \mathbf{WX}\gamma + \varepsilon$$

Here y is a measure of poverty (income) for each municipality and X includes inequality and the other control variables**.** The parameter ρ captures the magnitude of the spatial autoregressive process in the level of poverty; namely, how poverty rates between neighbouring regions mutually affect each other. If ρ is positive, the level of poverty in a particular municipality has a similar trend to municipalities in its neighbourhood. The parameter γ captures effects of neighbouring municipalities' independent variables on the poverty levels of each municipality. **W** is a spatial weight matrix, which is row-normalized form, i.e. the sum of each row equals one. We use both a contiguity spatial weight matrix and an inverse-distance spatial weight matrix. A contiguity spatial weight matrix captures only the effects from adjacent municipalities (which share the common border), while an inverse-distance spatial weight matrix captures the effects from all other municipalities weighted by the nearness (inverse-distance). ε is a vector of error terms, which are assumed to be i.i.d. across municipalities and follow a standard distribution with zero mean and constant variance σ^2. In order to deal with endogenous bias stemming from a spatially lagged dependent variable, $\mathbf{W}y$, we estimate the SAR and SDM using a maximum likelihood approach (LeSage and Pace, 2009). The SAR model incorporates spatial autoregressive process in the dependent variable y. In addition to the spatial autoregressive process in the dependent variable, the SDM captures spillovers of the effects of explanatory variables from neighbouring municipalities.

With the aim of disentangling the complex nature of the spatial poverty, we employ three categories of independent variables: historical, geographical, and socio-economic factors in order to take into account the fact that, in the case of South Africa, poverty and inequality are shaped by the country's geography and history.

Only 16.7 million hectares of South Africa's surface areas (13.7%) are arable and only 1.3 million hectares of arable land (10%) are irrigated. The rest of rural land is arid or semi-arid, suitable only for livestock farming and pastoralism, where returns from farming are extremely low. Since the colonial administration in 1900s until the country's independence in 1994, rich agricultural lands were reserved for the whites. The colonial administration established "native reserves" and subsequently "home lands" across the country, all in inhospitable and least fertile areas, and forcibly moved South Africans of African ethnicity to their respective homeland. They were deprived of education and other basic public services, and were governed under the traditional regime. In urban areas, only several metropoles have been developed, each adjacent to a major port or big mines; consequently, they are spatially separated. Each metropolis was spatially segregated by race, and hence, largely by income class. For non-Whites mobility was restricted to work reasons.

These systems of spatial segregation by race were abolished from the mid-1980s to 1994, but spatial separation in effect still remains to a large extent, and hence spatial inequality in income. Similarly, the Constitution (adopted in 1997) intended to redress the large disparities in the provisions of basic public services across the country by directly allocating certain proportions of national revenues to local jurisdictions – and earmarked to each category of public services – under fiscal federalism. However, large disparities in public services still remain – and hence, spatial inequality in the multiple deprivation index – owing in part to the capacity constraints of municipal government as well as differing geographical difficulties in spreading public service facilities uniformly across a municipality.

Given the history discussed above, homeland is expected to be a strongly significant determinant of poverty headcount. In our model, however, several important characteristics of homeland - such as its geography, educational attainment and homogeneity of its population - are separately accounted for. Therefore, in our model, the homeland variable captures the effects of only: (a) the traditional governance regime; and (b) ethnicity – i.e., residents in homeland are of African ethnicity. The regression results will reveal whether or not these factors are significant in determining the extent of poverty. In our model, homeland is a dummy variable taking the value 1 if the data is from a municipality in former Bantustans (or Bantu homelands).

The models further postulate that vertical inequality within a municipality raises poverty. This postulate is motivated by a historical observation – in both South Africa and elsewhere – that inequality within a community lowers trust in that community and hence hinders economic and social development over time. Although inequality generally impacts poverty with a considerable lag, the model assumes contemporaneous correlation due to data limitations. As a result, in the case where the poverty headcount is based on income in the dependent variable and a Gini coefficient of income distribution is adopted to represent inequality, the correlation between poverty and inequality captures two aspects of inequality of the same density function. To the extent that the functional forms of density functions are similar and because the mean income is not too different in most municipalities, we expect a strong positive correlation between poverty headcount and Gini coefficient. In other words, the impact of inequality on poverty via trust of a community may not be shown by regression in this case. When the Gini of the multidimensional poverty index is used as the independent variable, the model is free of this complication.

Furthermore, the models adopt an interaction between the share of the white population and the Gini, and an interaction between education and homeland. The former combines horizontal inequality (as measured by the share of white population) and vertical inequality (as measured by a Gini). This captures the extent of overall inequality in a community, and allows us to abstract from influences of other factors discussed above. The latter captures a combined impact of having been a homeland and the extent of educational attainment of residents in that municipality. Given the history and its traditional governance regime, we expect that having been a homeland has a unique impact on the effectiveness of education to reduce poverty in a municipality. However, it is not immediately clear whether such impact should be positive or negative, in part because having been educated, most men and many women leave former homelands and migrate to mining and urban areas; for others who remain, economic opportunities to raise income are generally very limited.

Geographical variables include the land slopes, the average air temperature 2001-2011, the average annual rainfall 2001-2011, the variance from the average air temperature 2001-2011, and the variance from the average annual rainfall 2001-2011. Among the socio-economic variables, we also control for the share of the adult population at least high-school education, the share of white population, , and the disparity of access to basic public services measured by the deprivation inequality index. We further control for the degree of development of each municipality by adding the urban household ratio variable.

As a baseline estimation, we run OLS regression without spatial terms which we only present in Table 2B in the appendix because, technically, it is inferior to our spatial models. The positive and significant correlation of the former homeland dummy in the both estimations shows the influence of historical factors on current poverty. Natural geographical factors suggest that greater rainfall is associated with higher poverty, while more land inclinations and variable temperatures will lower poverty.

Next, we turn to estimation results for the spatial models of equations 1 and 2. Table 3 and 4 respectively provide estimated coefficients using the SAR and SDM estimation models for the income poverty measure. The estimation results in Table 3 and 4 are based on using the row-normalized binary spatial weight matrix (both contiguity and inverse-distance spatial weights).[8] In both the SAR and SDM model estimates, we include all the variables used in the OLS model.

[8] We report here only results using the contiguity spatial weights. The corresponding estimations based on the inverse-distance spatial weights are provided in Table 3B and Table 4B in the Appendix.

The spatial lag coefficient ρ is positive and highly significant, suggesting that the spatial correlation is important and the spatial models are superior to the OLS model. Importantly, the sign and significance of this coefficient makes robust our observation of section 3 that poverty in South Africa shows a spatial correlation: i.e., poor municipalities are located next to each other. The validity of spatial models is also supported by the fact that the variances of error terms of the dependent variable are statistically significant.

Table 3: Correlates of income poverty (headcount): SAR models

		W: contiguity			
Beta	Homeland	0.030**	0.046*	0.0187	0.057**
	Slope	-0.004	-0.004	-0.006*	-0.006*
	Temperature (mean)	0.003	0.003	0.001	0.001
	Rain(mean)	0.001*	0.001*	0.001*	0.001*
	Rain(var)	-0.000	-0.000	-0.000	-0.000
	Temperature (var)	-0.025	-0.022	-0.111**	-0.010**
	Education (>high school)	-0.998***	-0.989***	-1.064***	-0.984***
	White population (%)	-0.033	-1.720	-0.030	-2.169*
	Income Gini	0.384***	0.208	0.325***	0.115
	Deprivation inequality	0.606**	0.618**	0.793***	0.828***
	Log GDP	-0.030***	-0.027***		
	Urban households (%)			-0.125***	-0.119***
	White population x Income _Gini		0.024		0.030*
	Education x Homeland		-0.143		-0.337*
	_cons	0.486***	0.588***	0.341***	0.467***
Rho	W*headc_i_hi	0.221***	0.228***	0.208***	0.219***
	var(e.headc_i_hi)	0.003***	0.004***	0.003***	0.003***
	Sample size	234	234	234	234

Source: Own estimates. * p<0.05 ** p<0.01 *** p<0.001
Note: The results presented were obtained using the inverse distance spatial weights in the appendix.

Table 4: Correlates of income poverty (headcount): SDM models

		W: contiguity			
Beta	homeland	0.030**	0.040	0.0128	0.030
	Slope	-0.003	-0.002	-0.003	-0.002
	Temperature (mean)	0.004	0.003	0.003	0.002
	Rain(mean)	0.000	0.000	0.000	0.000
	Rain(variance)	-0.000	-0.000	0.000	0.000
	Temperature(variance)	-0.018	-0.025	-0.098*	-0.104*
	Education (> high school)	-0.932***	-0.913***	-0.951***	-0.914***
	White population (%)	-0.014	-1.569	0.005	-2.367**
	Income _Gini	0.355***	0.194	0.287***	0.050
	Deprivation inequality	0.762**	0.793**	0.602*	0.628*
	Log GDP pc	-0.033***	-0.032***		
	Urban households (%)			-0.179***	-0.175***
	White population x Income _Gini		0.022		0.0332**
	Education x Homeland		-0.122		-0.161
	_cons	-0.028	0.094	-0.204	-0.063
Rho	W*headc_i_hi	0.472***	0.466***	0.437***	0.433***
Gamma	homeland	0.006	-0.018	0.003	0.007
	slope	-0.000	-0.002	-0.001	-0.003
	Temperature (mean)	-0.001	-0.001	-0.002	-0.002
	Rain(mean)	0.001	0.001	0.001	0.001
	Rain(variance)	-0.000	-0.000	-0.000	-0.000
	Temperature (variance	-0.059	-0.050	-0.030	-0.015
	Education (> high school)	0.280	0.225	0.295	0.267
	White population (%)	0.106	0.347	-0.024	0.416
	Income _Gini	0.215	0.277	0.509**	0.580*
	Deprivation inequality	-0.274	-0.391	0.045	-0.048
	Log GDP pc	0.0221**	0.019*		
	Urban households (%)			0.106**	0.103**
	White population x Income _Gini		-0.004		-0.007
	Education x Homeland		0.206		-0.038
	var(e.headc_i_hi)	0.003***	0.002***	0.002***	0.002***
	Sample size	234	234	234	234

Source: Own estimates. * p<0.05 ** p<0.01 *** p<0.001

In econometric terms, the existence of this autocorrelation may have caused biases in the OLS estimates of β in table 2B in the Appendix. We can expect that such biases will be corrected by including spatial lag terms. However, estimated β in tables 3 and 4 are not directly comparable with those from the OLS estimates because of cumulative nature of spatial correlation. We can see this point by transforming our two earlier equations into the following data generating process (DGP) form:

$$y = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1}(\boldsymbol{X\beta} + \boldsymbol{WX}\gamma + \varepsilon)$$

where $\boldsymbol{I}$ is an N×N unit matrix. This equation represents the DGP of SAR if $\gamma = 0$ is assumed, while it is the DGP of SDM if $\gamma \neq 0$ is assumed. According to the DGP, the coefficients in SAR and SDM do not denote marginal effects owing to $(\boldsymbol{I} - \rho \boldsymbol{W})^{-1}$.

Based on the DGP, we can consider the following spatial dependence structure in regional development in South Africa. First, the characteristics of municipality *i* are associated with the poverty rate of own municipality ***i***. This pass is labeled the direct effect. This includes feedback effects via other regions. Second, the endogenous variable, i.e. the poverty rate, is affected by own regional factors affecting poverty rates of its neighboring municipalities. This effect is called indirect impact.

The coefficient estimates of the *k*th variable are provided under three heading: *direct effects*, *indirect effects*, and *total effects* as proposed by LeSage and Pace (2009):

$$Direct\ Effect = \frac{1}{N} trace\left[(\boldsymbol{I} - \rho \boldsymbol{W})^{-1}(\beta_k \boldsymbol{I} + \gamma_k \boldsymbol{W})\right],$$

$$Total\ Effect = \frac{1}{N} \iota_N' \left[(\boldsymbol{I} - \rho \boldsymbol{W})^{-1}(\beta_k \boldsymbol{I} + \gamma_k \boldsymbol{W})\right]\iota_N,$$

$$Indirect\ Effect = Total\ Effect - Direct\ Effect,$$

where ι is an N×1 vector of ones. According to the form of Direct, Indirect, and Total effects, $\boldsymbol{WX}$ in the SDM boosts the indirect effect owing to $\gamma_k \boldsymbol{W}$. The SDM explicitly models the indirect impact, i.e. spatial spillovers, by containing the spatially lagged explanatory variable $\boldsymbol{WX}$, which represents the characteristics of the neighbouring municipality *j*.

Looking at the income poverty estimates shown in Table 5, the “Direct effect” panels of SAR indicates that coefficient estimates, and significance levels are similar when we use either the contiguity or inverse-distance spatial weight matrix. It is worth observing that the inclusion of interaction terms between the share of white population and income inequality variables slightly changes the results. Without the interaction term, the share of white population is not significant and the coefficient on the income Gini estimate is significant with a positive sign, while with the interaction term the coefficient on the share of white population is significant with a negative sign and income inequality becomes insignificant. In the case of SDM, with an inverse-distance spatial weight and with the interaction term, the coefficient on the share of white population is significant with a negative sign and income inequality is positive and marginally significant. This suggests that municipalities with higher white population tend to have lower income poverty incidences, but “whiter” municipalities with higher inequalities tend to have more poverty. These results imply that in municipalities where white population shares are insignificant, low levels of income inequalities can be associated with higher poverty because everyone there is almost equally poor. However, where white population shares are higher poverty rates are found only in municipalities with higher income inequalities.

The "Direct effect" panels of SDM show that the influences of natural geography are not significant, except for the positive correlation with mean temperature. This suggests that poverty is higher in hotter areas and is rather intuitive since areas with higher temperatures are more arid and with lower productivity, leading to higher income poverty incidence. As mentioned in section 3.2.2, poor municipalities are located in "hotspots" of poverty with poor municipalities being located adjacent to each other. In the regression without the interaction term, we can clearly see that having belonged to former homelands leads to higher poverty headcounts at the municipal level. When the interaction term between education and homeland dummy is included, the homeland variable loses significance. As expected, education has a strong effect on poverty reduction, with the variable having a highly significant negative coefficient. With the introduction of the interaction term, the poverty reduction effect of education is even stronger.

The indirect effect coefficients that measure spatial spillovers are bigger in the SDM than in the SAR. This is as expected. Also, they satisfy the expected sign conditions. However, in the SDM most of those effects are not significant. Nonetheless, it is important to control for these indirect effects because it is natural to expect such spatial spillovers across municipalities. Our results show that direct impacts of neighbourhood independent variables are not quite strong. One plausible explanation is that municipalities may be too large spatial unit to observe direct spatial interactions. It is also possible that transportation infrastructure is not adequately provided to support interactions among municipalities.

Table 5: Cumulative (direct and indirect) spatial models of income poverty (headcount)

	SAR/Wcontig		SDM/Wcontig	
Direct effect				
Homeland	0,019*	0,058***	0,014	0,032
Slope	-0,006**	-0,006**	-0,003	-0,002
Temperature (mean)	0,001	0,001	0,003	0,002
Rain(mean)	0,001**	0,001**	0,000	0,000
Rain(variance)	0,000	0,000	0,000	0,000
Temperature(variance)	-0,112***	-0,101***	-0,106**	-0,110***
Education (> high school)	-1,073***	-0,994***	-0,964***	-0,928***
White population (%)	-0,030	-2,191**	0,003	-2,431
Income _Gini	0,328***	0,116	0,354***	0,113
Deprivation inequality	0,800***	0,837***	0,635***	0,652***
Urban ratio	-0,127***	-0,120***	-0,176***	-0,172***
White pop x Income Gini		0,030**		0,034
Education x Homeland		-0,341**		-0,172
Indirect effect				
Homeland	0,005*	0,016**	0,014	0,033
Slope	-0,001**	-0,002**	-0,004	-0,006
Temperature (mean)	0,000	0,000	-0,001	-0,001
Rain(mean)	0,000**	0,000**	0,001*	0,001
Rain(variance)	0,000	0,000	0,000	0,000
Temperature(variance)	-0,028**	-0,027**	-0,120	-0,100
Education (> high school)	-0,270***	-0,267***	-0,201	-0,214
White population (%)	-0,008	-0,588**	-0,035	-1,010
Income _Gini	0,083***	0,031	1,059***	0,997**
Deprivation inequality	0,201***	0,224***	0,516	0,372
Urban ratio	-0,032***	-0,032***	0,047	0,045
White pop x Income Gini		0,008*		0,013
Education x Homeland		-0,091**		-0,179
Total effect				
Homeland	0,024*	0,073***	0,027	0,065
Slope	-0,007**	-0,007**	-0,007	-0,008
Temperature (mean)	0,002	0,001	0,002	0,001
Rain(mean)	0,001	0,001**	0,002**	0,002*
Rain(variance)	0,000	0,000	0,000	0,000
Temperature(variance)	-0,140***	-0,128***	-0,226**	-0,210*
Education (> high school)	-1,344***	-1,261***	-1,165***	-1,142***
White population (%)	-0,038	-2,779**	-0,032	-3,442
Income _Gini	0,410***	0,147	1,413***	1,110**
Deprivation inequality	1,002***	1,061***	1,151**	1,023*
Urban ratio	-0,158***	-0,152***	-0,128**	-0,127**
White pop x Income Gini		0,038**		0,047
Education x Homeland		-0,432**		-0,351

Source: Own estimates. * p<0.05 ** p<0.01 *** p<0.001

As mentioned, looking at ‘Total effects’ allows us to understand the determinants of poverty headcount at the municipal level, taking into account the direct effects as well as the spillover effects of the neighbouring municipalities. Our results show that once these spillovers are considered, having been part of a homeland is not correlated with current income poverty rates. Rather, these rates are mainly explained by education, urban ratio and the average rain volume.

It is now possible to compare the coefficients of the direct effects and the OLS estimates in table 2. We can see that the impacts of each of the variables are systematically smaller in the spatial models than in the OLS case. This suggests that the coefficients are overestimated in the latter. Notably, the coefficients of homeland dummy becomes smaller and even statistically insignificant in some spatial model estimations. The latter results imply that although contemporary spatial poverty and inequality in South Africa are often attributed to the direct historical reasons for being the former Bantustans, the clustering of poverty within these municipalities is not statistically different from that of non-Bantustan municipalities when we control for other geographic and socio-economic determinants of poverty. This does not mean that the historical roots of poverty should be discarded. Clearly, residing in a homeland area is correlated with socio-economic deprivation. That is why the estimation results of the homeland coefficient in the SDM (with inverse-distance spatial weight matrix) suggest an insignificant coefficient that then turns significant after adding the interaction term of homeland with the share of population having higher education. Our spatial models prove to be very useful in unpacking the large impact of the homeland dummy variable on poverty that we see in the non-spatial estimations of municipality-level data as well as in our earlier mapping. Some of this effect is seen to be due to spillovers attendant upon being surrounded by very poor municipalities. Some of this effect is due to fact that those who reside within these apartheid boundaries are still especially prone to the socio-economic deprivations that are driving contemporary poverty.

4. Conclusions

In this paper, we provide estimates of poverty and inequality at municipal level using the 2011 South African population census. We show that both income and multidimensional poverty and inequality levels vary greatly across municipalities. The poorest municipalities in both measures are located mainly in the Eastern Cape and KwaZulu-Natal provinces, where some of the largest former homeland areas are located. Using Moran's I statistics we find that there is a significant level of spatial dependency in regional development in South Africa. High poverty and inequality estimates are spatially clustered mainly in the Eastern Cape and KwaZulu-Natal provinces. Those residing within areas that were homelands under apartheid seem particularly badly off.

The determinants of the poverty headcount at the municipal level are explored further through a series of OLS and spatial regression models. Results from this analysis indicate that there is a negative and significant relation between the municipal poverty levels and lower urbanisation rates, local levels of education and economic activity (GDP per capita). A significant, positive relationship is found between municipal poverty levels and local inequality levels, suggesting that municipalities with higher levels of inequality also have higher incidences of poverty. In contrast, natural geographic factors such as rainfall and temperature are not significantly related to municipal poverty.

The spatial models allow for the estimation of a total effect, that includes both direct intra-municipality effects as well as spillover effects of neighbouring municipalities. Accounting for spillover effects is important. It reduces the coefficient sizes as estimated by non-spatial, OLS regressions. Now poverty rates are mainly explained by local education levels, urban ratios and the average rain volume. Most striking, the large negative coefficient that OLS attributes to residing within a historical homeland area is greatly reduced and even not statistically significant in some spatial models. However, when interactions between this historical geographical variable and contemporary socio-economic deprivations are included, then homeland becomes statistically significant once more. This makes the important point that while, across the county, it is these socio-economic deprivations that are particularly important in explaining contemporary income poverty, those who still reside in these homeland areas remain especially badly off in terms of these deprivations.

Although our analysis provides suggestive evidence linking poverty with inequality and other factors at the municipality level, the results from these estimates cannot be interpreted as causal relationships. First, our analysis of poverty and inequality, and the relationship between the two is based on a single census and, as such is a static analysis. Change in most of the variables including inequality and GDP per capita takes time and, as such, these static correlations are not a substitute for longer-term estimations of how changes in these variables impact on poverty and inequality. Second, the processes generating local level poverty are more complicated than our estimations can capture. There are other variables that can potentially affect poverty that we do not include in our estimations. These include the extent of public spending, local level capacity and the efficiency of local level spending and even corruption. These limitations make it clear that there is plenty of scope for further research.

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Appendix A: Multidimensional Poverty and Inequality Estimates

In order to estimate the extent of multidimensional poverty and inequality estimates, we consider four dimensions: education, health, living standards, and employment. Table 1A presents the list of indicators used to measure these dimensions, weights, and deprivation cut-offs. We use the counting methodology proposed by Alkire and Foster (2011) for aggregation. We use induvial as the unit of analysis to determine deprivation cut-offs for the health and education indicator, which is line with the approach used by Frame et al (2016) in calculating MPI for youth in South Africa. In the case of the Stata SA and Alkire and Foster (2011) approaches, deprivations are determined at a household level for all indicators and all individuals in a household assigned household-level deprivation scores. For example, irrespective of an individual's level of education, individuals are considered not deprived in years of schooling if at least one member of a household has six years of education. One key problem in using this approach is that it does not allow one to analyse intra-household inequalities (e.g. by age structure or gender).

Using the deprivation cut-offs and weights proved in Table 1A, we calculated a weighted deprivation score for each individual (the sum of weighted deprivation scores). Then we use a poverty cut-off k=33.3% (1/3 the weighted indicators) to identify poor and non-poor individuals. Thus, an individual is considered multidimensionally poor, if he or she is deprived in 1/3 the weighted deprivation scores. The incidence of poverty is measured as the multidimensional headcount ratio (H):

$$H = \frac{q}{n}$$

Where q is the number of people who are multidimensionally poor and n is the total population. The average proportion of deprivations poor people experience, intensity of poverty (A) is calculated using the following formal:

$$A = \frac{\sum C_i(k)}{q}$$

Where $C_i(k)$ is deprivation score of the poor (the censored deprivation score of individual i), k is a poverty cut-off (=33% of the weighted deprivation scores). The MPI value is given as the product of the multidimensional poverty headcount ratio (H) and the intensity of poverty (A).

The following formula to estimate inequality in deprivation levels given as follows:

$$I(C) = \frac{4}{n}\sum_{i=1}^{n}[c_i - \mu(c_i)]^2$$

Where C_i is a measure of weighted deprivation levels for each individual, and $\mu(c_i)$ is average deprivation levels for each municipality.

Table 1A: Dimensions, indicators, deprivation thresholds, and weights of the MPI

Dimensions	Indicators	Deprivation cut-off(deprived if)	Weights
Health	General health and functioning	Individual experiences difficulty in one or more functions: hearing, vision, communication, mobility (walking or climbing stairs), or cognition (remembering or concentrating)	1/4
Education	Years of Schooling	Children aged <7 -not deprived in schooling and children age 7 & 8 -not deprived if currently attending school (even though completed zero schooling). Not deprived if: Age 9-16 completed grades from 1 to 7 Age 17-20 completed at least grade 9 Age 21>above completed at least grade 12	1/4
Living standard			
	Dwelling type	Dwelling type is informal shack /traditional dwelling/caravan/tent /other	1/28
	Water	No piped water in a dwelling or on stand	1/28
	Sanitation	No flush toilet	1/28
	Fuel for cocking	Household is using paraffin/ wood/ coal animal dung/ other/ none	1/28
	Fuel for lighting	Household is using paraffin/candle/ other	1/28
	Fuel for heating	Household is using paraffin /wood /coal /animal dung/ other/ none	1/28
	Asset ownership	Household does not own more than one of television, radio, telephone or refrigerator and does not own a car	1/28
Economic Activity	Unemployment	All adults (aged 15 to 64) in a household are unemployed	1/4

Appendix B: Tables and Figures

Table 1B: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
Income poverty(headcount)	234	0.671	0.144	0.371	0.897
MPI	234	0.192	0.083	0.061	0.398
Independent variables					
History					
Homeland	234	0.333	0.472	0	1
Natural geography					
slope	234	2.892	1.905	0.266	8.331
Mean_temp		17.422	2.162	12.937	23.066
Mean_rain		68.564	58.613	1.222	465.040
Rain(variance)	234	0.192	0.063	0.068	0.475
Temperature(variance)	234	0.024	0.007	0.008	0.041
Socio-economic conditions					
Education (> high school)	234	0.137	0.062	0.044	0.361
White population (%)	234	0.073	0.069	0	0.386
Income _Gini	234	0.719	0.042	0.594	0.831
Deprivation inequality	234	0.186	0.023	0.124	0.236
Log GDP	234	9.866	1.498	4.937	11.824
Urban households (%)	234	0.529	0.349	0	0.998

Source: Own estimates

Table 2B. Ordinary least squares non-spatial model estimation results

	OLS	
Homeland	0.030**	0.063***
	(0.011)	(0.022)
Slope	-0.006	-0.006**
	(0.004)	(0.003)
Temperature (mean)	0.002	0.002
	(0.002)	(0.002)
Rain(mean)	0.001***	0.001***
	(0.0003)	(0.0003)
Rain(variance)	-3.49E-05	-1.33E-05
	(5.63E-05)	(8.53E-05)
Temperature(variance)	-0.119**	-0.110
	(0.045)	(0.041)
Education (> high school)	-1.131***	-1.068***
	(0.107)	(0.105)
White population (%)	-0.0424	-2.049**
	(0.055)	(1.025)
Income _Gini	0.452***	0.260*
	(0.118)	(0.139)
Deprivation inequality	1.087***	1.127***
	(0.226)	(0.224)
Urban households (%)	-0.136***	-0.131***
	(0.022)	(0.019)
Education x Homeland		-0.288*
		(0.155)
White population x Income _Gini		0.028*
		(0.014)
Constant	0.319***	0.439***
	(0.093)	(0.118)
adj. R-sq	0.832	0.882
Sample size	234	234

Source: Own estimates. Standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 3B: Correlates of income poverty estimates (headcount): SAR models

		W: inverse distance			
Beta	homeland	0.032***	0.052*	0.021*	0.062**
	slope	-0.004	-0.004	-0.006*	-0.006*
	Temperature (mean)	0.003	0.003	0.001	0.001
	Rain(mean)	0.001*	0.001	0.001*	0.001
	Rain(variance)	-0.000	-0.000	-0.000	0.000
	Temperature(variance)	-0.029	-0.026	-0.113**	-0.102**
	Education (> high school)	-1.037***	-1.022***	-1.096***	-1.013***
	White population (%)	-0.024	-1.615	-0.021	-2.056*
	Income _Gini	0.430***	0.263	0.369***	0.171
	Deprivation inequality	0.571*	0.586**	0.754***	0.787***
	Log GDP pc	-0.029***	-0.027***		
	Urban households (%)			-0.124***	-0.117***
	White population x Income _Gini		0.022		0.029*
	Education x Homeland		-0.165		-0.353*
	_cons	0.211*	0.290*	0.082	0.180
Rho	W*headc_i_hi	0.594***	0.619***	0.564***	0.604***
	var(e.headc_i_hi)	0.003***	0.003***	0.00310***	0.00296***
	Sample size	234	234	234	234

Source: Own estimates. Standard errors in parentheses

* p<0.05 ** p<0.01 *** p<0.001

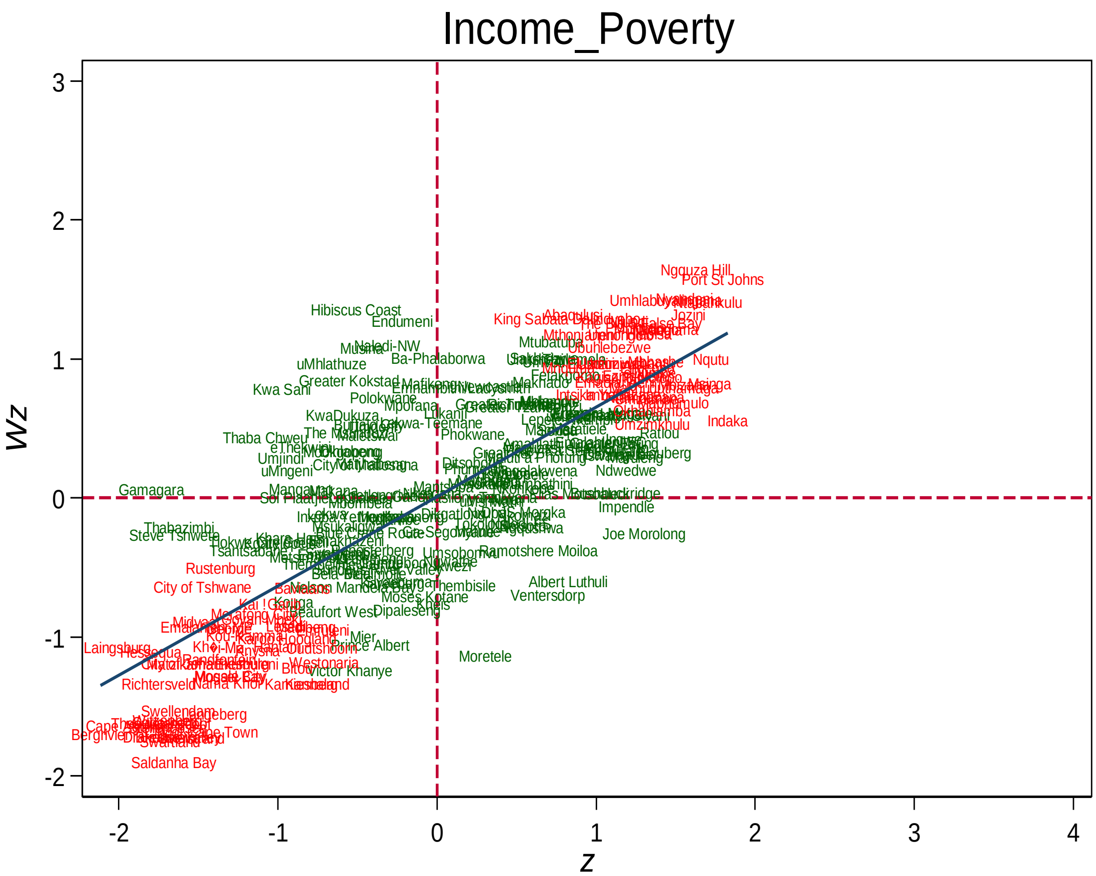
Table 4B: Correlates of income poverty estimates (headcount): SDM model

		W: inverse distance			
Beta	Homeland	0.027**	0.050*	0.0154	0.044*
	Slope	-0.002	-0.001	-0.003	-0.002
	Temperature (mean)	0.003	0.001	0.002	0.000
	Rain(mean)	0.000	0.000	0.000	0.000
	Rain(variance)	-0.000	0.000	0.000	0.000
	Temperature(variance)	-0.069	-0.076	-0.120**	-0.121**
	Education (> high school)	-0.879***	-0.854***	-0.940***	-0.887***
	White population (%)	-0.029	-2.190*	-0.0336	-2.434**
	Income _Gini	0.434***	0.232	0.383***	0.149
	Deprivation inequality	0.809**	0.869***	0.527*	0.582*
	Log GDP pc	-0.034***	-0.032***		
	Urban households (%)			-0.179***	-0.172***
	White population x Income _Gini		0.030*		0.033*
	Education x Homeland		-0.201		-0.266
	_cons	-2.477	-0.090	-3.291*	-2.451
Rho	W*headc_i_hi	0.695***	0.655**	0.700***	0.639**
Gamma	Homeland	0.213	0.223	0.143	0.567*
	Slope	-0.075*	-0.092*	-0.067	-0.073
	Temperature (mean)	0.019	0.020	0.023	0.027
	Rain(mean)	0.007	0.005	0.009*	0.007
	Rain(variance)	-0.000	0.001	-0.001	0.000
	Temperature(variance)	-1.181*	-1.059*	-1.151*	-0.916
	Education (> high school)	-1.609	-1.973	-1.602	-1.625
	White population (%)	-0.778	-29.01	-1.592	-15.84
	Income _Gini	4.573**	2.415	5.654***	5.179*
	Deprivation inequality	-6.468*	-8.542**	-5.367*	-7.045**
	Log GDP pc	0.061	0.036		
	Urban households (%)			0.422	0.402
	White population x Income _Gini		0.396		0.190
	Education x Homeland		-0.610		-4.261*
	var(e.headc_i_hi)	0.003***	0.003***	0.003***	0.002***
	Sample size	234	234	234	234

Source: Own estimates. Standard errors in parentheses

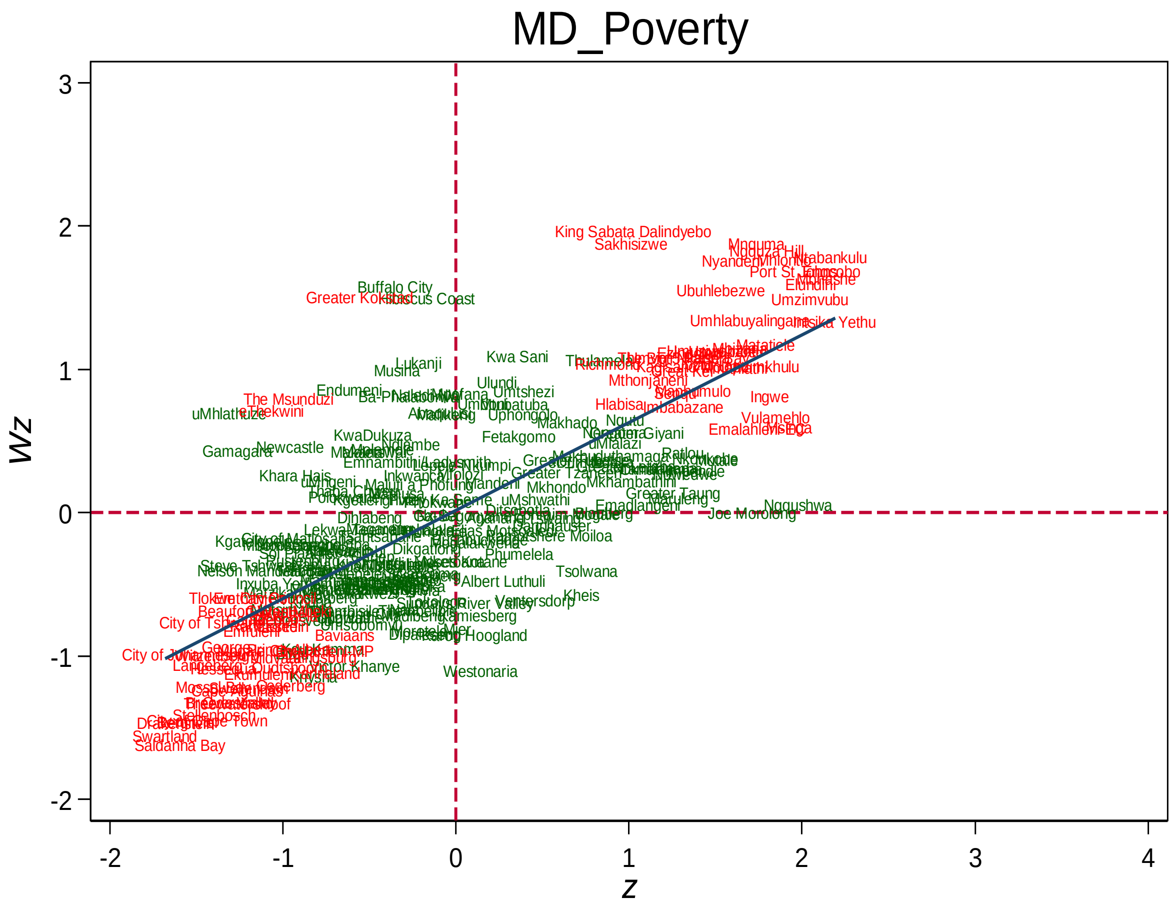
* p<0.05 ** p<0.01 *** p<0.001

Figure 1B: Local Moran's I scatterplot for income poverty



Source: Own estimates using data from South African Census, 2011.

Figure 2B: Local Moran's I scatterplot for multidimensional poverty



Source: Own estimates using data from South African Census, 2011.