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Reaching the Poor

Fine Tuning Poverty Targeting Using a 'Poverty Map'—The Case of Mozambique

Orlando San Martin*

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Abstract

Combining data from both, a nationwide standards of living survey (LSMS) and a national population and housing census, this paper generates a disaggregated map of poverty and living conditions in Mozambique. This analytical tool helps to overcome a problem very common until recently, namely that most nationwide studies of poverty were too general to support the design of policy interventions at the local level. In this paper, we disaggregate both expenditure and non-expenditure based indicators of poverty and well-being for the whole country. This paper also assesses geographic targeting schemes based on different ranking criteria. The analytical tool presented in this paper can be a useful contribution for the design of poverty alleviation strategies, by narrowing down the scope of action to the localities where the poor actually live.

Keywords: poverty, vulnerability, targeting, Mozambique

JEL classification: I31, I32, O15, O55

* Department of Economics and Social Sciences, Agricultural University of Norway

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UNU World Institute for Development Economics Research (UNU/WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1. Introduction

Poverty alleviation is a very important aspect of the national economic and social policy mix in many developing countries. Poverty alleviation programmes tied with growth enhancement policies are a high priority in national policy design in countries suffering from increasing population pressures and deteriorating living and economic conditions. Likewise, even in countries that have managed to achieve considerable levels of economic growth, special efforts to combat poverty are required, since considerable shares of their populations still live under poverty.

Our case of interest, Mozambique, belongs to this category of countries. Having achieved outstanding levels of economic growth during the late nineties, Mozambique still experiences relatively high poverty rates. Not only frustrating are the high rates of poverty, but also the significant levels of inequality in the regional or geographic distribution of poverty. As recent, as in September of this year, the President of Mozambique Mr. Chissano stressed that the Government's top priorities remain 'the struggle against absolute poverty, the reduction of regional imbalances, and rural development' (AIM, 2001a).

One major concern in efforts to combat poverty is related to identifying the poor. It is difficult, time consuming and costly to measure poverty on a nationwide scale. Typical LSMS surveys take more than two years to provide results and require a budget not less than USD500,000 and sometimes even over USD1 million.[1] In addition, these nationwide surveys on living conditions are based on sample designs that allow identifying poverty levels only for major regions or administrative divisions. Thus, they are usually not good enough to orient poverty alleviation efforts aimed to attack poverty at the local levels.

Geographic targeting has been widely recognized as a possible way out to the dilemma to reach and identify the poor. It is administratively easier and cheaper to orient poverty alleviation efforts to those localities where the poor live. However, the likelihood for successful allocation of efforts is greater the smaller the geographical unit that is chosen. Therefore, estimation of provincial poverty rates or poverty rates disaggregated only for urban and rural areas are still not appropriate for such purposes. Instead, so-called 'poverty maps' which provide a disaggregated picture of living conditions can be used for the identification of the poor and to orient poverty alleviation efforts (Elbers et al., 2000; Henninger, 1998; Hentschel et al., 1998; Minot, 2000).

We claim in this paper that even though important efforts have been devoted by the national statistics office (INE) to gather a good amount of key information, there is still lack of studies that make use of this data and put them into work to orient the decisions of policymakers. We pretend to illustrate the use of some of these sources of data in the combat against poverty, assessing the strengths and weaknesses of different targeting indicators.

[1] Scott (1998).

The objective of this paper is to estimate different disaggregated measures of people's well-being and to assess the potentialities and weaknesses of using such measures for geographic targeting. The paper is organized as follows. In the second section, we briefly discuss the relevance of geographic targeting for poverty alleviation in Mozambique. Section 3 presents the data sources used in our empirical exercises and descriptive statistics on general living conditions. Section 4 presents an econometric model to estimate and predict poverty measures. Section 5 presents the estimation of non-income based indicators of people's well being. Section 6 discusses and compares the performance of different geographic targeting schemes. We conclude with some final remarks in Section 7.

1.1 Poverty alleviation in Mozambique

Mozambique is a developing country with one of the lowest average income per capita indicators in the world (World Bank, 2001).[2] Since the early nineties, with the achievement of the peace agreements and the end of a prolonged war, the Government of Mozambique (GoM) has made important efforts to improve the living conditions of the majority of the population. Due to dramatic transformations in the political and economical system, the economy grew during the late nineties at rates close to 10 percent per year. However, poverty rates as measured in 1997 (close to 70 percent) are still considered very high.

The Government of Mozambique (GoM) has been very active in the promotion of plans and actions to reduce poverty. They recently issued an Action Plan to Reduce Absolute Poverty, known as PARPA (from its Portuguese name) [3] confirming its strong commitment in attacking poverty. The new action plan builds on previous documents such as: *Lines of Action for the Eradication of Absolute Poverty* from 1999, the PARPA 2000-2004 (known as the *Interim PRSP*), and the *Government Programme* 2000-2004. The *new* PARPA 2001-2005 presents the GoM's strategic vision for reducing poverty, their main objectives, and the key actions to be pursued. The PARPA 2001-2005 is also Mozambique's first Poverty Reduction Strategy Paper (PRSP). The stated objective of the *new* PARPA is to improve the capacities of, and the opportunities available to all Mozambicans, especially the poor. The quantitative targets in PARPA aim to reduce the incidence of absolute poverty from 70 percent in 1997 to less than 60 percent by 2005 and less than 50 percent by the end of this decade.

There are, in particular, two issues mentioned in the PARPA which we consider of interest and which our paper pretends to deal with. The first issue has to do with the concern about the notable urban-rural and *regional imbalances* in terms of economic opportunities and living conditions of the population. The document recognizes the need to search for a better regional balance, with special attention given to regions with the greatest concentration of poor people. In line with this, only recently (in January 2001) for the first time, the GoM released the National State Budget broken down at the province level. Making explicit the geographical allocation of state resources is an important step to reduce the imbalances. However, the actual budget allocation was received with criticism due to the resulting inequalities in the per capita shares by province (AIM, 2001b).

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[2] Mozambique was ranked number 191 among 206 countries in terms of 'PPP-Adjusted' GNP per capita in the World Development Report 2001.

[3] PARPA:Plano de Acção para a Redução da Pobreza Absoluta.

The second issue is the important step taken in the conceptual framework of the PARPA by recognizing the multidimensional character of poverty, going beyond a strictly income or monetary based conception of poverty. Related to this issue the PARPA recognizes that in addition to poverty many Mozambicans are also suffer from a high degree of *vulnerability* to natural disasters and economic shocks. Following this conceptual framework, the poverty reduction strategy proposed by the PARPA is based on **six priorities,** aiming to promote human development and to create a favourable environment for rapid, inclusive and broad-based growth. The main areas of action proposed by the PARPA are:

(i) education
(ii) health
(iii) agriculture and rural development
(iv) basic infrastructure
(v) good governance
(vi) macroeconomic and financial management.

In this paper, we will provide additional tools (not used yet) which complement GoM's efforts and are easily available to improve the effectiveness of poverty alleviation efforts. In line with the concerns expressed in PARPA, these tools aim to illustrate in a disaggregated manner the heterogeneity in living conditions of the population. In addition, we avoid focusing only on income/expenditure-based indicators and instead suggest a *multidimensional* indicator of living conditions, which covers also some of the areas of concern included in the six priority areas indicated above.

2. Assessing poverty and living standards in Mozambique

2.1 Data sources

Mozambique is administratively divided in 10 provinces plus the capital city of Maputo, 146 districts and 426 'postos administrativos'[4] (INE, 1999). The current nationwide poverty measures available in Mozambique are only representative at the provincial level. These measures do not provide a complete picture of the intra-provincial variation in living conditions. The population of districts and postos administrativos also varies widely. While districts mean population is 104 646 inhabitants, for postos is 35 784. Districts population ranges from 7 063 to 424 662; while postos population from 439 to 227 869 inhabitants.

In this paper we combine two main data sources in order to construct a disaggregated poverty map. The two data sources are: (i) a standards of livings survey from 1996-7 (following the LSMS pattern of household surveys) done by the Ministry of Finance with the support of the IFPRI which covered a province-wide representative sample of some 8000 households in all ten provinces and (ii) the most recent National Population and Housing Census (from 1997), covering all the population.

[4] According to the dissagregation of the most recent National Population and Housing Census.

The household survey, the Inquérito Nacional aos Agregados Familiares sobre as Condições de Vida (MIAF), was carried out during February 1996 and March 1997 by the National Statistics Institute (INE) and follows closely the typical World Bank's Living Standards Measurement Surveys (LSMS). The MIAF data set has been extensively used for poverty assessments in Mozambique[5]. The MIAF sample consists of 8274 households and is nationally representative. Household information was collected in urban and rural areas in all 10 provinces and the city capital of Maputo. The sample in each province was collected selecting cluster of households in almost every single district. The representativity of this living standards survey is limited to country, provincial or (urban/rural) area levels. For lower levels of disaggregation, the MIAF sample does not reproduce results that can be representative of the population.

The second source of information used in this paper is the latest National Population and Housing Census from 1997, carried out just a few months after the completion of the MIAF. The National Population Census provides detailed demographic information about the households covering the total of the population. In addition to the demographic information, the Census also included a section on housing conditions. This section provides information on the main characteristics of the house, access to public services and on the possession of some basic assets. We had access to the Census data at a fairly low level of disaggregation[6], the postos administrativos, to conduct the analysis presented in this paper.

Table 1 shows a list of variables that appear to be relevant for poverty analysis. Those variables included in our two main data sources are the most attractive ones for the construction of our econometric exercise in the next section.

2.2 Expenditure-based poverty measures

Using the household-level MIAF data set is possible to calculate different expenditure-based poverty or well-being measures. In this paper, we use the Foster-Greer-Thorbecke[7] (FGT) family of poverty measures for our expenditure-based poverty estimates (Foster, Greer and Thorbecke, 1984). The most used FGT poverty measures are generated by the cases when $\alpha = 0$, $\alpha = 1$ and $\alpha = 2$. In this paper, we will limit the use to the first two cases. When $\alpha = 0$, P_0 corresponds to the headcount ratio, i.e. the proportion of the population below the poverty line. When $\alpha = 1$, P_1 corresponds to the poverty gap, which can be interpreted as a per capita measure of the total shortfalls divided by the population and expressed as a ratio of the poverty line (Deaton, 1997).

In Table 2, we present the 'headcount ratios (P_0)' and the 'poverty gaps (P_1)' by province for urban and rural areas in Mozambique. Comparing the figures for P_0 and P_1, for urban

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[5] For instance in (MPF, UEM, IFPRI, 1998) and (GoM, 2001).

[6] Unfortunately, not to the household or unit level.

[7] The FGT family of poverty measures is given by the expression:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1-y_i}{z}\right)^\alpha \quad \text{(for all } y_i < z\text{)}$$

where y is income/expenditures, z the poverty line, and α an 'inequality aversion 'parameter.

and rural areas separately shows that they follow each other very close. However, comparing the rankings of urban poverty measures with the rankings of rural poverty rankings show a much more heterogeneous pattern.

Table 1
Poverty descriptors in household survey and national census for Mozambique

Description	MIAF97	Census
Economics		
Consumption expenditures		n.a.
Demographics		
Household size		
Number of persons age > 14 years		
Sex of household head		
Ethnic origin of household head		
Locally born household head	Province level only	
Number of locally born age > 14 years		
Dependency ratio		
Household head age		
Household age (average)		
Households with young mother (< 17 years)		
Human capital / Education		
Head of household literate (read/write)		
Head of household speaks Portuguese		
Highest education level: head of household		
Highest education level: head and couple		
Literate ratio: literate adults/total adults		
Schooling enrolment		
Assets and housing conditions		
Habitational density: # persons/#bedrooms		
Use of electricity		
Quality/material of house floor		
Quality/material of house roofs		
Sanitation type		
Quality/material of house walls		
Source of drinking water		
Radio ownership		
Provincial dummies		

Sources: INE (1998) and INE (1999).

Figure 1 (all figures in Appendix) shows the geographical distribution of poverty at the provincial level for Mozambique according to the MIAF. It is evident from the picture that in large administrative units, such as provinces, there is plenty room for internal variation. The MIAF cannot capture intra-provincial variations given the size and distribution of the survey sample. Later, in sections 4 and 5 we will suggest alternative indicators to capture the intra-provincial variations in living conditions of the population.

Table 2
Poverty measures by province and area of residence

	Rural areas				Urban areas			
	P_0	Rank	P_1	Rank	P_0	Rank	P_1	Rank
Niassa	0.72	5	30.6	5	0.67	6	28.1	5
Cabo Delgado	0.57	10	19.1	10	0.67	5	28.7	4
Nampula	0.65	7	24.6	8	0.83	1	44.4	1
Zambezia	0.69	6	26.1	6	0.60	8	24.9	6
Tete	0.84	3	39.5	3	0.74	2	35.2	2
Manica	0.64	9	24.7	7	0.58	9	21.4	9
Sofala	0.92	1	54.1	1	0.71	3	30.8	3
Inhambane	0.87	2	41.4	2	0.62	7	24.1	7
Gaza	0.64	8	23.0	9	0.69	4	22.8	8
Maputo prov.	0.77	4	32.8	4	0.48	10	20.0	10
Maputo city	-	-	-		0.48	11	16.5	11

Source: INE (1998).

Note: P_0 is the 'headcount ratio'; P_1 is the 'poverty gap'.

2.3 Poverty assessment and 'basic needs' indicators

It is usually very difficult to find reliable and up-dated data to assess income- or expenditure-based poverty on a nationwide basis in developing countries. These assessments often require a rather detailed and systematically collected set of information on household's income/expenditure patterns. The process of gathering, processing and analysing this type of information is usually time consuming and expensive, especially when one is interested in a nationwide representative sample.

However, poverty and well-being can also be proxied with other 'welfare' indicators. A series of so-called 'basic needs' poverty or 'human poverty' indicators have been developed and widely used in poverty assessments. These well-being indicators are often constructed in an ad-hoc manner depending on the purpose of the assessment and on the type of available data. Usually they build up on data of the sort presented in Table 3; this Table presents a set of variables that provide information on other dimensions of population's well-being, beyond the income/expenditure-based poverty measures. We divide these variables into three main categories: demographic, human capital and asset position. We use most of these variables in our econometric estimations in the next section and in the calculation of non-monetary indicators of living conditions in section 6. When these indicators are constructed on the basis of disaggregated data sets, they become a useful tool for disaggregated poverty and well-being assessments. Tables 4 and 5 show a provincial breakdown for the same variables, for urban and rural areas, respectively.

Table 3
Summary socioeconomics indicators

	Country	Urban	Rural
Demographic			
Household size[a]	4.20	4.75	4.01
Persons > 14 years old[c]	55.54	56.98	54.94
Female household heads[b]	30.46	28.61	31.10
Minority household heads[b]	16.41	24.71	13.53
Local heads (never left location)[b]	76.73	60.92	82.20
Locals > 14 years old[d]	76.98	65.31	81.95
Dependency ratio[a]	47.41	44.70	48.35
Household head age[a]	40.52	39.72	40.80
Household age[a]	24.93	24.02	25.25
Young mother (<17 years old)[b]	1.21	0.96	1.36
Human Capital			
Literate heads of household[b]	38.47	65.58	29.08
Head of household speaks Portuguese[b]	42.76	74.15	31.88
Head of household with education above basic[b]	11.78	30.12	5.43
Head and spouse with education above basic[b]	2.68	8.97	0.50
Literate ratio[a]	32.20	59.93	22.59
Schooling rate[a]	40.55	60.99	31.16
Assets position			
House density[a]	3.17	3.57	3.21
Electricity[b]	5.21	18.17	0.73
Deficient floors[b]	85.71	57.41	95.43
Deficient roofs[b]	82.56	51.11	93.38
Deficient sanitation[b]	96.62	89.31	99.06
Deficient walls[b]	88.58	67.52	95.79
Drinking water (low quality)[b]	91.17	70.09	98.39
Ownership of radio[b]	28.27	49.06	21.06
Male population (%)	47.92	49.34	47.33
Female population (%)	52.08	50.66	52.67
Total population	15278324	4447160	10831164
Total number of households	3634315	935440	2698875

Source: INE (1999).

Note: [a]average; [b]as % of households; [c]as % of population;[d]as % of population > 14 years.

Table 4
Socioeconomic indicators for urban areas

	Niassa	Cabo Delgado	Nampula	Zambezia	Tete	Manica	Sofala	Inhambane	Gaza	Maputo province	Maputo city
Demographic											
Household size [a]	4.53	4.33	4.25	4.43	4.65	5.11	4.75	4.22	4.93	5.02	5.41
Persons > 14 yrs. old [c]	53.49	58.80	56.49	55.54	54.00	54.44	57.63	57.22	54.86	57.05	59.52
Female household heads [b]	28.19	27.97	20.75	28.70	32.59	22.16	21.08	43.82	47.33	33.64	28.60
Minority household heads [b]	23.17	20.24	21.17	22.89	19.28	33.62	22.27	9.39	17.71	33.15	32.34
Local heads (never left location) [b]	75.16	60.53	85.44	91.77	72.17	53.54	59.93	87.09	78.09	32.93	22.46
Locals > 14 yrs. old [d]	77.06	63.98	85.11	91.54	74.15	60.89	66.09	85.88	79.91	43.76	41.19
Dependency ratio [a]	46.42	42.44	43.41	45.27	48.11	46.87	43.19	48.18	49.80	46.02	42.06
Household head age [a]	37.47	39.13	38.16	37.21	38.78	39.15	39.86	43.33	42.23	41.34	40.63
Household age [a]	21.97	24.85	23.73	22.30	22.97	22.44	23.83	28.14	25.55	25.07	23.98
Young mother (<17 yrs. old) [b]	1.76	1.59	1.28	1.08	1.11	1.29	1.13	0.87	0.76	0.70	0.76
Human Capital											
Literate heads of household [b]	57.46	49.15	55.54	53.09	61.54	71.13	68.27	56.70	59.67	74.63	83.95
Head of household speaks portuguese [b]	69.59	60.28	67.01	68.70	64.05	78.57	79.91	62.14	60.01	79.91	89.03
Head of household with education above basic [b]	28.60	23.19	24.71	22.70	34.37	34.77	32.92	18.68	21.38	31.98	42.03
Head and spouse with education above basic [b]	6.80	4.88	6.01	5.62	10.97	9.24	8.79	5.50	5.85	10.45	15.69
Literate ratio [a]	48.81	39.64	44.63	45.38	57.45	64.26	59.47	55.87	60.46	72.89	82.14
Schooling rate [a]	49.34	42.72	44.46	52.56	58.54	57.69	56.38	66.00	70.28	71.21	75.17
Assets position											
House density [a]	3.28	2.38	2.75	3.12	3.18	3.41	3.18	2.94	3.18	3.14	3.11
Electricity [b]	9.29	11.11	15.59	8.64	20.14	9.53	13.36	6.44	18.33	20.24	37.82
Deficient floors [b]	90.13	77.53	77.59	88.85	74.25	76.77	50.77	65.02	53.28	35.39	16.26
Deficient roofs [b]	92.58	92.35	86.78	91.11	63.82	69.13	39.94	66.19	32.86	7.62	2.81
Deficient sanitation [b]	96.84	95.83	95.37	96.21	90.13	93.75	87.16	96.09	92.69	88.30	74.36
Deficient walls [b]	92.38	93.05	88.53	90.18	74.22	82.35	68.68	82.56	74.29	41.78	26.16
Drinking water (low quality) [b]	86.87	76.69	75.96	90.70	72.05	89.52	68.81	84.78	62.36	50.76	50.37
Ownership of radio [b]	37.82	37.04	36.25	33.81	48.23	50.94	46.01	44.77	50.81	59.09	71.15

[a] : average
[b]: as percentage of households
[c]: as percentage of population
[d]: as % of population > 14 yrs.

Source: INE (1999).

Table 5
Socioeconomic indicators for rural areas

	Niassa	Cabo Delgado	Nampula	Zambezia	Tete	Manica	Sofala	Inhambane	Gaza	Maputo province
Demographic										
Household size [a]	3.85	3.74	3.63	3.90	4.21	4.72	4.61	4.35	4.57	4.04
Persons > 14 yrs. old [c]	52.79	57.59	55.15	54.46	51.48	53.00	55.35	56.90	56.59	59.87
Female household heads [b]	29.76	25.94	22.89	29.84	33.50	32.94	31.42	44.44	50.15	42.38
Minority household heads [b]	12.93	9.82	7.19	27.16	9.46	21.39	5.05	5.73	10.48	15.11
Local heads (never left location) [b]	79.45	92.69	91.73	87.44	47.52	67.17	81.95	86.00	81.13	50.93
Locals > 14 yrs. old [d]	79.79	92.52	90.73	87.62	47.73	68.70	83.76	85.29	81.25	55.43
Dependency ratio [a]	48.31	43.85	46.02	47.15	52.52	51.51	49.38	52.91	53.81	49.49
Household head age [a]	39.28	38.97	38.83	38.65	41.30	42.13	42.42	46.93	46.99	47.16
Household age [a]	23.44	25.51	24.62	23.43	23.99	23.88	24.56	30.25	29.83	32.06
Young mother (<17 yrs. old) [b]	1.85	2.01	1.57	1.20	1.01	1.36	1.72	0.91	0.66	0.47
Human Capital										
Literate heads of household [b]	28.18	25.71	26.40	27.33	27.17	32.53	28.85	37.47	36.39	41.25
Head of household speaks portuguese [b]	32.07	28.54	31.96	33.98	19.89	32.05	35.02	36.29	32.54	43.54
Head of household with education above basic [b]	6.43	6.17	5.35	4.36	5.84	7.47	6.01	4.80	4.63	6.90
Head and spouse with education above basic [b]	0.53	0.40	0.50	0.31	0.58	0.92	0.50	0.60	0.61	0.81
Literate ratio [a]	20.14	17.68	17.97	19.96	21.47	27.33	21.30	34.85	36.27	39.85
Schooling rate [a]	24.66	23.30	25.39	28.92	25.62	28.58	21.79	49.97	52.15	51.04
Assets position										
House density [a]	3.51	2.82	2.98	3.30	3.79	3.60	3.53	2.96	3.12	3.02
Electricity [b]	0.20	0.23	1.34	0.23	0.31	0.98	1.14	0.41	1.22	2.12
Deficient floors [b]	98.89	98.34	97.53	98.95	98.46	97.47	96.77	86.39	77.95	79.85
Deficient roofs [b]	99.08	99.11	98.33	98.98	97.97	95.80	94.97	81.57	66.13	44.66
Deficient sanitation [b]	99.51	99.04	99.09	99.32	99.31	98.99	98.62	99.18	98.25	97.73
Deficient walls [b]	97.48	99.20	98.42	97.38	97.00	96.64	97.29	89.99	82.71	81.42
Drinking water (low quality) [b]	99.38	99.53	96.97	99.82	99.40	98.77	97.57	99.31	96.79	91.39
Ownership of radio [b]	18.35	18.23	16.79	17.84	21.94	26.15	25.72	27.85	32.51	33.13

[a] : average
[b]: as percentage of households
[c]: as percentage of population
[d]: as % of population > 14 yrs.

Source: Source: INE (1999).

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3. Disaggregating poverty measures

3.1 Estimation strategy

Although policymakers and analysts express concern about the regional imbalances in living conditions, in Mozambique there are no expenditure-based poverty measures at geographic/administrative levels lower than the provincial level. For that reason, we need to estimate a model that could allow us to predict well-being measures at lower levels of disaggregation. We will follow a two-step procedure with this objective. First, we estimate a maximum likelihood probit model of poverty measures at the household level. For this estimation, we use MIAF data on demographic, human capital, and the possession of assets by the households. Not least important for our exercise, the MIAF also provides a detailed description of the household consumption expenditures. The household's consumption expenditure used to measure poverty is an aggregate measure, including not only actual expenditures, but also self-consumption of food and non-food items, imputed values for owner-occupied houses and household durable goods. The figures of per capita consumption expenditure and the poverty line used to assess the incidence of poverty were properly adjusted to correct for temporal and spatial differences.[8] With this information, we were able to classify the households into poor and non-poor categories.

We estimate two econometric models, for urban and rural areas respectively, to assess the probability that a household is poor, i.e. that the per capita aggregate consumption is below a poverty line.[9] The set of explanatory variables used to estimate the probability of being poor belongs to four major categories: demographic characteristics, human capital/education status, assets possessions, and provincial dummies. We are aware that some of the explanatory variables in our model are problematic. The variables related to the household's possession of assets may be endogenous, in partly determined by household expenditures. This is a common problem in poverty regressions (Minot, 2000). One may also argue that some of the variables related to human capital formation or education of the household members are not a determinant of poverty but rather an outcome. Maintaining these variables in our model is partly justified because we are not modelling the 'determinants' of poverty; rather we are interested in identifying the poor.

We use a slightly different set of explanatory variables in the urban and rural poverty models. In the urban poverty model we include variables related to some services (electricity, sanitation) or quality of house (floors) materials that we consider can help to capture differences between poor and the non-poor households. Meanwhile, in the rural poverty model we include provincial 'dummy' variables to capture any other difference not properly explained by the other variables included in the model.

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8 Since the MIAF data was gathered during a period of approximately one year, it was necessary to correct for changes in the price levels occurred during this period. In addition, since the sample covers the ten provinces, the capital city of Maputo and the rural and urban areas, the value of the basic basket considered as the poverty line was also adjusted for the spatial changes in the cost of living.

9 We use the same poverty lines as in (MPF, UEM, IFPRI, 1998).

Table 6
Maximum likelihood probit estimation results

Variable	Urban	Rural
Household size	0.0883	0.552
	(3.547***)	(11.91***)
Household size squared	-	-0.026
	-	(-9.70***)
Population > 14 years	-0.2456	-0.583
	(-0.558)	(-2.12**)
Female head household	0.0381	-0.091
	(0.311)	(-1.26)
Household head belongs to a ethnic minority	-0.1708	-0.358
	(-1.739*)	(-2.08**)
Household head local	-	0.075
	-	(0.54)
Interaction term: local & minority	-0.2351	0.253
	(-1.291)	(1.27)
Proportion of local population > 14 years	0.0881	-0.338
	(0.805)	(-1.99**)
Dependency ratio	0.0013	0.0029
	(0.382)	(1.63)
Household head age	0.0138	-0.0032
	(2.533**)	(-1.05)
Average household age	-0.0349	0.0048
	(-3.861***)	(0.84)
Household with young mother (< 17years)	0.4534	0.0012
	(1.369)	(0.01)
Household head read & write	-0.0954	-0.097
	(-0.389)	(-1.16)
Household head speaks Portuguese	0.0117	-0.048
	(0.07)	(-0.70)
Household head w/education above basic	-0.2444	-0.269
	(-1.806*)	(-2.07**)
Household head and spouse w/education above basic	-	-0.417
	-	(-1.03)
Literate ratio in household (adults literate/# adults)	-0.6891	-0.201
	(-3.714***)	(-1.65)
Schooling attendance rate	-0.2602	-0.347
	(-2.33**)	(-3.18***)
Habitational density	0.0665	0.052
	(2.76***)	(2.65***)
Household with electricity	-0.7196	
	(-5.857***)	
Household with poor quality floors	0.2567	
	(2.849***)	
Household with poor quality sanitation	0.3872	
	(2.49***)	

table continues…

Household with poor quality drinking water	-0.0297	
	(-0.216)	
Radio ownership	-0.3259	-0.403
	(-3.6***)	(-6.79***)
Provincial dummies:		
CABO DELGADO		-0.346
		(-1.69*)
NAMPULA		-0.182
		(-0.89)
ZAMBEZIA		0.003
		(0.02)
TETE		0.317
		(1.49)
MANICA		-0.481
		(-2.15***)
SOFALA		0.747
		(3.57**)
INHAMBANE		0.491
		(2.43**)
GAZA		-0.329
		(-1.66**)
MAPUTO province		0.062
		(0.29)
Constant	0.3051	-0.845
	(0.708)	(-2.85***)
Observations	2385	5722
Number of strata	11	10
Number of PSU	77	196

Source: author's compilation.

Note: Dependent variable equals 1 if household is poor, 0 otherwise (t-statistics in parenthesis). *significant at 10% level; ** significant at 5% level; *** significant at 1% level. All standards errors corrected for sample design effects.

Table 6 shows the coefficients and t-statistics for the models for urban poverty in the first column and for rural poverty in the second column.[10] Most of the coefficient signs in our model resulted as expected. In the urban model, those with older head of household tend to be poorer, while households with higher average age tend to be less poor. In the urban sector also, with higher proportion of literate adults in the household, the probability that the household is poor is lower. The presence of electricity in the household is also strongly significant for the urban sector model. In the rural sector, the largest the proportion of persons older than 14 years is, the less likely that the household is poor. Other variables that resulted significant for both models were, household size, household head belonging to an ethnic minority, household head with education above basic, schooling attendance rate,

[10] Due to the nature of the sample design used to collect the MIAF data, all standards errors in the econometric analysis and in our descriptive statistics are corrected for sample design effects. Since we are not interested in marginal effects or elasticities, we only show coefficients and significance levels.

habitational density, and ownership of a radio. Finally, statistical significance of some of the provincial 'dummies' indicate that, even after controlling for the variables included in our rural model, some provinces are poorer than Niassa province, the reference region.

3.2 Predicting poverty measures

The second step is an 'out-of-sample' econometric prediction of the headcount ratios at the posto administrativo level. For this prediction, we used the posto administrativo means of the relevant independent variables contained in the probit model and the coefficients obtained from the urban and rural sector models respectively. Figures 1 to 7 show different versions of the 'poverty map' for Mozambique. Figure 2 presents again a poverty map at the provincial level, but this time illustrating headcount ratios for rural areas. There are only minor differences between Figure 1 and Figure 2. Since rural population is considerable larger than urban population in Mozambique, the headcount ratios for rural areas have the largest incidence in the national and provincial averages. Figures 1 and 2 show the headcount ratios at the 'lowest' disaggregation level allowed by the MIAF data set.

The results of our econometric exercise allow us to construct an equivalent poverty map for rural areas disaggregated at the posto administrativo level. Figure 3 illustrates different ranges for predicted headcount ratios in a disaggregated manner. In contrast with the original provincial-level poverty map, produced from the MIAF data set, the disaggregated map shows a wider range of variations in headcount ratios within provinces. In section 7 we use these predicted ratios as one criteria for geographic targeting. We will compare its performance with respect to other targeting/allocation indicators. Table 7 shows the predicted headcount ratios for urban and rural areas and the provincial ranking for each indicator. Comparing the predicted headcount ratios with the actual ratios at the provincial level show that the model, especially for rural areas performs reasonable well. Although the magnitude of the obtained rates may differ, the ranking of provinces by headcount ratios remains very much the same.

Figure 4 illustrates the deviations between the actual (provincial) rates calculated from the MIAF data set and the predicted rates (at the posto administrativo level) for rural areas[11] obtained from our econometric estimation. The postos administrativos labelled as 'worse cases' are those where the predicted headcount ratios *are larger* than the actual provincial headcount ratios obtained from the MIAF. This means that it is worth investigating in these postos whether the provincial poverty rates are representative of the actual living conditions of the population. These postos are candidates for actually having larger shares of their population under poverty conditions than the average figures obtained from the MIAF. On the opposite side, the postos labelled 'better cases' are those where the predicted headcount ratios *are significantly smaller* than the actual provincial headcount ratios obtained from the MIAF. In these postos the predicted headcount ratios are at least 20 percent lower than the actual provincial ratios. Thus, these postos are likely to be enjoying actually better living conditions than those suggested by the provincial averages from the MIAF.

[11] Equivalent maps to those presented in Figures 2, 3 and 4, but for urban areas not shown, are available from the author.

Table 7
Comparing predicted and actual headcount ratios

	Rural areas				Urban areas			
	MIAF	Rank	Predicted	Rank	MIAF	Rank	Predicted	Rank
Niassa	0.72	5	0,65	4	0.67	6	0.45	2
Cabo Delgado	0.57	10	0,47	10	0.67	5	0.42	3
Nampula	0.65	7	0,53	8	0.83	1	0.42	5
Zambezia	0.69	6	0,63	5	0.60	8	0.46	1
Tete	0.84	3	0,82	2	0.74	2	0.39	9
Manica	0.64	9	0,55	7	0.58	9	0.40	6
Sofala	0.92	1	0,91	1	0.71	3	0.42	4
Inhambane	0.87	2	0,80	3	0.62	7	0.40	8
Gaza	0.64	8	0,53	9	0.69	4	0.40	7
Maputo prov.	0.77	4	0,61	6	0.48	10	0.34	10
Maputo city	-	-	-	-	0.48	11	0.31	11

Source: INE (1998), INE (1999) and own calculations.

Note: Reported provincial predicted headcount ratios are population-weighted averages of predicted ratios at the posto administrativo level.

4. Multidimensional poverty and vulnerability

It is possible to identify in its most simplistic form two extreme approaches to define and to measure poverty. One extreme represented by the 'conventional' approach, where income or consumption measures are used to proxy poverty. The other extreme is represented by a 'participatory' approach, where multiple and sometimes more subjective elements define poverty and well-being (Moser, 1998). Nevertheless, there is by today a more or less generalized agreement among economist regarding the advantages and shortcomings of using whether monetary-based (income or expenditure) or non-monetary based poverty measures.[12] Monetary-based indicators are thought to be easier to quantify and to allow comparisons among different groups. They fall short however, in representing a whole range of important aspects of people's livelihoods.

In Mozambique, we find poverty appraisals representing both approaches. For example, the 'traditional' approach is well represented by the 'Understanding Poverty' report (MPF, UEM, IFPRI, 1998) using the data set from the MIAF. Meanwhile, the 'participatory' approach can be illustrated by a series of participatory diagnoses of poverty, organised also by the Ministerio do Plano e Finanzas in collaboration with the Universidad Eduardo Mondlane, and carried out during January 2001 in 21 districts in 7 provinces (Cabo Delgado, Nampula, Zambezia, Sofala, Tete, Inhambane, and Maputo province).[13]

[12] The most recent World Development Report 2001 'accepts the now established view of poverty as encompassing not only low income and consumption but also low achievements in education, health, nutrition and other areas of human development' (World Bank, 2001).

[13] We have unfortunately still not had the opportunity to see the preliminary results of these appraisals.

One indicator extensively used as a 'compromise' solution to these two types of approaches is the 'Human Development Index' or HDI. The HDI is used to measure and illustrate the overall level of well-being and living conditions in a given country. More recently a similar index, 'the Human Poverty Index' or HPI has also been developed. These indicators provide a wider perspective to poverty and well-being by including into their measurements a broader range of variables.[14]

Other authors have proposed alternative frameworks for analyzing people's well-being for urban (Moser, 1998) and rural (Bebbington, 1999) areas respectively. We find particularly interesting a framework that focus on: i. access to different resources, such as credit, land, skills, labour, etc., ii. the opportunities to turn these resources into livelihood enhancement, iii. means to enhance the existing ways of using these resources, and iv. access to institutions and relationships e.g. kin, ethnic networks, social, governmental and non-governmental organizations, etc. (Bebbington, 1999).

In this section, we construct an indicator to characterize people's living conditions. We follow the conceptual framework mentioned above in the construction of our non-monetary indicator of living conditions, attempting to capture household's consumption levels, living conditions, human and social capabilities and their assets base. Our 'vulnerability' indicator is a non-monetary expression of people's living conditions. The indicator complements the results from the previous section, where we modelled poverty using a monetary-based measure. We claim that our proposed 'vulnerability' indicator is wider and richer than for example, that proposed by the HPI. In addition, by disaggregating the welfare indicator at the 'posto administrativo' level, we provide a disaggregated measure of poverty and well-being not available for Mozambique before.

There are two reasons to produce such type of indicator. The first is based on conceptual or theoretical grounds, while the second is a practical matter. First, there is a need to represent other aspects of people's livelihood beyond their consumption expenditures. This calls for a more comprehensive type of measure. The second is the fact that accurate measures of people's incomes or consumption expenditures are difficult, costly and time-consuming.

We define vulnerability as a bidimensional measure. The *first dimension* is represented by the demographic characteristics of the household. The *second dimension* is given by the household's housing/assets conditions. Three demographic characteristics define the *first dimension* of our vulnerability indicator. These variables are (i) the dependency ratio (ii) education achievement of the household head, and (iii) the presence of a 'young' mother (less than 17 years old) in the household. To define the *second dimension* of vulnerability we choose six variables. These variables express the possession or deprivation of key assets and housing conditions (i) access to tap water in the household (ii) type of sanitary services (iii) type of wall materials (iv) habitational density (defined as number of persons per bedroom) (v) electricity (vi) ownership of a radio. Different

[14] The Human Poverty Index (HPI) is defined in terms of three types of deprivations. Deprivation in *health* is indicated by vulnerability to death at a relatively early age, quantified in the percentage of people expected to die before the age of 40 years; deprivation in *knowledge* captured by the percentage of adults who are illiterate; and deprivation in *overall economic provisioning* quantified by three variables, namely (i) percentage of people without access to safe drinking water (ii) percentage of people without access to health services (iii) percentage of children under 5 who are moderately and severely underweight (UNDP, 1997).

combinations of these two dimensions allow us to classify the households into three major vulnerability groups (i) non-vulnerable (ii) vulnerable, and (iii) very vulnerable.[15]

Figure 5 shows the percentage of the households considered 'very vulnerable' by posto administrativo according to the criteria described above. Different categories are distinguished in the map, with the highest level of vulnerability shown by the postos where 35 percent or more of the population falls into the 'very vulnerable' category. The coastal areas in Maputo, Gaza and Inhambane provinces show the lowest percentages of very vulnerable households.

According to information presented in the latest PARPA, Zambezia, Nampula and Cabo Delgado provinces show the lowest performance in terms of the Human Development Index (HDI and simultaneously the highest Human Poverty Indexes (GoM, 2001). This claim is in part in line with our results shown in Figure 5. However, again the actual situation is, as shown in the map, more like a mosaic of heterogeneous living conditions in the different localities instead of a homogeneous provincial situation. In addition, another flaw in both the HDI and HPI figures shown in PARPA is that they do not distinguish between rural and urban areas.

Figure 6 compares the predicted poverty rates and the percentage of vulnerable population in rural areas at the posto administrativo level. The areas labelled 'larger headcount ratios' are those postos where the predicted poverty rates are *higher* than the share of vulnerable households among the population. It is mainly in the southern and central provinces, especially in the coastal zones, where expenditure-based poverty rates appear to be higher than our vulnerability indicator. One possible interpretation is that in these postos the population tends to be better off than what a monetary-based poverty measure would suggest. The household's characteristics in these postos predict that households are (income/expenditure) poor, although they perform much better in terms of the vulnerability indicator. The postos labelled 'more vulnerable' mainly in the Northern provinces represent the opposite situation. In these postos, the shares of vulnerable households among the population are considerable larger than the population predicted to be under the poverty line. In these areas, the households' characteristics predict poverty rates that are in general *lower* than the shares of vulnerable households among their population. The households in the postos labelled 'more vulnerable' may be facing more critical living conditions than suggested by a monetary-based poverty measure.

Table 8 compares the results (for rural areas) of the predicted headcount ratios from section 4 with the vulnerability indicators obtained in this section. The predicted headcount ratios are compared with the percentage of very vulnerable population and the average vulnerability[16] by province. The table also shows measures of variability for each indicator. It shows that the percentage of very vulnerable population has the largest coefficient of variations. These coefficients correspond to the variations across postos by province, and across postos for the whole country. Table 9 shows the ranking, by province of the provincial averages of these three measures. More interesting than the ranking for themselves is the (Spearman's) rank correlation coefficient shown in the last row of the

[15] Appendix 1 presents a detailed description of the construction of the vulnerability indicator.

[16] Vulnerability was defined in the range 1 to 5 (see appendix).

table. The coefficient is positive but relatively low, meaning that ranking postos nationwide, by both predicted headcount ratios and percentage of very vulnerable households would produce a considerable different picture of nationwide living conditions.

Table 8
Comparing monetary and non-monetary indicators of living conditions, by province for rural areas

	Predicted poverty (1)	% very vulnerable households (2)	Average vulnerability (3)	CV of (1)	CV of (2)	CV of (3)
Niassa	0.65	0.23	2.98	0.066	0.433	0.073
Cabo Delgado	0.47	0.28	3.08	0.108	0.279	0.051
Nampula	0.53	0.24	2.99	0.070	0.355	0.070
Zambezia	0.63	0.28	3.10	0.075	0.388	0.065
Tete	0.82	0.28	3.07	0.044	0.367	0.068
Manica	0.55	0.32	3.11	0.187	0.551	0.107
Sofala	0.91	0.31	3.13	0.034	0.361	0.076
Inhambane	0.80	0.13	2.61	0.056	0.843	0.137
Gaza	0.53	0.12	2.53	0.200	0.855	0.162
Maputo prov.	0.61	0.09	2.48	0.150	0.803	0.126
Mozambique (only rural)	0.63	0.24	2.97	0.232	0.510	0.107

Source: INE (1998), INE (1999) and own calculations.

Note : CV is the coefficient of variation.

Table 9
Ranking and Spearman's rank coefficient for selected indicators, rural areas

	Predicted poverty (rank)	% very vulnerable households (rank)	Average vulnerability (rank)
Niassa	4	7	7
Cabo Delgado	10	5	4
Nampula	8	6	6
Zambezia	5	3	3
Tete	2	4	5
Manica	7	1	2
Sofala	1	2	1
Inhambane	3	8	8
Gaza	9	9	9
Maputo prov.	6	10	10
Spearman's (rho) coefficient (1)	0,202		

Source: INE (1998), INE (1999) and own calculations.

Note: (1) Spearman rank correlation coefficient between predicted poverty and % very vulnerable households.

5. Geographic targeting for poverty alleviation

In this section, we present the use of geographic targeting as a poverty alleviation tool. For that purpose, first we present the rationale for using geographic targeting; secondly, we show different allocation mechanisms that are typically used in such targeting schemes and finally, we assess the performance of three allocation schemes, each based on a different criteria.

5.1 Geographic targeting: why?

The success of poverty alleviation efforts typically depend on their ability to properly identify and to target the objective population, i.e. the poor. Ideally, one would like to identify the poor population at the individual level,[17] and to design targeting programmes that reach them adequately. This level of accuracy and efficiency obviously requires large amount of resources for gathering information and administering the targeting programmes. With scarce resources and under time pressures for finding solutions for the large shares of the population living in poverty conditions, most countries have put aside the 'ideal' scheme and instead try to find alternative, but more practical approaches. Geographic targeting is recognized as one possible way out to the dilemma to identify the poor. Instead of aiming to identify and target the poor individuals and the households where they belong, it is administratively easier and cheaper to orient poverty alleviation efforts to the geographic areas where the poor live.

5.2 Allocation mechanism: how?

Geographic targeting is usually done in a three-step procedure. *First*, one decides a ranking criterion to characterize the living conditions of the population. Usually the ranking follows some kind of welfare or poverty measure. In our case, instead of selecting only one ranking criterion, we will test the performance of targeting poverty according to two different welfare measures: predicted headcount rates and a vulnerability indicator. In addition, we also assess the performance of allocating poverty resources according to the same provincial distribution of resources as the one used in the most recent National State Budget.

In the *second* step, one decides the allocation mechanism. This means, a rule or criteria to allocate the funds available for the poverty alleviation efforts. In order to make a fair comparison of the different welfare indicators, we will use the same allocation rule for all the indicators. We use a simple and straightforward linear distribution[18] as the allocation rule.

The *third* step is to allocate the funds at a selected geographic level. For example, if we choose to use the district as the geographical unit for targeting, the district *i* will receive the share of funds given by the expression *($allocation_i$)*. Dividing the percentage of targeting

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[17] Since one may find households composed by poor and non-poor persons at the same time, targeting at the household level in theory is not good enough.

[18] Shown by the following expression:

$$allocation_i = \frac{Welfareindex_i * Population_i}{\sum_i^N (Welfareindex_i * Population_i)}$$

funds allocated to each district by its total district population we obtain the transfers (as per capita percentage) that each person in district *i* will receive as a result of a given targeting programme.

5.3 Assessing performance

Poverty measures, such as headcount rates, based on consumption expenditures compare households or per capita consumption expenditure levels with a given measure of what is considered a minimum welfare standard—or poverty line. Under this framework, households or persons with consumption expenditures below the given poverty line are considered poor. However, non-income based indicators, such as the vulnerability indicator used in this paper, do not have an equivalent measure of minimum welfare. Therefore, it is not possible to compare the headcount ratios directly with a vulnerability indicator. Instead, we compare the performance of different allocation mechanisms by assessing their ability to identify and reach the poorest 20 percent of the population. For that purpose, we calculate *leakage rates* resulting from each allocation rule. Leakage rates often refer to the share of total programme resources that benefit non-intended beneficiaries, i.e. the non-poor. We estimate leakage rates to compare three different ranking criteria: (i.) allocation according to the latest National Budget, (ii.) allocation based on the 'vulnerability' indicator estimated in previous section, and (iii.) allocation done following the predicted poverty measures obtained in our econometric estimations in Section 4.

Using the allocation formula presented before, we calculated the per capita percentage of transfers that would be allocated to each district assuming that geographic targeting had been based on each of the different ranking criteria. Then, we merged by districts the information of per capita percentage of transfers with the household-level data from the survey, which contains information on the consumption expenditures by household, and thus, allow us to classify the households into five quintiles. By merging these two data sets, we are able to compare the transfers received by every household—according to their district of residence—and classify them into different consumption expenditures categories. For the comparisons, we assumed that the goal of the targeting programme was to reach the poorest quintile (20 percent) of the households. Our comparison consists thus, in assessing how much resources are actually allocated to the lowest quintile (in terms of consumption expenditures) of the households when geographic targeting is based on different ranking criteria.

Table 10 shows the results of three geographic targeting exercises. Exercise 1 consists in allocating funds according to our composite 'vulnerability' indicator. The results show that 28 percent of those benefiting from the transfers actually belong to the intended beneficiaries (i.e. the poorest 20 percent). The rest of the resources distributed by our hypothetical programme benefit the other higher 4 quintiles, with the richest 20 percent of the population still receiving 16 percent of the total. Exercise 2 distributes the funds of our hypothetical programme following the same share of funds shown by the most recent National State Budget 2001.[19] The second column in Table 10 shows that this allocation scheme performs poorer than using the vulnerability indicator. That is, if poverty alleviation funds were distributed in the same proportion as the National State Budget for

[19] We understand that this is the first time the figures of the National State Budget are released broken down by provinces.

2001, only a 19.5 percent of the beneficiaries belong to the target population. The last column (Exercise 3) in Table 10 shows the results of an allocation based on *predicted* poverty rates obtained from our econometric estimation. This allocation criterion outperforms the others by a significant margin. Following this targeting criterion will correctly allocate over 40 percent of the resources to the poorest 20 percent of the population.

Table 10
Distribution of beneficiaries by expenditure quintile

Consumption Expenditures	Experiment 1	Experiment 2	Experiment 3
	Vulnerability indicator	National Budget 2001	Predicted Poverty
Poorest 20% - 1st quintile	0.276	0.195	0.426
2nd quintile	0.207	0.216	0.207
3rd quintile	0.181	0.199	0.149
4th quintile	0.172	0.214	0.116
Richest 20% - 5th quintile	0.163	0.177	0.102

Source: author's calculations.

Finally, in Figure 7 we identify the postos administrativos whose population is suffering the most critical living conditions. We use two criteria to classify the living conditions in each posto administrativo: the predicted headcount ratios and the percentage of very vulnerable households. We identify the lowest quartile (25 percent of postos) for each of these two variables. The map shows (in red) those postos which classify as both: the poorest (in terms of headcount ratios), and the most vulnerable (according to the criteria presented in Section 5). Those postos that only classify as very vulnerable (25 percent of highest vulnerability) or very poor (highest 25 percent of headcount ratios) are also shown.

6. Final comments

In this paper, we have calculated, for the first time for Mozambique, living standard indicators disaggregated at the posto administrativo level. We have obtained disaggregated indicators of living conditions for both: monetary and non monetary-based measures. We use the headcount ratios as our monetary-based indicator of poverty. To obtain the disaggregated figures for the headcount ratios at the posto administrativo level, we first estimate a probit model using detailed household level data from a nationwide household survey. Then, using the estimated coefficients we predict headcount ratios at the posto administrativo level using average values of the explanatory variables at the posto level. The model for rural areas performs reasonable well when comparing the predicted headcount ratios with the actual ratios at the provincial level. The ranking of provinces by headcount ratios remains very much the same.

We are also concerned with the regional imbalance in living conditions expressed in different policy papers. For that purpose, we show in a map disaggregated at the posto administrativo level the geographical heterogeneity in living conditions and provide statistical measures of variability. The coefficients of variation for predicted headcount ratios is larger at the posto administrativo level than for the inter-provincial variation. The magnitudes of the coefficients of variation of our vulnerability indicator across posto administrativos are also large, both for the whole country and for each individual province.

These indicators confirm the concerns of authorities about the regional imbalances in living conditions. Using a simple framework our exercise in geographic targeting shows how by choosing an appropriate ranking criteria can reduce leakage rates, optimizing poverty alleviation efforts.

One important limitation in our prediction of monetary-based poverty indicators arises from the fact that our data source allows us to work only with posto administrativo averages instead of household unit records. Further research based on the availability of unit record data from the Census can be used to assess the accuracy of the results presented in this paper. In contrast with the potential accuracy losses of our results, the appeal of the methodology presented in this paper is that it is simple and fast to compute. In addition, it is based in ‘almost’ publicly available information, and do not demand special computing efforts from the corresponding national statistic offices.

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APPENDIX

Construction of the 'vulnerability' indicator

Our broad based composite 'vulnerability' indicator is based on the posto administrativo's average of nine relevant variables, all of them captured in the most recent National Population and Housing Census from 1997. Three demographic characteristics define the first dimension of our vulnerability indicator. These variables are:

(i) the dependency ratio
(ii) education achievement of the household head, and
(iii) the presence of a 'young' mother (less than 17 years old) in the household.

To define the second dimension of vulnerability we choose six variables. These variables express the possession or deprivation of key assets and housing conditions:

(i) access to tap water in the household
(ii) type of sanitary services ownership of a radio
(iii) type of walls materials
(iv) habitational density (defined as number of persons per bedroom)
(v) electricity
(vi) ownership of a radio.

The selected variables are the following:

Variable	Description	Cut-off values
First dimension: demographics		
Dependency ratio	Number of inactive members/total number of members in household	> 0.5
Education/Literacy achievement head of household	Education or literacy of household head	Urban: below basic Rural: illiterate
Young motherhood	Household having a young mother (< 17 years old)	Yes
Second dimension: assets possession		
Water	Type of access to drinkable water	Urban: no tapped Rural: no wells, only rivers/lakes
Sanitation	Type of access to sanitary installations	Urban: no WC Rural: no latrine / no WC
Walls	Type of house walls	Urban: adobe, bamboo, tree branches Rural: tin plates, cardboard, etc.
Habitational density	Total members of household/number of bedrooms	> 3
Electricity	Household with electricity	No (urban areas only)
Radio	Ownership of a radio in the household	No

To construct the index, we classified each dimension in three main categories. These three categories characterize (in increasing order) different levels of deprivation and vulnerability. Finally, using the different combinations of the three categories of each dimension we obtained 9 possible vulnerability conditions, which we grouped in 5 categories as shown in the table below.

		Second dimension: Deprivation of asset possessions		
		Low	Medium	High
First dimension Vulnerability	Low	1	2	3
	Medium	2	3	**4**
	High	3	**4**	**5**

We used data on household characteristics from the National Population and Housing Census from 1997 to establish the number of households, both in urban and rural areas, by posto administrativo, belonging to each of the 5 categories shown above. For the purposes of our study, we further grouped them into three main groups. Categories 1 and 2 were aggregated in the category labeled: non-vulnerable, whereas the rest are considered vulnerable households. As a sub-category among the vulnerable, we classified households falling into categories 4 and 5 as very vulnerable.

Figure 1
Headcount ratios, by province.

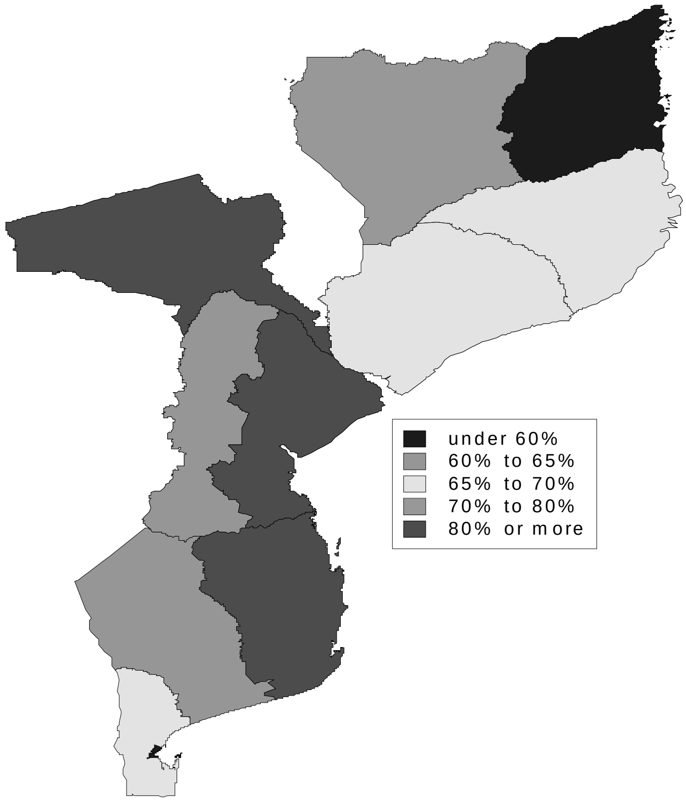

Figure 2
Headcount ratios for rural areas, by province.

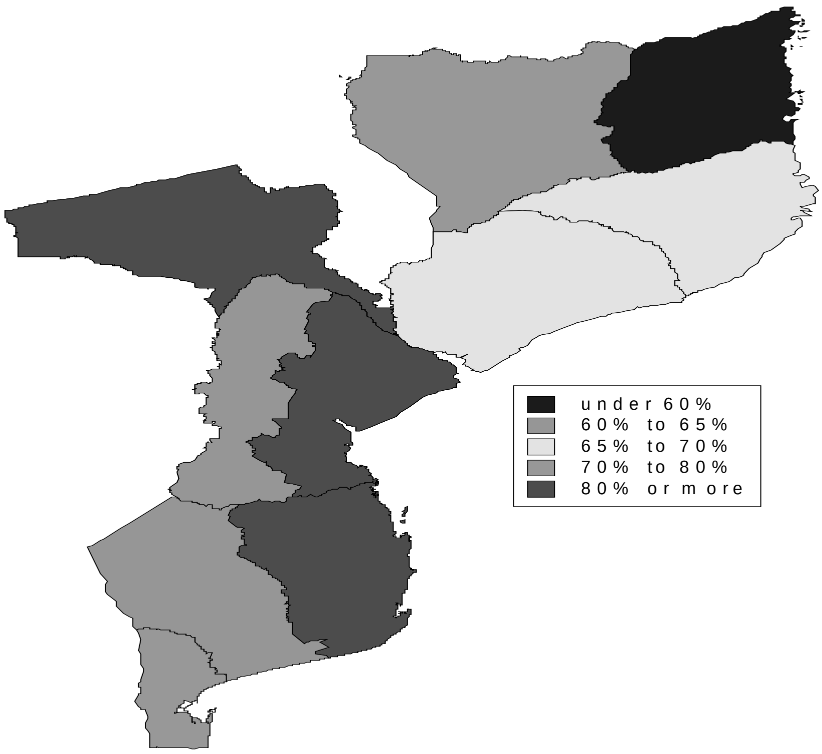

Figure 3
Predicted headcount ratios for rural areas, by posto administrativo.

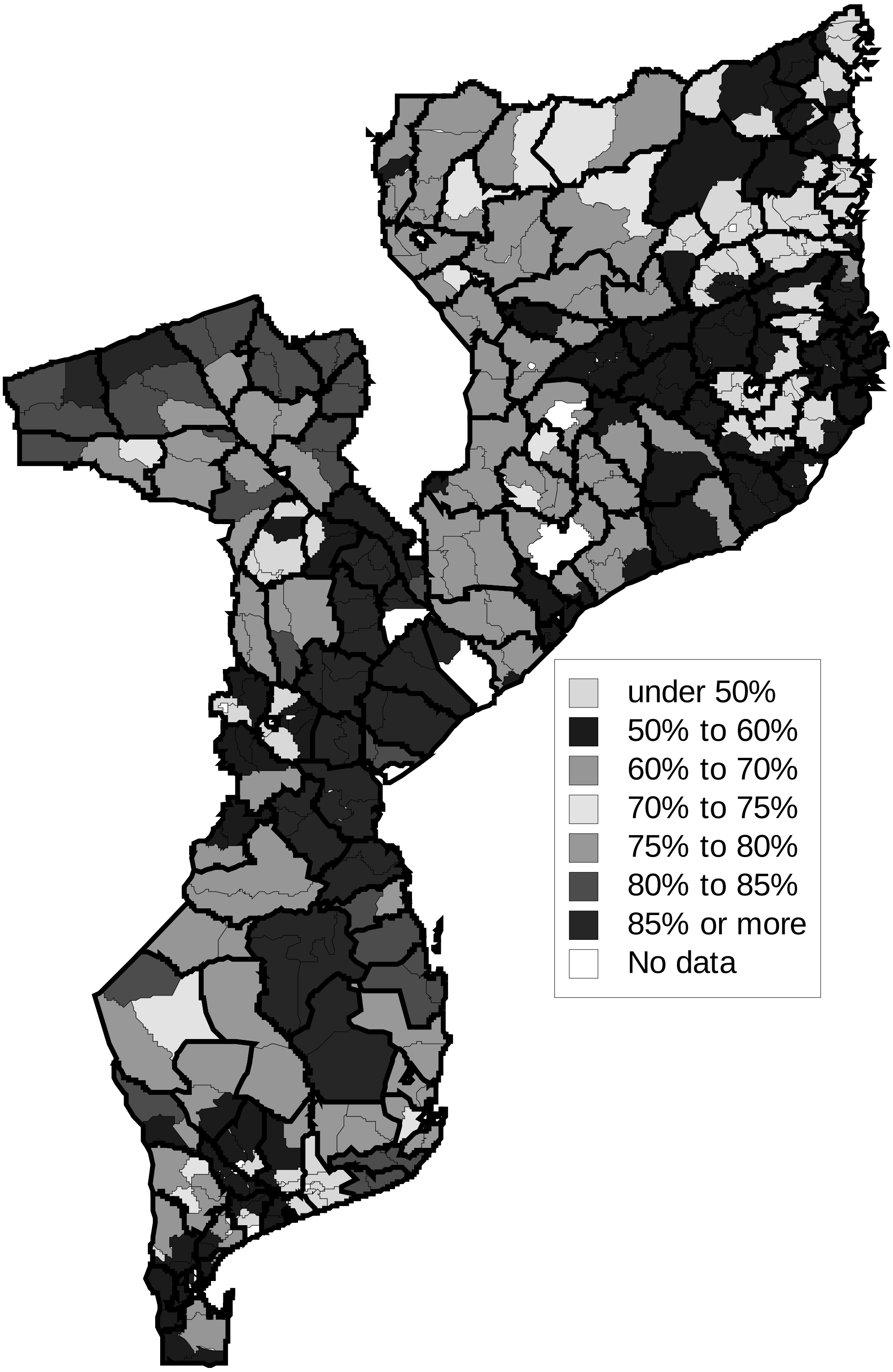

Figure 4
Comparing actual and predicted headcount ratios for rural areas.

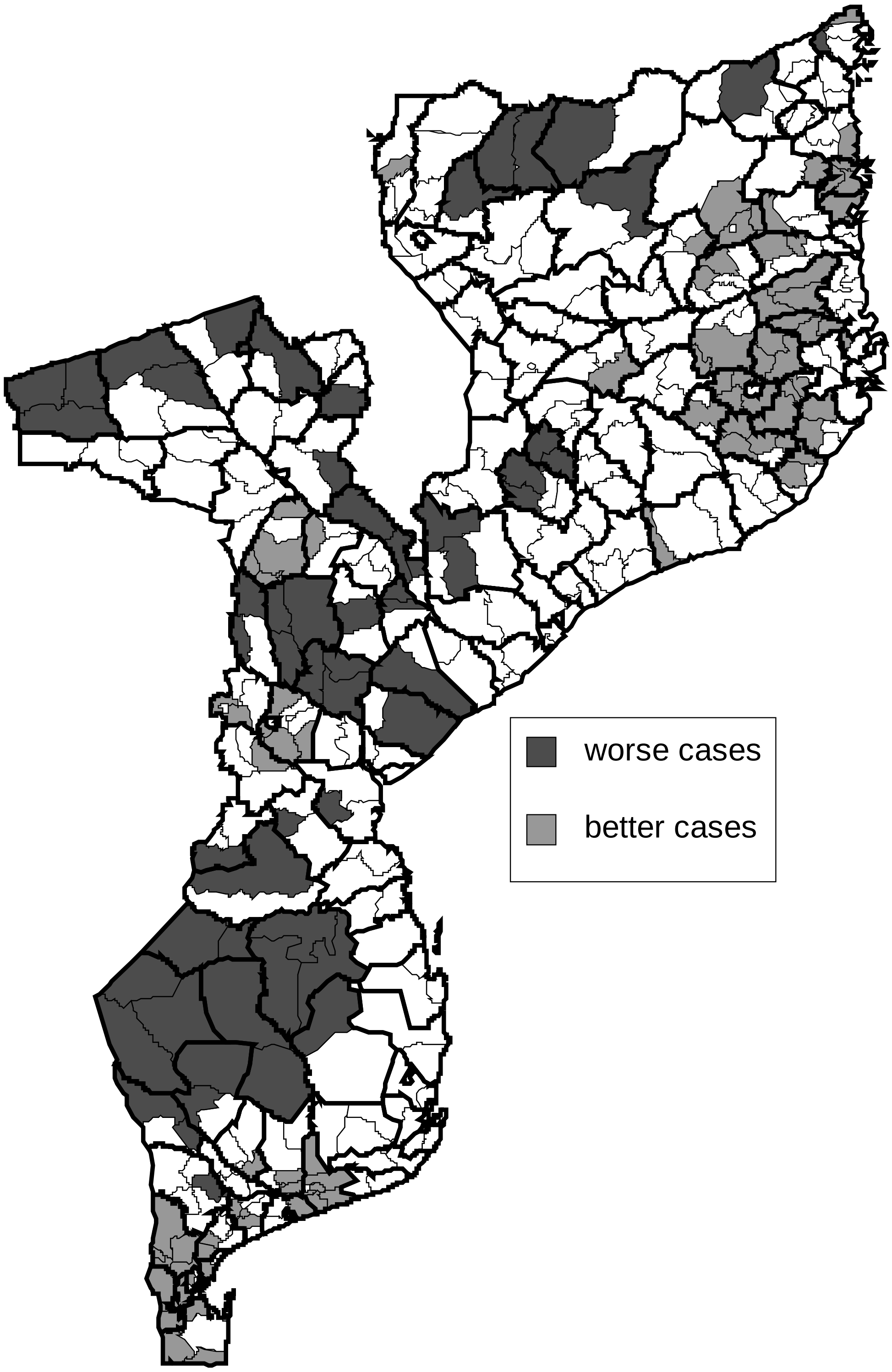

Figure 5
Percentage of very vulnerable households in rural areas, by posto administrativo.

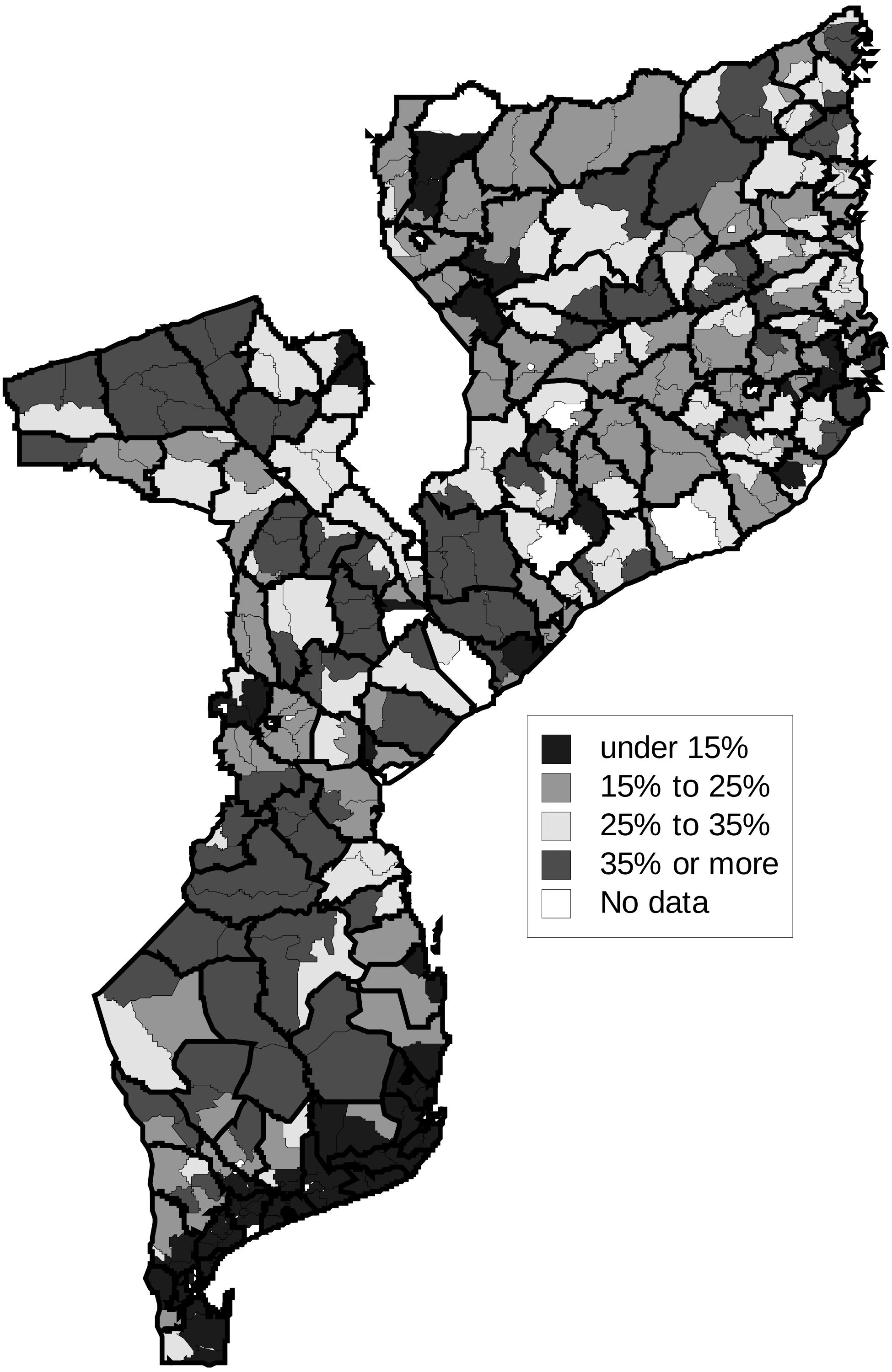

Figure 6
Comparing predicted headcount ratios and vulnerable households in rural areas, by posto administrativo

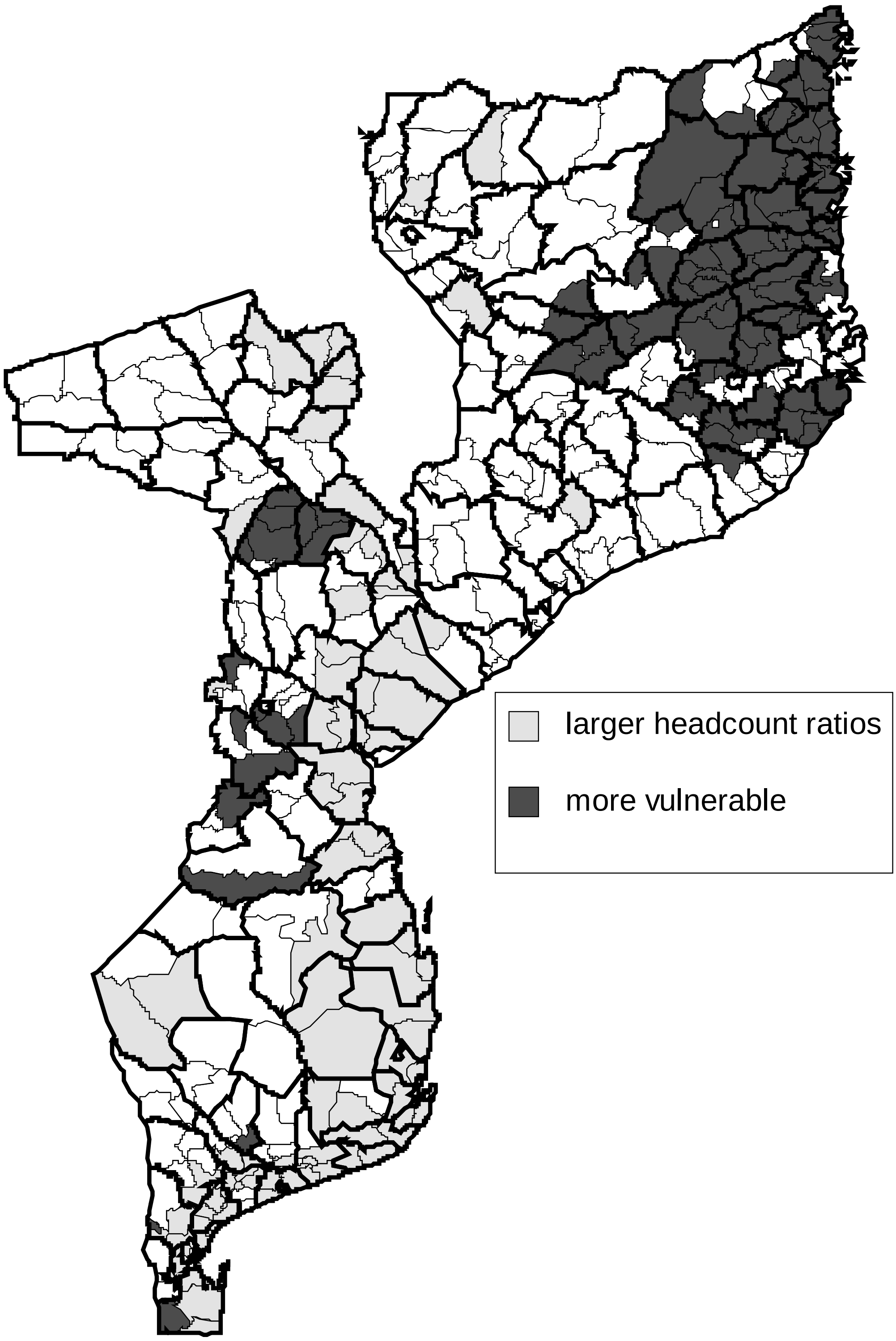

Figure 7
Comparing very vulnerable and poor households in rural areas, by posto administrativo.