Poverty, inequality, and geographic targeting: Evidence from small-area estimates in Mozambique

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Abstract

Typical living standard surveys can provide a wealth of information about welfare levels, poverty, and other household and individual characteristics. However, these estimates are necessarily at a high level of aggregation, because the total samples of such survey are usually only a few thousand households. Larger data bases, such as national censuses, provide sufficient sample sizes for more disaggregated analysis, but typically collect very little useful socio-economic information. This paper combines data from the 1996-97 Mozambique National Household Survey of Living Conditions with the 1997 National Population and Housing Census to generate small-area (sub-district) and sub-group estimates of welfare, poverty, and inequality, with the associated standard errors. These small area estimates are then used to explore several dimensions of poverty and inequality in Mozambique, particularly with regard to geographical targeting of anti-poverty efforts.

Reliably identifying and targeting the poor can be administratively costly, especially in rural Africa. Geographical targeting, or targeting poor areas, is sometimes proposed as a feasible alternative to targeting poor people, and poverty mapping using census data may serve as a valuable tool in this regard. Unfortunately, the notion of poor areas might not always be especially useful, as appears to be the case in Mozambique. Decomposition of the small area estimates shows that only about 20 percent of consumption inequality is accounted for by inequality between districts or between administrative posts. Even at the level of the village, less than one half of inequality is between-village; most is within-village. The picture that emerges of the poor living alongside the nonpoor indicates that targeting poor areas is likely to result in leakage to the nonpoor in that area, and considerable under coverage of the significant numbers of poor households is areas that are less poor.

Concern about leakage to the nonpoor in poorer areas is mitigated by another interesting result from the small area estimates in Mozambique. According to most measures of poverty and inequality, the correlation between poverty and inequality for these small geographic units is negative and significant. This suggests that if areas with higher poverty le vels are targeted for assistance, the risk of leakage of benefits (or elite capture) is limited, and decentralization of distribution decisions within that area may be warranted.

Introduction

Typical living standard surveys can provide a wealth of information about welfare levels, poverty, and other household and individual characteristics. However, these estimates are necessarily at a high level of aggregation, because the total samples of such survey are usually only a few thousand households. Larger data bases, such as national censuses, provide sufficient sample sizes for more disaggregated analysis, but typically collect very little useful socio-economic information.

This paper combines data from the 1996-97 Mozambique National Household Survey of Living Conditions with the 1997 National Population and Housing Census to generate small-area (sub-district) and sub-group estimates of welfare, poverty, and inequality, with the associated standard errors. These small area estimates are then used to explore several dimensions of poverty and inequality in Mozambique, particularly with regard to geographical targeting of anti-poverty efforts.

Country setting

For many years, Mozambique could consistently be found among the poorest five countries listed in the World Bank's annual *World Development Report*, typically in the company of Ethiopia, Cambodia, Sierra Leone, and others. According to Mozambique's first national poverty assessment, in 1996-97 almost 70 percent of the Mozambican population was living below the poverty line (MPF/UEM/IFPRI, 1998). The poverty gap index and Foster-Greer-Thorbecke (FGT) P_2 index were also extremely high, at 0.293 and 0.156,respectively. The high levels of consumption poverty are consistent with other indicators of deprivation. The adult literacy rate is only 40 percent, with female literacy especially low at only 26 percent (INE, 2000). The educational picture is only slightly better for the current school generation: the gross primary enrollment rate is 67 percent, and the net enrollment rate is only 40 percent. For secondary schools the corresponding rates are seven percent and two percent. According to the 1997 population census, the infant mortality rate stood at 146 per 1000 live births, with underfive mortality reaching 246 per 1000 live births, and a life expectancy at birth of only 42 years (INE, 2001). The life expectancy figure has since been revised downwards to 35 years, following a recent study of the demographic impact of the HIV/AIDS pandemic (INE/MISAU, 2001). Only 33 percent of households have a toilet or latrine, only 15 percent of households have regular access to safe water supplies, 5 percent have electricity in their dwelling, and 28 percent of households own a radio.

From the poverty assessment, which was based on the first nationally representative survey of living standards, poverty rates were somewhat higher in rural areas than in urban areas. More pronounced were the differences across provinces, with the poverty headcount ranging from 48 percent in the capital city of Maputo, to 88 percent in Sofala province, as shown in Figure 1. Regional disparities have often been a source of tension in Mozambique, a tension that has not abated much even during the past several years of rapid economic growth, as there is a common perception that most of the benefits of this growth have been concentrated in the south of the country. Recent official government statements have spoken to the need to reduce regional disparities, and addressing regional disparities is an explicit objective of the government's Poverty Reduction Strategy Paper (PRSP) and Plan of Action for the Reduction of Absolute Poverty (PARPA) (Government of Mozambique, 2001). Indeed, the PARPA notes "The size of Mozambique's provinces are equal in some cases to the size of some European states. As a result, the success of territorially-based interventions will be improved if sub-provincial units are targeted, which in the current political-administrative make-up of the country means districts." (Government of Mozambique, 2001).

Methodology

On the surface, the methodology is straightforward. The household survey data are used to estimate the statistical relationship between the empirical variable used to measure welfare (consumption per capita, adjusted for spatial and temporal variation in prices) and a set of independent variables that are expected to be correlated with welfare. The set of variables considered for the right hand side of the regression equation is limited to those variables that appear in both the household survey and the population census. The estimated regression coefficients are then applied to the census data to produce estimates of consumption per capita for each of the households in the census. The estimates of consumption per capita are then used to calculate summary measures of poverty and inequality, such as the Foster-Greer-Thorbecke (FGT) class of P_a poverty measures, the Gini index, or generalized entropy (GE) inequality measures. Because consumption estimates are available for the entire population, it is possible to calculate welfare measures for small sub-groups of the population, be they geographic regions (such as sub-districts), occupational classifications, or some other classification. This method for linking surveys with census-type data is used in geography for small area estimation. It has been adapted for the disaggregated study of poverty and inequality, with an application to Ecuador, by Hentschel et al. (1999). Further refinements of the method are presented in Elbers et al. (forthcoming).

More formally, the natural logarithm of per capita consumption is modeled as a function of a set of observable household characteristics. We estimate this relationship by a linear approximation of the form

(1) $\ln y_{ch} = \mathbf{x'}_{ch}\, \mathbf{ß} + ?_c + e_{ch}$

where y_{ch} is per capita consumption of household h residing in cluster c, $\mathbf{x}_{ch}$ are the observable characteristics of that household that are available in both the survey and census data sets, and **ß** is a coefficient vector.[1] The disturbance term has two components. The first component, $?_c$, applies to all households within a given cluster, while the second, e_{ch}, is specific to the household. These two components are uncorrelated with one another and independent of the regressors. This specification of the disturbance term allows for heteroscedasticity of the household-specific error component. It also accommodates the possibility of spatial autocorrelation, i.e., a location-specific effect common to all households within a cluster.

Elbers et al. (forthcoming) note that for any given disturbance variance s^2_{ch}, as the proportion attributable to the location-specific component increases, the precision of welfare estimates is reduced, and the lower will be inequality. It follows that failure to account for intra-cluster correlation would lead to underestimated standard errors on welfare estimates and overestimated (biased) inequality measures. We reduce the magnitude of the unexplained location-specific component by including cluster-specific variables among the regressors. These are cluster-level means of the household-level variables that exist in both the survey and the census. Because of the small sample size of the survey, these variables are calculated from the census data, and merged with the survey data for the regressions.

[1] Here the term cluster refers to the administrative post, the most disaggregated level at which we group the data in the analysis that follows. In the household survey sample design the first stage of clustering was one level lower, at the level of the *bairro* (urban areas) or *localidade* (rural areas). In the future we intend to experiment with clustering the census data at levels smaller than an administrative post.

Equation (1) is estimated using generalized least squares (GLS), taking into account the heteroscedasticity of the household component of the disturbance term, e_{ch}. The survey is not self-weighting, so regressions are estimated using the survey probability weights, which are the inverse of the probability of selection into the sample. Rather than impose an assumption of homogeneous coefficients throughout Mozambique, separate regressions are estimated for each of the 11 strata of the survey dataset. The same set of candidate variables is considered for each of the models, with final variable selection determined by a stepwise procedure supplemented with extensive ex post diagnostics. In this case the number of variables in the regressions is not constrained by the number of common variables in the survey and the census, but rather by the number of clusters in the first stage of sampling within each stratum, as the appropriate Wald test for the regression is based on an F distribution with (k, d-$k+1$) degrees of freedom, where k is the number of terms in the model (excluding the constant) and d is the number of primary sampling units minus the number of strata (Korn and Graubard, 1990).

The resulting parameter estimates are then applied to the census data. Estimates of consumption for the census households must take into account the disturbance term, that is, the portion of the variation in consumption in the survey data that is not explained by variation the regressors. Otherwise, poverty estimates for the census data would be biased (the direction depending upon whether the position of the poverty line relative to the distribution of consumption) and inequality estimates would be biased downwards. Instead, we simulate the level of consumption for each household as

(2) $$\hat{y}_{ch} = \exp\left(x'_{ch}\,\hat{b} + \hat{h}_{c} + \hat{e}_{ch} \right),$$

where the c and h now index clusters and households in the census data. In the results reported in this paper, the simulations draw the $\hat{b}$ coefficients from the multivariate normal distribution described by the point estimates and the variance-covariance matrix estimated in the first stage regression. The estimated disturbance terms are drawn from a t-distribution.

Data

The survey data used in the analysis are from the *Inquérito Nacional aos Agregados Familiares sobre as Condições de Vida, 1996-97* (National Household Survey of Living Conditions). The survey is a multi-purpose household and community survey, in the same vein as the World Bank's Living Standard Measurement Study (LSMS) surveys, and was designed and implemented by the National Institute of Statistics. Data collection took place from February 1996 through April 1997, covering 8,250 households living throughout Mozambique. The sample is designed to be nationally representative, as well as representative of each of the ten provinces, the city of Maputo, and along the rural/urban dimension. It is the first survey of living conditions in Mozambique with national coverage, and is the only national survey that measures welfare using comprehensive income or expenditure data.

The household survey, also known by the shorthand IAF96, has been used for numerous poverty studies in recent years (see, for example, MPF/UEM/IFPRI, 1998; Datt et al., 2000; Handa, forthcoming; Handa and Simler, 2000; Tarp et al., forthcoming). Most of those studies, like the present one, use a comprehensive welfare measure based upon per capita consumption. The consumption measure includes food and nonfood items, acquired through home production, market purchases, transfers, or payments in kind. Consumption also includes the imputed use value of household durables, and an imputed rental value for owner-occupied housing. As the survey took place over a period of 14 months, and there is significant temporal variation in food prices corresponding to the agricultural season, nominal consumption values were deflated by a temporal price index. Similarly, spatial differences in the cost of living were incorporated by using a spatial deflator, which is based on the cost of region-specific cost of basic needs poverty lines. Additional details are presented in MPF/UEM/IFPRI (1998).

The second data source is the *II Recenseamento Geral de População e Habitação* (Second General Population and Housing Census), which was conducted in August 1997. In addition to providing the first complete enumeration of the country's population since the initial post-independence census in 1980 and basic demographic information, the 1997 census collected information on a range of socioeconomic variables. These include educational levels and employment characteristics of those older than six years old, dwelling characteristics, whether the household owned a functioning radio, and possession of agricultural assets. The 1997 census covers approximately 16 million people living in 3.6 million households.

It is convenient that the census and the IAF96 are almost contemporaneous, as a pivotal assumption of the method is that the parameters estimated from the survey data are equally applicable to the period covered by the census.

The empirical modeling of household consumption is limited by the set of variables that is common in the two data sets. Common variables include the age and sex composition of the household, the sex of the head of household, educational levels, employment characteristics, dwelling characteristics, and possession of agricultural and other assets. Close examination of the data revealed that several variables that appear to be the same in the two data sets were really quite different, with differences in the position and distribution of the variables that are inexplicably large given the close timing of data collection. One possibility is that because of differences in definitions or field protocols, the two exercises measured distinctly different things for these variables. Another possibility is that the survey simply was not representative of the population for those variables. Either explanation is sufficient justification for excluding the variable(s) for consideration in the model. It is unlikely that the timing of data collection (i.e., over 14 months for the household survey versus concentrated in two weeks for the census) is a significant factor, because the common variables are not subject to a great deal of intra-annual variation.

Results

Estimation of models of consumption

The GLS estimates of the strata-level equations to predict log per capita consumption are presented in Tables 1a-c. As described earlier, the location-specific component of the disturbance term in equation (1) is captured by variables defined at the level of the administrative post. These results also account for heteroscedasticity. The most common variables that enter the models are dwelling characteristics (materials of walls, floor, roof; source of water; type of illumination; type of sanitation); asset ownership (land, livestock, poultry, radio); adult educational levels; adult employment characteristics; age and sex composition of the household; and administrative post-level means of some of these variables. The last category captures a large part of the location effect.

Poverty indices

The estimated poverty headcount for each of Mozambique's 128 districts is shown in Figure 2. Some of these results closely mirror the more aggregated information from the household survey alone, such as the high poverty rates throughout Sofala province, with the exception of the port city of Beira and the adjoining district of Dondo. More commonly, however, the map shows considerable inter-district variation within a given province. For example, both Tete and Inhambane provinces have poverty headcounts over 80 percent, but the rates are noticeably higher in the north of Tete and the interior districts of Inhambane. Conversely, Gaza province, which has below average rates of poverty, has districts that are among the poorest in the country in its northern interior. As expected, finer disaggregation to the level of the administrative post reveals additional intra-provincial and intra-district variation, as shown in the map of poverty gap index in Figure 2. Similar results obtain when the poverty gap measure is used (Figure 3).

Distribution of the poor

The distribution of the poor depends upon both poverty rates and the distribution of the population in a country. Figure 4 shows the shaded area map of the poverty headcount index from Figure 2 alongside a dot map illustrating the number of poor in each administrative post. From this map it may be seen that in the south of the country, the bulk of the poor are distributed in a thin band that runs along the coast, which also corresponds to the location of the main national highway. Despite its low poverty indices relative to the rest of the country, the capital city of Maputo is home to a large number of poor by virtue of its large population. The same is true for most provincial capitals. Another concentration of poor people appears along the Beira corridor, the east-west transportation route that forms Mozambique's "waist". Conversely, many of the dark shaded (high poverty index) areas in the southwest and northwest of the country are semi-arid zones that are sparsely populated. Some exceptions to this are found in the "spine" of the country (inland Sofala), and also in Angônia district, which forms the western "collarbone" of the country. In these areas both poverty rates and populations are high, with a resulting large share of the country's poor. Further north, the poor are more uniformly distributed throughout the two most populous provinces, Zambézia and Nampula.

Distribution of the total poverty gap

One potentially useful way to combine information on poverty indices and the physical location of the poor is to calculate the aggregate gap between current conditions and a hypothetical state in which poverty is eliminated, and map the distribution of that gap. To the extent that poverty may be considered the lack of resources to meet one's basic consumption needs, one could call this the "distribution of the total poverty gap," a measure that reflects not only whether a person is above or below the poverty line, but also how far the poor are below the poverty line. In the simplest example, consider an increase in incomes that is perfectly targeted to the poor, so that each person currently below the poverty line exactly reaches the poverty line. This increase could come from economic growth, a transfer program, or some other means. In this context, the total poverty gap (*TPG*) in place *i* may be calculated as:

(3) $$TPG_i = P_{1i} * Z_i * N_i$$

where P_{1i} is the poverty gap measure in place *i*, Z_i is the poverty line in place *i*, and N_i is the population of *i*. We estimate that in 1996-97, the total poverty gap in Mozambique was approximately US$2.3 million per day. The share (W_i) of the total poverty gap of sub-unit *i* among the K sub-units within a country is simply

(4) $$W_i = \frac{TPG_i}{\sum_{i=1}^{K} TPG_i}$$

The distribution of the total poverty gap by district and administrative post is shown in Figure 5. The areas that stand out as accounting for the largest shares of the total poverty gap are the parts of Sofala province along the Beira corridor, large sections of Zambézia (to the northeast of Beira), and a band stretching further northeast through Nampula province to the port city of Nacala. Other areas highlighted by these maps include Angônia district in the northwest, coastal areas of Inhambane in the south of the country, and the city of Maputo (which does not stand out because of its small area, but has a large share of the total poverty gap because of its large population).

Poverty and infrastructure

Up to this point of the paper, mapping has largely been used as no more than a useful presentation tool. The estimated poverty indices and distribution of the total poverty gap could have been presented as a (rather long) data table, albeit with considerably reduced ability to spot spatial patterns of poverty in Mozambique. Figure 6 makes explicit use of additional geo-referenced information, namely the location of good quality roads in Mozambique. With only few exceptions, the presence of a good road is associated with lower than average poverty indices. However, the converse is not always true. Some of the areas with lower poverty rates (lightly shaded areas), such as those along the Tanzanian border in the north of the country, are sparsely populated, and there are few roads at all. However, many of the better off areas in Zambézia province are populous and not particularly well served by the road network.

Inequality

Within Mozambique there is considerable interest about regional (spatial) inequality, particularly in inequality trends during the recent years of rapid aggregate economic growth (Government of Mozambique, 2001). More generally there is a lively debate in the development economics literature about the distribution effects of economic growth. Putting the causality the other way around, there is also a debate about the extent to which inequality is a catalyst, or a hindrance, to economic development. Much of this debate is based on cross-country growth regressions, as there is little data available on inequality within a country; the small area estimation process used here can help to alleviate that constraint.

Several inequality measures estimated from the simulated consumption data, including the Gini index, the Atkinson index, and generalized entropy (GE) indices. Both the Atkinson and GE indices are parameterized, so that the index is more sensitive to inequality in a certain range of the total distribution of consumption.[2] The Atkinson index was estimated with parameter e=2, and the GE index was estimated with parameter a = -1, 0, 1, and 1.5. The more positive is the Atkinson "inequality aversion parameter" e ($e > 0$), the more sensitive the Atkinson index is to

[2] The standard Gini index places greatest weight on inequality around the mode of the distribution, but it, too, may be parameterized, as described by Yitzhaki (1983). The standard Gini index corresponds to their extended Gini when the parameter v takes the value 2.

differences at the lower end of the distribution. The GE inequality measures are more sensitive to inequality at the lower end of the distribution as *a* becomes more negative, and more sensitive to inequality at the upper end as *a* becomes more positive. Special cases of the GE index are GE(1), which is the well-known Theil inequality index, and GE(0), which is the mean log deviation.

Figure 7 maps the GE(0) inequality index at the district and administrative post levels, and Figure 8 maps the GE(1), or Theil, inequality index. It may be seen that the high poverty areas in the central part of the country also tend to have high levels of inequality, with the inequality extending further west to areas in Manica province, along the border with Zimbabwe. The south of the country, especially Maputo province and the city of Maputo, also has some of the highest rates of inequality, although poverty rates are relatively low there. Provincial capitals also stand out has having high inequality measures – these are especially visible as small dark spots in the district level map on the left. Inequality is low in the populous provinces of Nampula and especially Zambézia.

Using the administrative post level estimates of poverty and inequality, we note that for almost all of the poverty and inequality measures used, there is a negative and significant correlation between poverty and inequality (Table 2). This is not unexpected, as the larger the proportion of the population below the poverty line, the less scope there is for variance in the per capita consumption measure, and therefore the less inequality there is likely to be.

The generalized entropy inequality indices are decomposed in Table 3, for GE(-1), GE(0), and GE(1). Recall that as one moves to finer levels of disaggregation, the proportion of between-group inequality will tend to increase. Of the total inequality in Mozambique, between 83 and 86 percent occurs within districts; in other words, differences in the district level means of per capita consumption only accounts for about one-sixth of the total variance in per capita consumption. At the more disaggregated level of the administrative post, the share of within-post inequality is still very high, at 78 to 80 percent of the total.[3]

There are several possible distributions of per capita that could generate the decomposition results in Table 3. For example, it could be that all of the administrative posts

[3] We have not yet conducted this analysis for smaller administrative units using the census data, but from the IAF survey alone we observe that at the next level of disaggregation (*localidade* in rural areas and *bairro* in urban areas), between 71 and 75 percent of inequality is within. Even at the level of the village or city block, more than one-half of inequality is found within geographic unit. Caveats about the small sample sizes (typically 9 to 36 households) at these levels of survey data apply.

have roughly similar levels of inequality, i.e., that the poor and the nonpoor are both situated more or less uniformly around the country, with high degrees of heterogeneity in all administrative posts. Alternatively, the decompositions could occur if some areas were highly equal and others highly unequal, so that the 80-plus percent of within-area inequality is a composite of vastly different situations. In Figure 9, the administrative posts in Mozambique are arrayed from left to right in ascending order of GE(0), with the vertical axis indicating the estimated GE(0), which is the within-post inequality. The horizontal line at 0.36 corresponds to the national total estimate for GE(0). It may be observed that, with the exception of the sharp upward swing at the right of the curve[4], the large majority of the 424 administrative posts in Mozambique have GE(0) indices of approximately 0.2 and slightly higher.

Figure 9 shows the corresponding information for the 354 magisterial districts in South Africa. Like Mozambique's administrative posts, approximately 80 percent of consumption inequality in South Africa is found within magisterial districts (Alderman et al., forthcoming). However, from the figure we see not only that South Africa has much higher levels of inequality overall, but also that there is much more variation in inequality levels among South African magisterial districts than there is among administrative posts in Mozambique.

Discussion

We have used survey and census data to estimate welfare (per capita consumption) for every household in the 1997 Mozambique national census, and estimated poverty and inequality indices – and standard errors – disaggregated to the levels of districts and administrative posts. It was already known that poverty rates varied considerably across the provinces of Mozambique, and this analysis showed that large variation occurs within provinces, and districts, as well. It was also seen that many of the areas with high poverty indices are sparsely inhabited, while a large proportion of the poor are found in populous areas with only average or below average poverty indices. Consistent with this, we saw that most of the inequality found in Mozambique is explained not by differences in averages from one administrative post to another, but by large variations in consumption levels within administrative posts.

[4] The high inequality administrative posts are mostly urban areas, although there are also some rural areas among them. Almost all of the urban areas in Mozambique are in the rightmost 20 percent of the line.

One of the key motivations for poverty mapping is to identify areas where there are concentrations of poor people, or especially high poverty rates, to facilitate the targeting of anti-poverty programs geographically. Geographic targeting has the advantage of being less costly to administer than household- or individual-level means testing for poverty programs. It also has the potential for tailoring such programs to the specific environment of these areas, such as focusing on production of certain crops or development of certain infrastructure. However, these results call into question the proposition of targeting anti-poverty efforts to "poor areas" of Mozambique. Because the most disaggregated territorial level examined here – administrative posts – are heterogeneous, with poor and nonpoor living in close proximity, it is likely that there would be little efficiency gain from targeting exclusively by administrative post. That is, programs that treated all persons within an administrative post equally will likely result in large errors of inclusion (directing benefits to the nonpoor, or leakage) and exclusion (failing to direct benefits to the poor who live in less poor areas).

The findings in this paper run counter to most of the evidence from South Asia and Latin America, which identifies physically separate poor areas and nonpoor areas (see Ravallion and Wodon, 1977; Baker and Grosh, 1994)). However, it is consistent with findings elsewhere in sub-Saharan Africa, such as Alderman et al. (forthcoming) in South Africa and Jayne et al. (2001) (with specific respect to land) in five countries in east and southern Africa. Some early poverty mapping studies seemed to assume that the Asian and Latin American patterns of poverty pockets applied in sub-Saharan Africa as well, without critically examination of the question, often because of data limitations (see Bigman et al., 2000 for an example).

However, there may be an argument for using geographic targeting as an initial step in a multi-step targeting procedure. For example, central government funds could be allocated to decentralized governmental units using the poverty mapping results as a guide, with the decentralized units then employing other information (such as information about the characteristics of the poor) to reduce errors of inclusion and exclusion. The feasibility and cost-effectiveness of multi-stage targeting is a useful avenue for future research.

One concern that is sometimes raised about decentralization of targeting is the prospect that local elites will capture most of the benefits, with the poor receiving little or nothing (Bardhan and Mookherjee, 1999). The heterogeneity that was found in most of Mozambique indicates that this is a valid area of concern. Resolution of this issue requires more specific examination of programs and settings.

In future work we intend to investigate these questions, in the context of specific interventions. We will also explore the correlates of consumption inequality.

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Table 1a: GLS results of strata-level estimations

	Stratum							
	1		2		3		4	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Constant	8.656	0.113 **	8.660	0.130 **	8.066	0.216 **	8.606	0.127 **
Any member literate			-0.249	0.081 **				
Any member with EP1	-0.280	0.130 **						
Any member with EP2			0.507	0.144 **				
No. of large livestock								
No. of small stock	0.012	0.006 **						
Has agricultural land								
Has radio	0.149	0.060 **	0.171	0.057 **	0.172	0.056 **	0.107	0.042 **
Good quality floor	0.397	0.122 **	0.263	0.156 *	0.281	0.100 **		
HH head literate								
HH head EP1	0.254	0.097 **	0.149	0.055 **				
HH head EP2	0.294	0.082 **						
Good quality roof							0.281	0.138 **
Electric lighting	0.281	0.161 *	0.382	0.345			0.313	0.153 **
Has latrine or toilet								
Highest educ level in HH	0.138	0.045 **						
No. of males with EP1	-0.188	0.044 **					-0.184	0.026 **
No. of males with EP2			-0.436	0.124 **			0.124	0.041 **
No. of literate males	0.128	0.043 **						
No. of females with EP1								
No. of females with EP2								
No. of literate females	-1.291	0.159 **	-0.870	0.185 **	-1.066	0.112 **	-0.484	0.121 **
Proportion of adults employed			0.428	0.126 **			0.424	0.089 **
Good quality w alls			0.357	0.471	0.301	0.151 **		
PA-level: Prop of heads with EP1							3.651	2.243
PA-level: Prop of heads with EP2					-7.533	1.394 **		
PA-level: Prop of heads literate					4.349	0.968 **	-4.011	2.939
PA-level: Prop of heads female								
PA-level: Prop of dwellings with good quality roof			-115.199	25.176 **			8.532	3.554 **
Proportion of adults employed in commerce or service sectors	0.922	0.454 **			0.747	0.293 **		
Proportion of members with disabilities								
Females 10-16 (proportion)	-1.315	0.217 **	-1.064	0.231 **	-1.129	0.173 **	-0.683	0.124 **

Table 1a: GLS results of strata-level estimations

	Stratum											
	1			2			3			4		
	Coeff	Std Error		Coeff	Std Error		Coeff	Std Error		Coeff	Std Error	
Females 16-30 (proportion)				-0.382	0.145	**						
Proportion of males literate				0.897	0.206	**				0.810	0.122	**
PA-level: proportion of dwellings with electric lighting												
PA-level: proportion of dwellings with latrine or toilet	0.448	0.201	**							0.775	0.613	
Males 10-16 (proportion)	-0.974	0.233	**	-0.893	0.241	**	-1.205	0.160	**	-0.849	0.160	**
Males 16-30 (proportion)												
PA-level: highest educ level in household										-0.288	0.270	
Members 0-5 (proportion)	-1.495	0.166	**	-0.767	0.183	**	-1.302	0.130	**	-0.787	0.129	**
PA-level: proportion of dwellings with good quality walls				121.699	26.844	**	2.287	0.542	**	-4.621	2.421	*
PA-level: proportion of school age children enrolled in school												
N	657			743			955			884		
Adjusted R^2 (OLS)	0.384			0.362			0.265			0.398		

Table 1b: GLS results of strata-level estimations

	Stratum							
	5		6		7		8	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Constant	6.418	0.438 **	8.427	0.357 **	7.090	0.165 **	7.826	0.167 **
Any member literate			-0.087	0.104			-0.181	0.054 **
Any member with EP1					-0.415	0.114 **		
Any member with EP2					-0.189	0.096 **		
No. of large livestock			-0.008	0.004 *	0.390	0.153 **		
No. of small stock							0.022	0.003 **
Has agricultural land								
Has radio					0.125	0.050 **		
Good quality floor							0.230	0.047 **
HH head literate								
HH head EP1					0.167	0.061 **		
HH head EP2					0.252	0.083 **		
Good quality roof					0.195	0.072 **		
Electric lighting	0.644	0.138 **					0.934	0.110 **
Has latrine or toilet			0.313	0.060 **	0.240	0.054 **	0.204	0.049 **
Highest educ level in HH			0.112	0.033 **	0.164	0.047 **		
No. of males with EP1	-0.126	0.032 **	-0.155	0.035 **	-0.118	0.030 **	-0.123	0.021 **
No. of males with EP2							0.140	0.037 **
No. of literate males								
No. of females with EP1			0.038	0.044				
No. of females with EP2								
No. of literate females	-1.236	0.140 **	-0.863	0.243 **	-0.695	0.182 **	-0.375	0.158 **
Proportion of adults employed			0.474	0.187 **	0.385	0.123 **	0.574	0.112 **
Good quality walls			0.234	0.080 **	0.177	0.080 **		
PA-level: Prop of heads with EP1			-5.331	2.768 *			4.672	0.918 **
PA-level: Prop of heads with EP2	-7.070	1.374 **			-3.744	1.168 **		
PA-level: Prop of heads literate	8.382	1.616 **	3.374	1.891 *	5.446	0.741 **	-3.293	1.169 **
PA-level: Prop of heads female	3.705	0.886 **	0.492	0.597				
PA-level: Prop of dwellings with good quality roof			-1.097	0.849				
Proportion of adults employed in commerce or service sectors			0.375	0.224 *			0.859	0.202 **
Proportion of members with disabilities								

Table 1b: GLS results of strata-level estimations

	Stratum											
	5			6			7			8		
	Coeff	Std Error		Coeff	Std Error		Coeff	Std Error		Coeff	Std Error	
Females 10-16 (proportion)	-0.914	0.172	**	-0.755	0.297	**	-0.499	0.189	**			
Females 16-30 (proportion)												
Proportion of males literate	0.601	0.151	**	0.232	0.240		0.992	0.158	**	0.969	0.167	**
PA-level: proportion of dwellings with electric lighting												
PA-level: proportion of dwellings with latrine or toilet	-1.014	0.145	**							0.662	0.175	**
Males 10-16 (proportion)	-1.327	0.178	**	-0.462	0.262	*	-1.041	0.208	**	-0.521	0.197	**
Males 16-30 (proportion)										-0.217	0.145	
PA-level: highest educ level in household				0.223	0.284		-0.708	0.161	**			
Members 0-5 (proportion)	-0.958	0.148	**	-0.782	0.239	**	-0.621	0.173	**	-0.337	0.155	**
PA-level: proportion of dwellings with good quality walls							1.825	0.579	**	-2.714	0.718	**
PA-level: proportion of school age children enrolled in school	-3.063	1.225	**	2.623	2.123					-2.690	0.565	**
N	610			661			762			729		
Adjusted R^2 (OLS)	0.299			0.352			0.465			0.465		

Table 1c: GLS results of strata-level estimations

	Stratum					
	9		10		11	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Constant	6.134	0.315 **	9.481	0.467 **	7.717	0.186 **
Any member literate						
Any member with EP1						
Any member with EP2			-0.255	0.086 **		
No. of large livestock						
No. of small stock						
Has agricultural land			-0.285	0.091 **		
Has radio	0.146	0.053 **	0.123	0.056 **	0.202	0.061 **
Good quality floor			0.260	0.065 **		
HH head literate					0.331	0.084 **
HH head EP1					-0.253	0.057 **
HH head EP2			0.329	0.098 **		
Good quality roof						
Electric lighting	0.485	0.155 **	0.651	0.127 **	0.413	0.059 **
Has latrine or toilet	0.103	0.061 *				
Highest educ level in HH	0.065	0.031 **			0.043	0.016 **
No. of males with EP1	-0.054	0.027 **	-0.141	0.035 **	-0.140	0.024 **
No. of males with EP2			0.215	0.052 **		
No. of literate males			0.085	0.025 **	-0.135	0.046 **
No. of females with EP1					0.087	0.051 *
No. of females with EP2	0.317	0.067 **			0.075	0.033 **
No. of literate females	-0.303	0.186	-0.234	0.192	-0.654	0.216 **
Proportion of adults employed	0.926	0.125 **	0.523	0.116 **	0.693	0.137 **
Good quality walls						
PA-level: Prop of heads with EP1						
PA-level: Prop of heads with EP2	10.265	4.062 **	2.264	1.004 **	1.402	0.320 **
PA-level: Prop of heads literate	-2.361	1.135 **				
PA-level: Prop of heads female	3.799	0.647 **	-1.281	0.701 *		
PA-level: Prop of dwellings with good quality roof						
Proportion of adults employed in commerce or service sectors						
Proportion of members with disabilities			-0.952	0.252 **		

Table 1c: GLS results of strata-level estimations

	Stratum					
	9		10		11	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Females 10-16 (proportion)	-0.243	0.215				
Females 16-30 (proportion)						
Proportion of males literate			0.801	0.159 **	0.613	0.149 **
PA-level: proportion of dwellings with electric lighting	-7.042	3.211 **				
PA-level: proportion of dwellings with latrine or toilet	-0.527	0.235 **				
Males 10-16 (proportion)						
Males 16-30 (proportion)			-0.312	0.217	-0.419	0.161 **
PA-level: highest educ level in household			-0.443	0.158 **		
Members 0-5 (proportion)			-0.879	0.200 **	-0.627	0.203 **
PA-level: proportion of dwellings with good quality walls	3.295	0.872 **				
PA-level: proportion of school age children enrolled in school						
N	637		718		893	
Adjusted R^2 (OLS)	0.346		0.375		0.547	

Table 2: Pearson correlation coefficients of FGT poverty measures and inequality indices

	Gini	GE(-1)	GE(0)	GE(1)	Atkinson (2)
P_0	-0.42*	-0.42*	-0.40*	-0.28*	-0.46*
P_1	-0.22*	-0.23*	-0.22*	-0.15*	-0.24*
P_2	-0.14*	-0.14*	-0.14*	-0.09	-0.15*

(* = $p < 0.01$, N=424)

Table 3: Decomposition of inequality

	GE(-1)	GE(0)	GE(1)
Total	**0.441**	**0.363**	**0.411**
Within districts	0.377	0.300	0.353
Within %	85.6	82.7	85.8
Within AP	0.353	0.283	0.330
Within %	80.2	78.0	80.2

Figure 1: Provincial-level poverty map from household survey alone

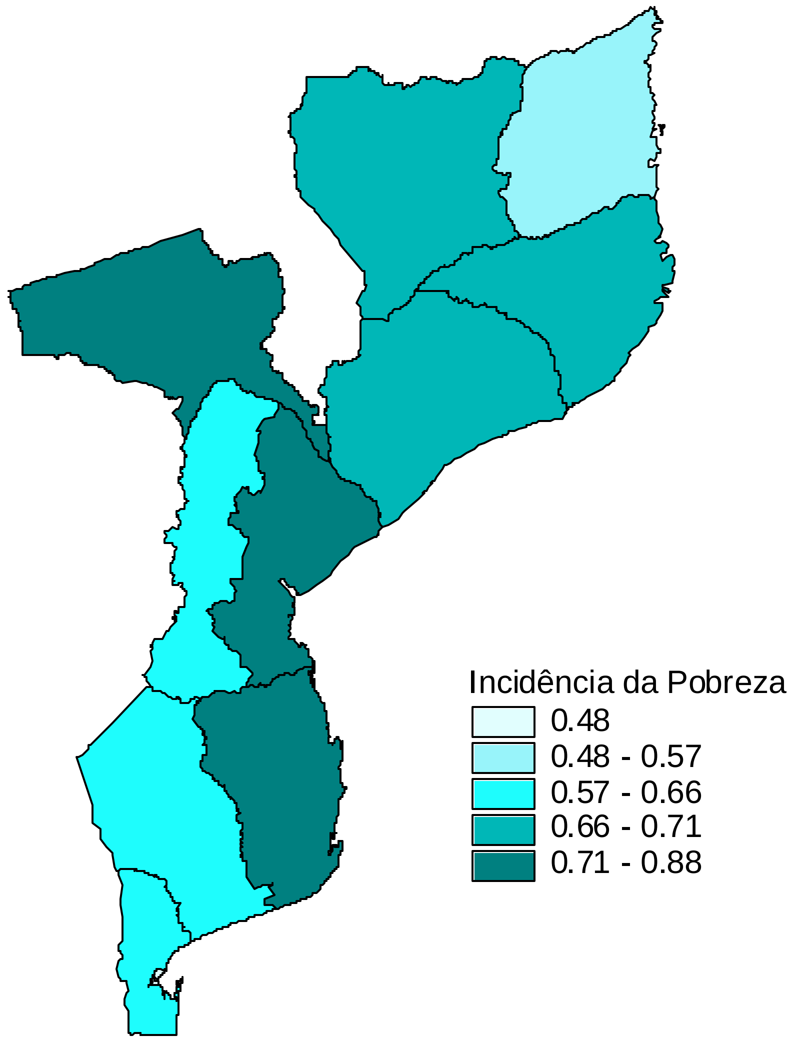
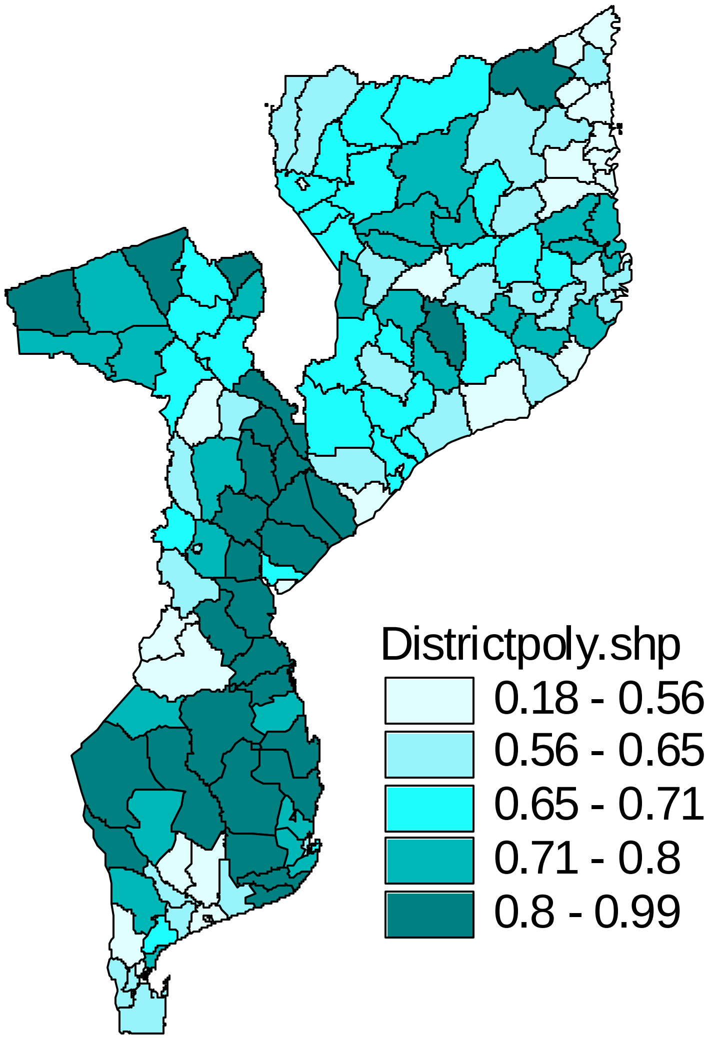


Figure 2: Poverty headcount by district (left) and administrative post (right)



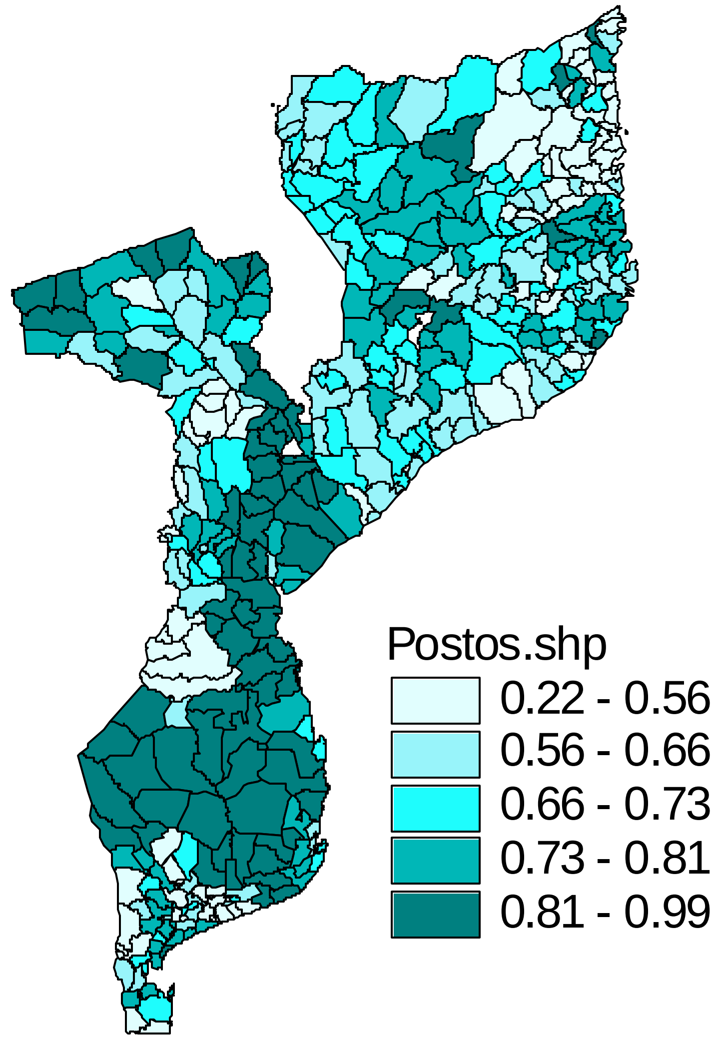


Figure 3: Average poverty gap by district (left) and administrative post (right)

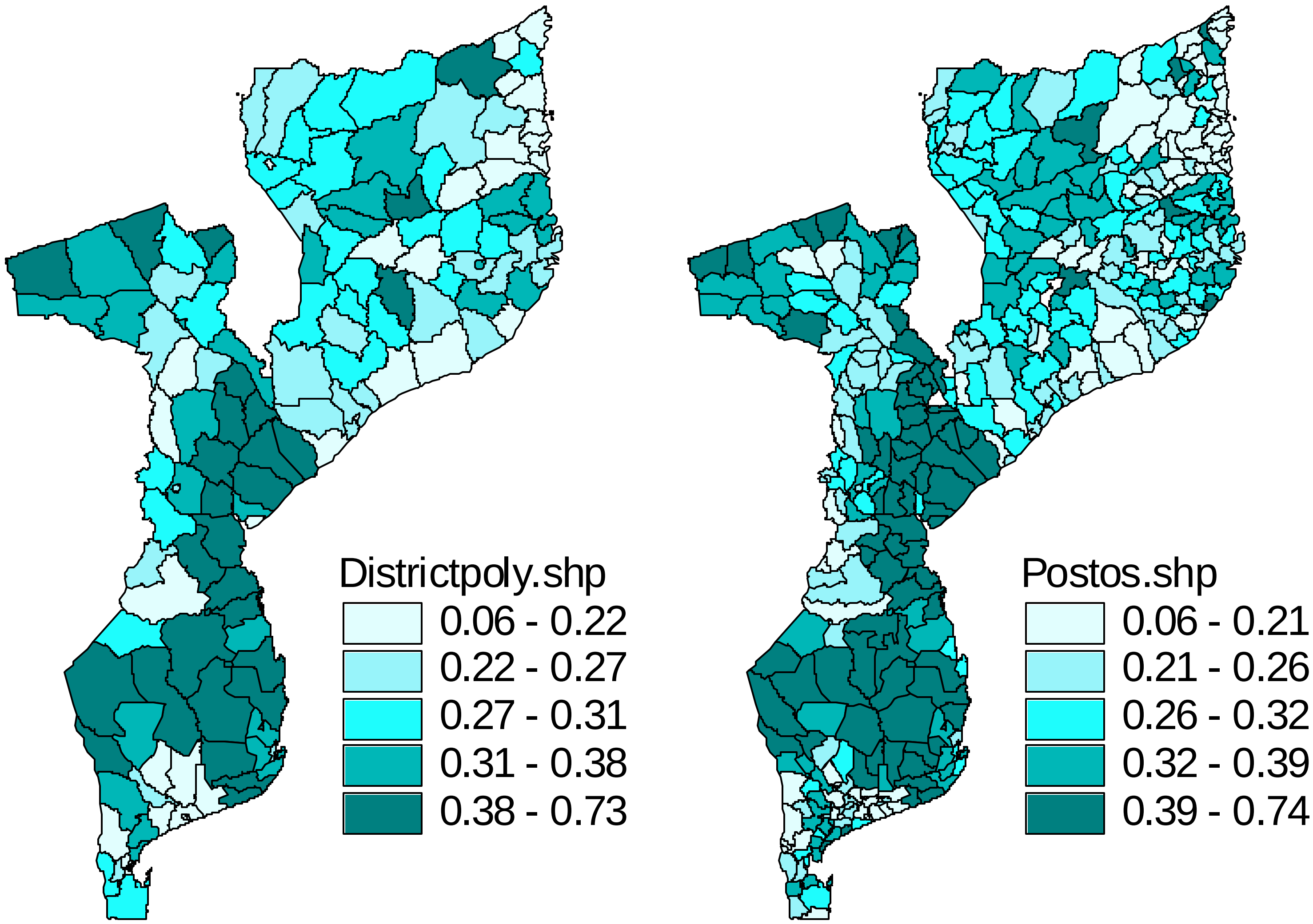


Figure 4: Poverty headcount by district (left) and distribution of poor by administrative post (right)

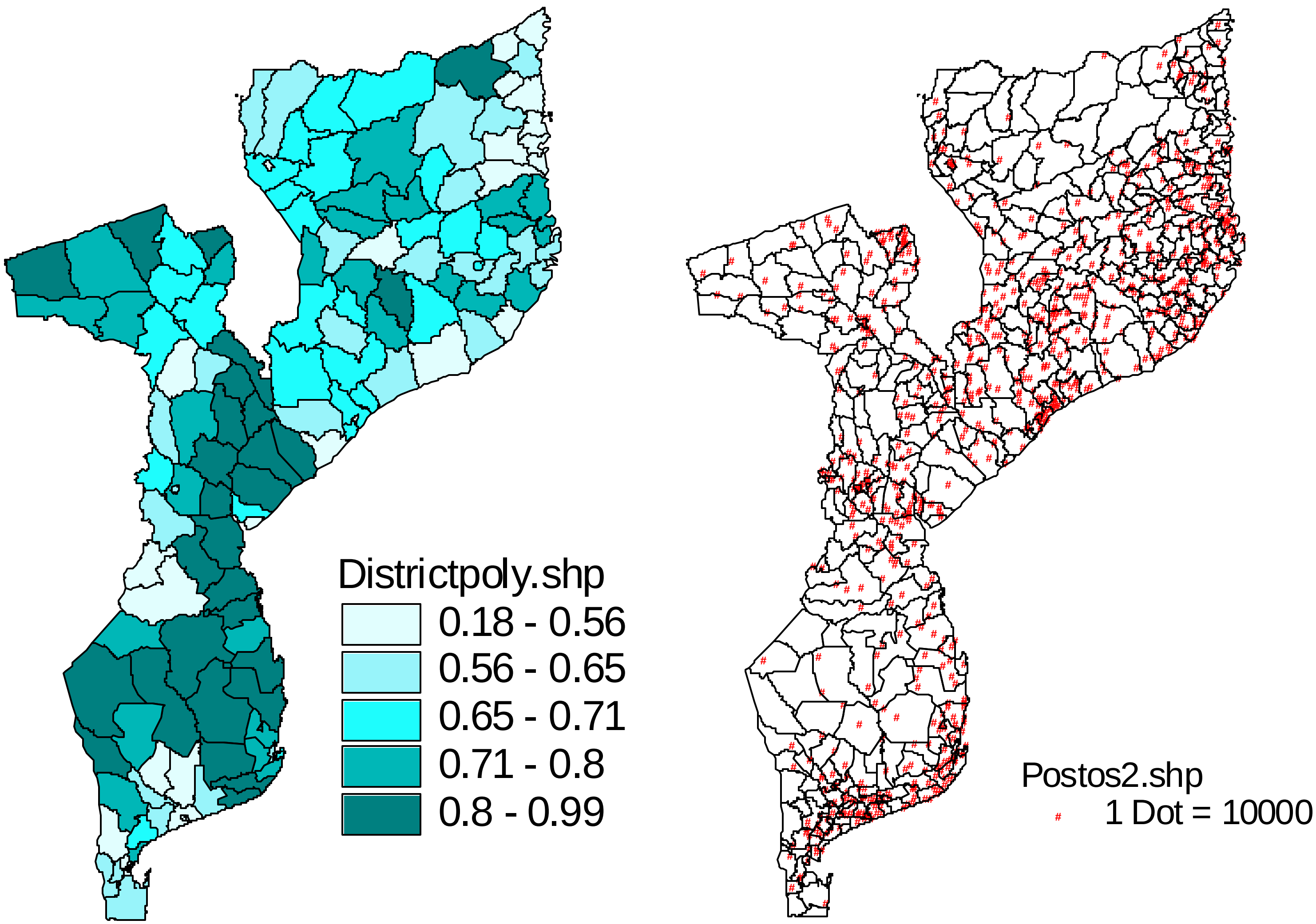


Figure 5: Distribution of total poverty gap, in percent, by district (left) and administrative post (right)

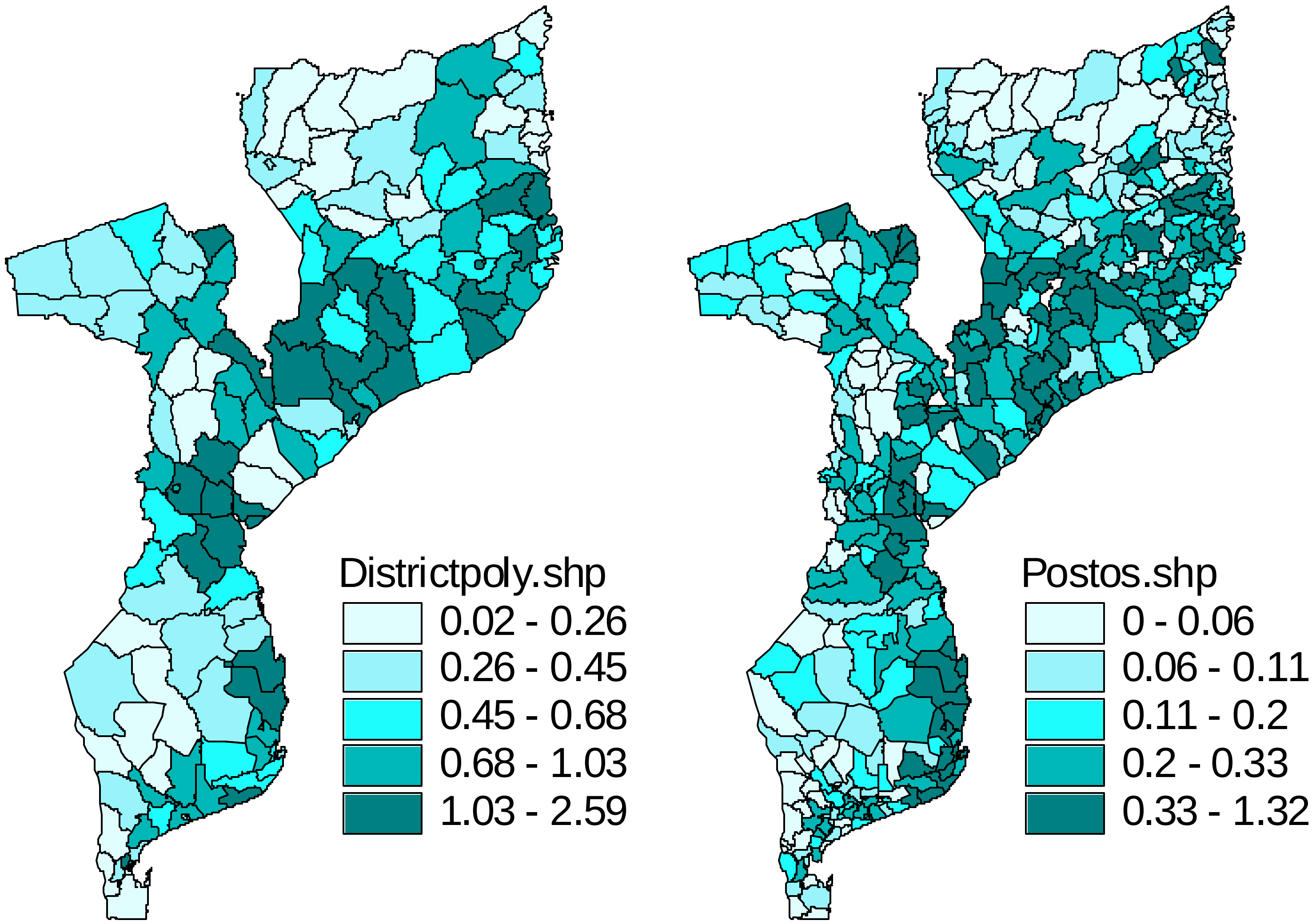


Figure 6: Condition of road network and average poverty gap (left) and distribution of the poor (right)

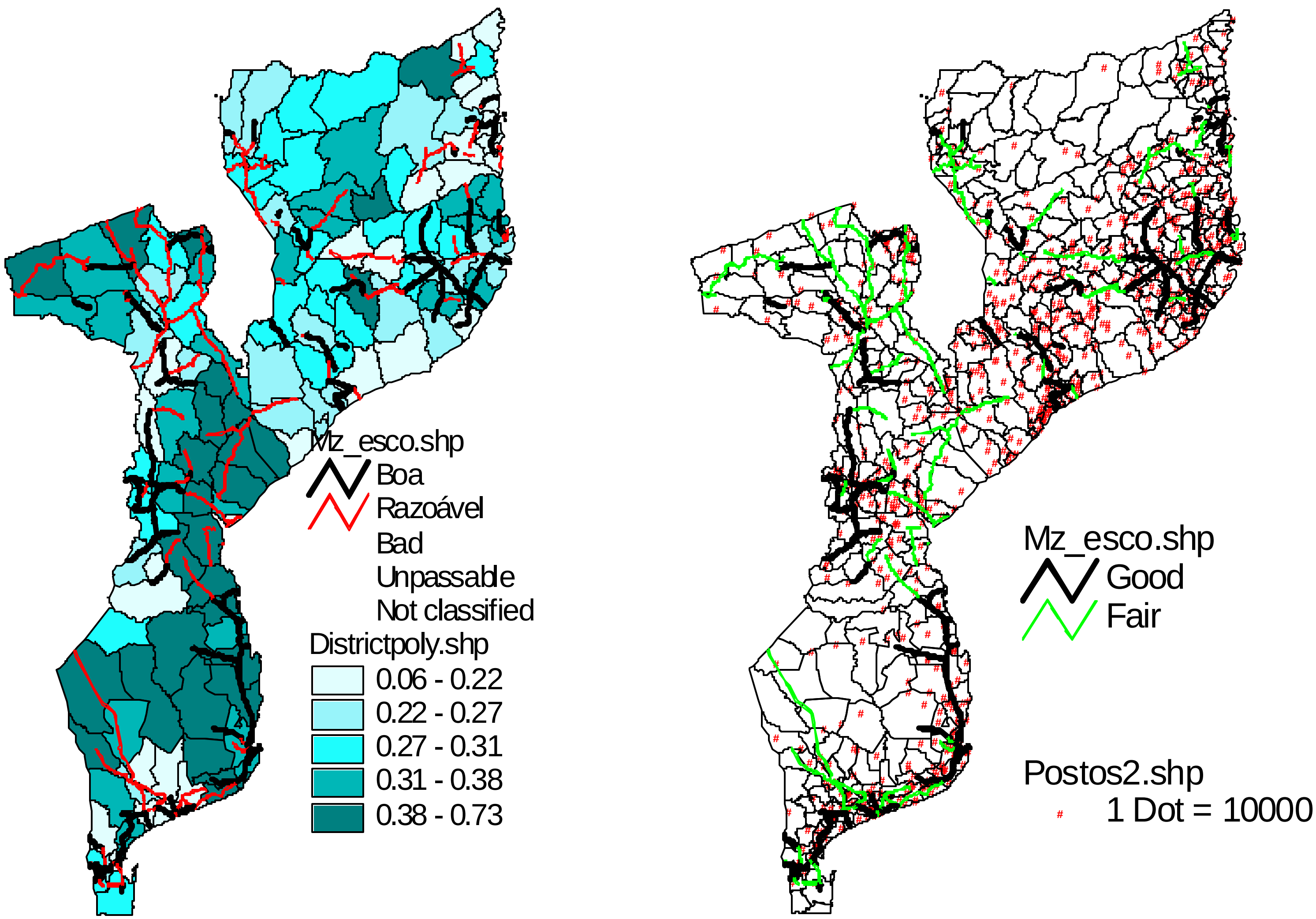


Figure 7: GE(0) inequality index by district (left) and administrative post (right)

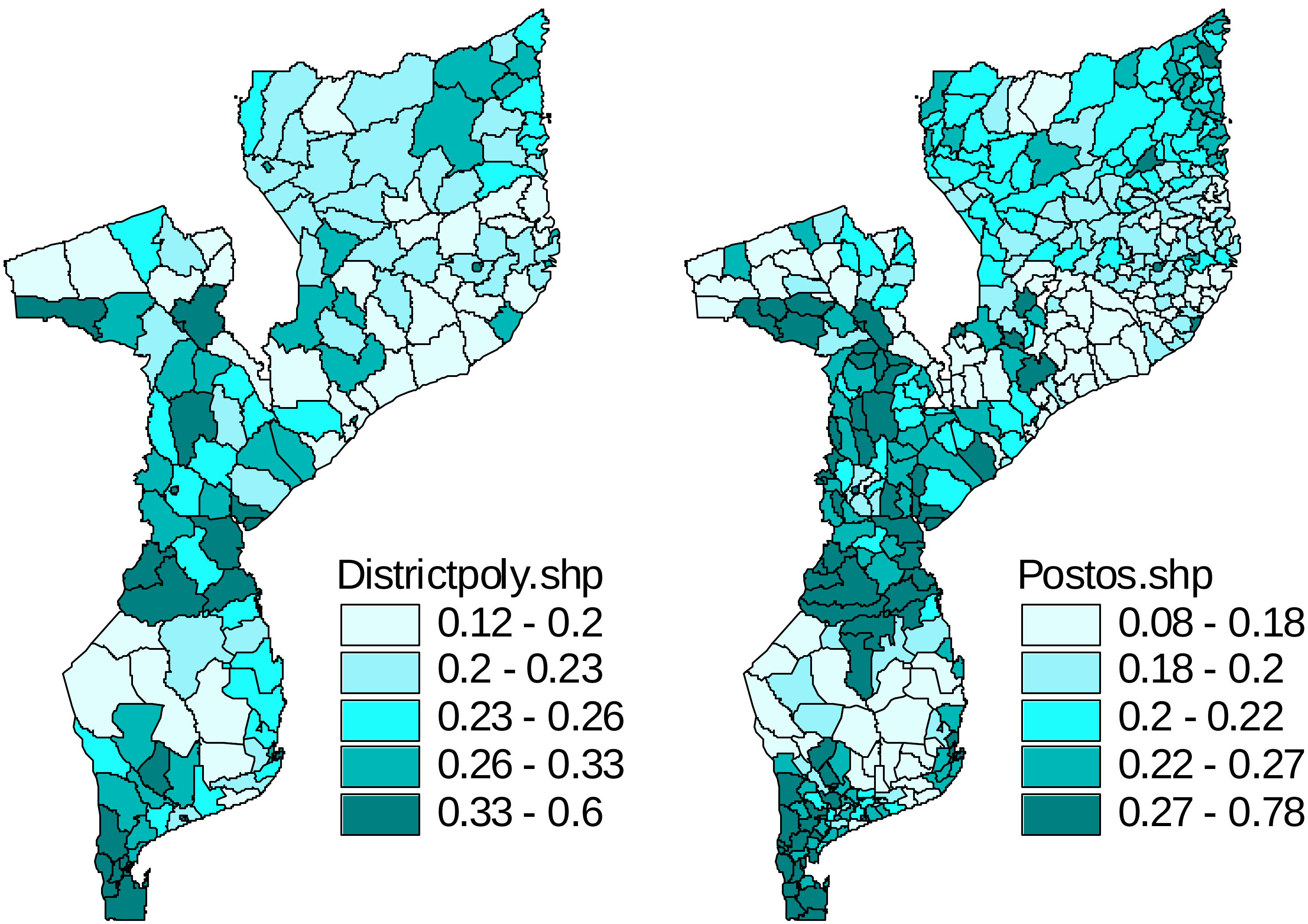


Figure 8: GE(1) (Theil) inequality index by district (left) and administrative post (right)

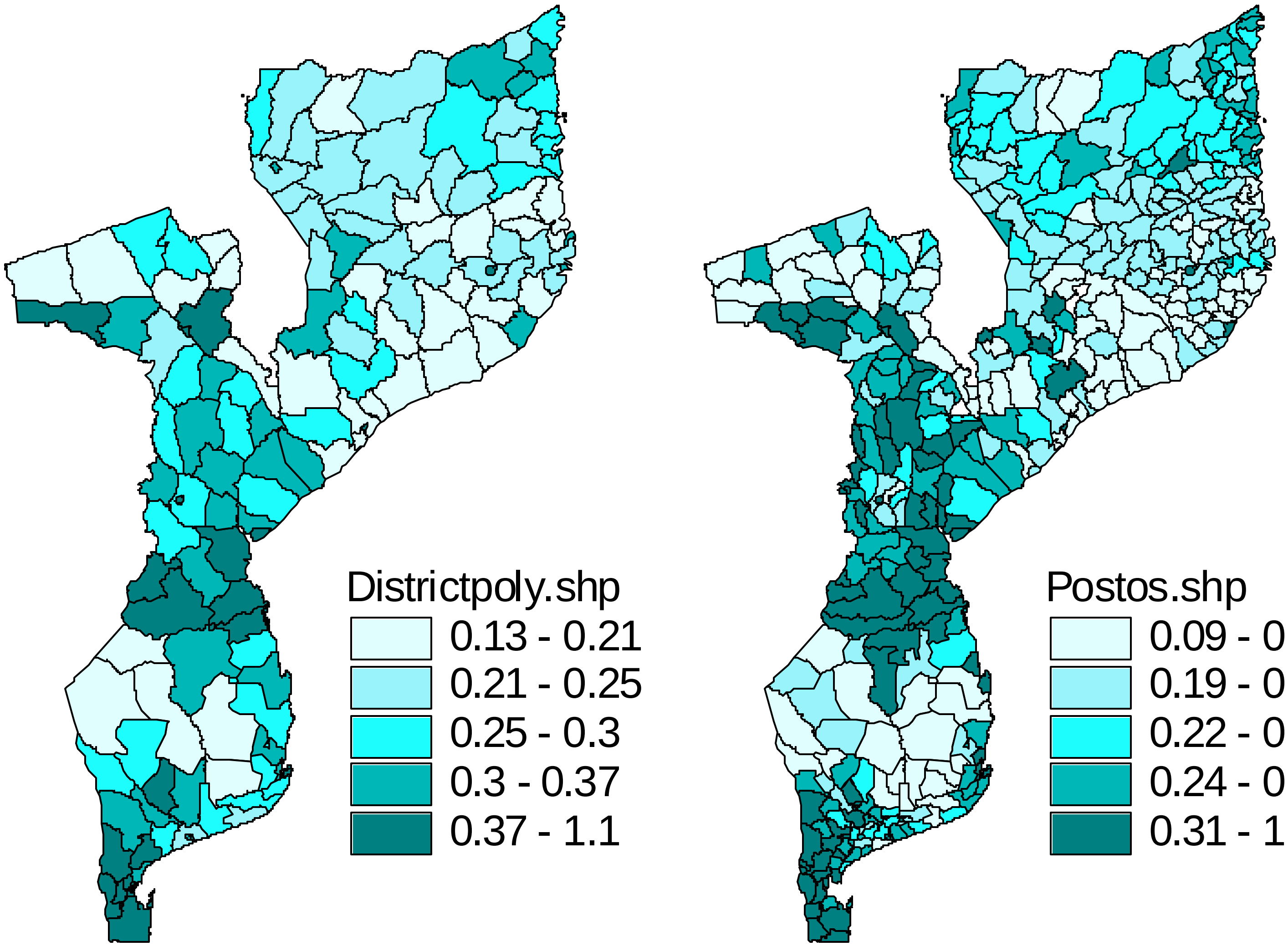


Figure 9: Inequality levels (GE(0)) by administrative post in Mozambique and magisterial districts in South Africa