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MULTIDIMENSIONAL POVERTY IN MOROCCO: AN EXPLORATORY SPATIAL APPROACH

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Multidimensional Poverty in Morocco: An Exploratory Spatial Approach

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Abstract. In spite of the overall decrease in poverty in Morocco in the recent past, the pace of change did not affect regions equally. Poorer provinces faced slower reductions, increasing the relative gap in poverty indicators. In this paper, we explore the results of a multidimensional poverty indicator produced by the High Commission for Planning (HCP), the Moroccan official statistical agency, for the period 2004-2014. The Multidimensional Poverty Index (IPM) allows investigating the spatial aspects of different dimensions of poverty in the country. We find a clear spatial process underlying the distribution of the IPM. Moreover, the analysis undertaken at the province level suggests a persistent poverty hot spot in the northeast part of the country associated with poor infrastructure. Other poverty areas are more heavily associated with low quality of public services, particularly education and health. We provide a typology of geographically targeted sectoral policies, showing that there is no single recipe for all regions, since structural features matter.

Keywords: spatial analysis; multidimensional poverty; policy targeting; Morocco

1. Introduction

Poverty has different facets. In Morocco, until recently mapping of poverty has been usually defined (measured) with the use of monetary poverty lines, estimated according to World Bank guidelines. Since 2008, the High Commission of Planning (HCP) has joined the efforts of the Oxford Poverty and Human Development Initiative (OPHI) to enhance the methodological approach to map poverty in the country. In an effort to combine information from different household surveys, HCP has developed the Multidimensional Poverty Index (IPM in French).

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The OPHI approach (Alkire and Foster, 2011) is a way of measuring multidimensional poverty consisting of counting the different types of deprivation that individuals experience at the same time, such as a lack of education or employment, or poor health or living standards. These deprivation profiles are analyzed to identify who is poor, and then used to construct a multidimensional index of poverty.[4] This approach has been adapted to be applied in different countries. Methodological twists are often needed to make the approach useful in different contexts of data availability. Moreover, the original Alkire-Foster methodology considers that the choice of dimensional weights may be seen as a value judgment, which should be open to public debate and scrutiny (p. 480), opening the possibilities for different *ad hoc* weighting definitions in different applications. This strategy resolves a potential problem based on a more pragmatic perspective. Table 1 presents the weighting of the different dimensions in the case of Morocco.

Table 1. IPM Methodology: Morocco

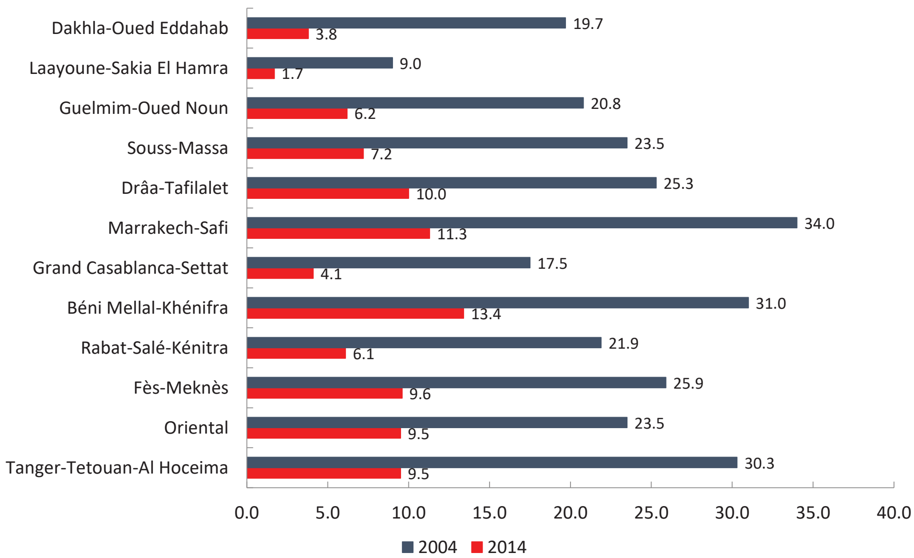
Dimension	Indicator	Deprived if	Weight	
Education	Years of schooling	No household member has completed five years of schooling	1/6	1/3
	Child school attendance	Any child between 7 and 15 years is not attending school	1/6	
Health	Mortality	Any child has died in the family	1/6	1/3
	Disability	Any person in the household is disabled (lack of child nutrition in Census data)	1/6	
Living standard	Electricity	The household has no electricity	1/18	1/3
	Sanitation	The household's sanitation facility is not improved or it is improved but shared with other households	1/18	
	Water	The household does not have access to safe drinking water or safe drinking water is more than a 30 minute walk from home	1/18	
	Floor	The household has dirt, stand, or dung floor	1/18	
	Cooking fuel	The household cooks with dung, wood, or coal	1/18	
	Assets	The household does not own one of the following assets: radio, TV, telephone, motorbike, or refrigerator and does not own a car or truck	1/18	

Source: Doaoudim (2016).

[4] https://ophi.org.uk/research/multidimensional-poverty/alkire-foster-method/

According to HCP[5], incidence of multidimensional poverty in Morocco dropped from 25.0% to 8.2% between 2004 and 2014. As of 2014, around 2.8 million individuals remained poor in Morocco. Despite the overall decline in poverty, the relative importance of its main dimensions remained roughly the same, and the country did not witness significant geographical shifts in its occurrence. Multidimensional poverty remains primarily a rural phenomenon: in 2014, 85.4% of poor people lived in rural areas compared to 80.0% in 2004 (incidence of multidimensional poverty fell from 9.1% to 2.0% between the two periods in urban areas, and from 44.6% to 17.7% in rural areas). At the regional level, poverty incidence also declined across all regions of the country (Figure 1). The poorest regions in 2004 experienced the greatest decline in poverty, namely Marrakech-Safi (from 34.0% to 11.3%), Tangier-Tétouan-Al Hoceima (from 30.3% to 9.5%), and Béni Mellal-Khénifra (from 31.0% to 13.4%). Moreover, the relative contribution of the sources of deprivation – education, health and living standard – vary across regions. While education contributes to a greater degree to multidimensional poverty in regions such as Casablanca-Settat and Rabat-Salé-Kénitra, the living standard dimension is relatively more important in Béni Mellal-Khénitra, Drâa-Tafilalet, Oriental and Fés-Meknés.

Figure 1. Evolution of Poverty Incidence in Morocco, 2004-2014



Source: HCP (2020).

[5] https://www.hcp.ma/Principaux-resultats-de-la-cartographie-de-la-pauvrete-multidimensionnelle-2004-2014-Paysage-territorial-et-dynamique_a2126.html

Nonetheless, as we move to a finer level of spatial disaggregation (i.e. provinces, communes), we find significant intra-regional heterogeneity, reversing the regional-level conclusion. Poorer provinces in 2004 faced slower reductions in poverty indicators increasing the relative gap.

The IPM developed by HCP adds important information to a broader understanding of the geography of poverty in Morocco. As notice by Doaoudim (2016), the IPM (i) complements monetary measures of poverty, (ii) helps measuring and monitoring changes in poverty, improving the people's access to basic social services, (iii) monitors the effectiveness of poverty interventions, and (iv) improves targeting and eradicating poverty in all its forms. We add to this list the spatially disaggregation nature of the IPM, presenting poverty estimates for highly disaggregated geographic unit, which also allows better targeting (Bigman and Fofack, 2000).

In this paper, we will investigate the spatial aspects of different dimensions of poverty in the country, taking a closer look at province-level data. Our goals are threefold. First, we explore the HCP IPM-database to examine the spatial patterns of different dimensions of poverty in Morocco. We use *exploratory spatial data analysis (ESDA)* to identify poverty "hot spots" at the province level and shed light on the discussion on how to improve poverty reduction programs in the country. Second, in order to assess the evolution of poverty in the provinces of Morocco, we rely on the *analysis of spatial convergence* of the poverty indicators, including the aggregate index (IPM) and its two components, namely urban and rural. Third, we propose an alternative multidimensional poverty indicator with endogenous weights and compare the results with the HCP poverty indicator. We use *factor analysis (FA)* to explore the variability of different dimensions of poverty using spatially disaggregated information from the 2014 Census.

2. Methodology

2.1. Exploratory Spatial Data Analysis (ESDA)

The main point of exploratory spatial data analysis (ESDA) is to test the hypothesis of spatial randomness. In other words, ESDA aims to verify whether the values of a given attribute in a region depend or not on the values of that same attribute in neighboring regions (Anselin, 1988).

This type of analysis is important because it allows us to check for the existence of spatial dependence among regions. Based on key socio-economic variables, for example, it is possible to prepare a diagnosis of socio-economic territorial development which may be used to design policies to stimulate the development of backward regions.

2.1.1. Global Spatial Autocorrelation

Global spatial autocorrelation can be investigated by the use of the Moran's *I* statistics. This statistics provides a formal indication of the degree of linear association between the vectors of values observed at time t (z_t) and the weighted average of the neighboring values – the spatial lags (Wz_t). Moran's I that exceeds (falls below) the expected value, $E(I) = -1/(n-1)$, indicates positive (negative) spatial autocorrelation.

Following Cliff and Ord (1981), in formal terms, the Moran's *I* statistics can be expressed as:

$$I_t = \left(\frac{n}{S_o}\right)\left(\frac{z_t' W z_t}{z_t' z_t}\right) \quad t = 1,\dots n \tag{1}$$

where z_t is the vector of n observations for year t in the form of deviations from the mean; W is the matrix of spatial weights, with the elements w_{ii} in the diagonal equal to zero and elements w_{ij} off-diagonal indicating how the region i is spatially connected with the region j; and S_o is a scalar equal to the sum of all elements of W.

When the matrix of spatial weights is normalized in the line, that is, when the elements of each line add up to one, Equation (1) is given by:

$$I_t = \left(\frac{z_t' W z_t}{z_t' z_t}\right) \quad t = 1,\dots n \tag{2}$$

Moran's *I* provides three types of information: (i) its significance level provides information about the randomness of the spatial distribution; (ii) a positive sign of the Moran's *I* statistics, as long as significant, indicates that the data are concentrated across the regions, and a negative sign, in turn, indicates the dispersion of the data; and (iii) the magnitude of the statistics provides the strength of the spatial association: higher Moran's *I* in absolute terms indicates greater autocorrelation. The closer the value is to +1, the stronger is the concentration; and the closer to -1, the more dispersed the data are.

2.1.2. Local Indicators of Spatial Association (LISA)

The global Moran's *I* statistics can hide local patterns of spatial autocorrelation. As suggested by Anselin (1995), local indicators of spatial association assess a null hypothesis of spatial randomness by comparing the values in each specific location with values in neighboring locations.

The LISA statistics, according to Le Gallo and Ertur (2003), based on the local Moran's *I* can be specified as follows:

$$I_{i,t} = \frac{\left(x_{i,t} - \mu_t\right)}{m_o} \sum_j w_{ij} \left(x_{j,t} - \mu_t\right) \quad with\ m_o = \frac{\left(x_{i,t} - \mu_t\right)^2}{n} \tag{3}$$

which is the observation of a variable of interest in region *i* for year *t*; μ_t is the mean of observations among regions in year *t* for which the sum in relation to *j* is such that only neighboring values of *j* are included.

The statistics can be interpreted as follows: positive values mean that there are spatial clusters with similar values (high or low); and negative values mean that there are spatial clusters with different values between the regions and their neighbors.

According to Anselin (1995), LISA statistics are used to measure the null hypothesis of the absence of local spatial association. It is important to note that, as well as the distribution for global statistics, the generic distribution for LISA statistics is also difficult to determine.

Based on the values of the local Moran's I, another useful feature of the ESDA is the LISA cluster map. This map shows the groupings of the regions, classified in High-High, Low-Low, High-Low, and Low-High, however, only those statistically significant.

It is worth mentioning that the identification of clusters allows to evaluate, depending on the variables under analysis, important issues related to the socio-economic development of a region. Low-Low clusters of per capita income or poverty indicators, for example, may indicate regions that are backward and somewhat removed from more developed regions or, otherwise, away from "economic opportunities". High-High clusters, on the other hand, can indicate developed regions, close to "economic opportunities". High-Low or Low-High spatial outliers, in turn, can indicate areas of instability since they point to "islands" of development or "enclaves", respectively.

2.2. Analysis of Spatial Convergence

The analysis of spatial convergence serves to identify whether public policies in Morocco have, in the recent period, made it possible to promote the distribution of the fruits of development across the country, focusing on poverty. In this context, we will perform an analysis of convergence of total poverty, as well as urban and rural poverty.

We will estimate the general model of spatial absolute β-convergence given by:

$$\begin{aligned} y_i &= \alpha + \rho W y_i + \beta Y_{i0} + u_i \\ u_i &= \lambda W u_i + \varepsilon_i \end{aligned} \tag{4}$$

where y_i is the ratio of the poverty indicator in 2014 in relation to 2004; Y_{i0} denotes the poverty indicator in 2004; W is the spatial weights matrix; u_i is the error term; and ε_i is an independent and identically distributed random error term.

When the restrictions on the parameters are expressed as $\rho = 0$ and $\lambda = 0$, there is the so-called classic linear regression model. When the restrictions on the parameters are such that $\rho \neq 0$ and $\lambda = 0$, there is the spatial lag model, which denotes a process of spatial spillover of poverty across provinces. In turn, when the restrictions on the parameters are such that $\rho = 0$ and $\lambda \neq 0$, there is the spatial error model, which denotes the existence of non-modeled effects that present a spatial pattern in the regression's error component.

If there is convergence, β will be negative, that is, the provinces with higher initial poverty indicators will have higher reductions in the poverty indicator. With this, we try to test whether, over the time interval between 2004 and 2014, the poverty indicators (total, urban and rural) of the different provinces would be converging to common lower values. On the other hand, if the provinces with lower IPM face stronger poverty reductions, the tendency is that the regional poverty gap increases over time.

In order to identify the best specification of the β-convergence model, the approach proposed by Florax, Folmer and Rey (2003) recommends the following script, adapted to our context

1. Estimate the initial model by means of OLS.
2. Test the hypothesis of no spatial dependence due to an omitted spatial lag or due to spatially autoregressive errors, using the Lagrange Multiplier statistics, LM_ρ (spatial lag) and LM_λ (spatial error), respectively.
3. If both tests are not significant, the initial estimates from step 1 are used as the final specification. Otherwise, proceed to step 4.
4. If both tests are significant, estimate the specification pointed to by the more significant of the two tests. For example if $LM_\rho > LM_\lambda$, then estimate the model including a spatially lagged dependent variable (MLLAG). If $LM_\lambda > LM_\rho$, estimate by maximum likelihood estimators the spatially autoregressive error model (MLERR). Otherwise, proceed to step 5.
5. If LM_ρ is significant but LM_λ is not, estimate the model including a spatially lagged dependent variable (MLLAG). Otherwise proceed to step 6.
6. Estimate the spatially autoregressive error model (MLERR).

2.3. Factor Analysis

The essential purpose of factor analysis is to describe the covariance relation among many variables in terms of a few underlying, but unobservable, random quantities called factors or latent variables (Johnson and Wichern, 2007). These variables, although we use in economics and regional science, differ from other variables that cannot be directly observed – which is why they are called latent.

Factor analysis aims to explain the outcome of p components in the data matrix **X**, and mean $\boldsymbol{\mu}$, using fewer variables, the so-called factors. Ideally, all the information in **X** can be reproduced by a few unobservable random variables $F_1, F_2, \dots, F_m$, called common factors, and p additional sources of variation $\boldsymbol{\varepsilon}$, called errors or specific factors. These factors are interpreted as latent common characteristics of the observed **X**. In particular, the factor analysis model is given by:

$$\mathbf{X} - \boldsymbol{\mu} = \mathbf{LF} + \boldsymbol{\varepsilon} \tag{5}$$

where **L** is the matrix of factor loadings; **F** is the k-dimensional vector of the m factors. When using the factor model, it is often assumed that factor **F** is centered, uncorrelated and standardized. Thereby, some assumptions about the random vectors **F** and $\boldsymbol{\varepsilon}$, the model in (4) implies the covariance relationships: $\mathrm{E}(\mathbf{F}) = 0$ e $\mathrm{E}(\boldsymbol{\varepsilon}) = 0$ (Johnson and Wichern, 2007; Härdle and Simar, 2012). These assumptions and the relation in (4) constitute the orthogonal factor model.

The orthogonal factor model implies a covariance structure for **X**. From the model in (5):

$$\mathrm{Cov}(\mathbf{X}) = \mathbf{LL}' + \boldsymbol{\Psi} \tag{6}$$

where $\boldsymbol{\Psi}$ is a diagonal matrix with $\mathrm{Cov}(\boldsymbol{\varepsilon})$. The variance of the ith variable contributed by the m common factors is called the ith communality. The ith communality is the sum of squares of the loadings of the ith variable on the m common factors. The Var (**X**) due to the specific factor is often called the uniqueness, or specific variance.

3. Multidimensional Poverty in Morocco

According to HCP, the adaptation of the OPHI approach to Morocco consists of:

(i) To identify deprivations on the basis of unmet needs in education and health, access to basic social services and housing conditions – overall, 10 deprivations are identified (see Table 1).

(ii) To establish a deprivation score aggregating the 10 elementary deprivations using the following weighting scheme: a weight of 1/6 for the 4 deprivations in terms of education (2) and health (2), and a weight of 1/18 for the 6 deprivations in terms of living conditions.

(iii) To set the poverty line: a person is considered multidimensionally poor if his deprivation score is higher than the poverty line, conventionally set by this approach at 33%.

(iv) To calculate the indices of multidimensional poverty namely:

- ✓ *the multidimensional poverty rate*: it gives the proportion of poor people, cumulating a number of deprivations above the poverty line - at least 30% of the basic deprivations to which households are exposed -; it expresses the ratio of the number of the poor to the total number of the population;
- ✓ *average intensity of deprivation*: this index provides information on the shortcomings experienced by the poor simultaneously; it has the merit of reporting the acuity of deprivation within the population in multidimensional poverty;
- ✓ *the multidimensional poverty index (IPM)*: it extrapolates the intensity of deprivation to the whole population, whether poor or not.

3.1. Initial Exploratory Analysis

Table 2 presents the summary statistics for the eight poverty indicators available for all Moroccan provinces. We compare different dimensions of the IPM (total, urban and rural) over time (2004 and 2014) and two additional 2014 poverty indicators, multidimensional poverty rate and monetary poverty, the latter based on threshold values defined by monetary poverty lines.

Table 3 shows the correlations between the different indicators measured at the province level. In all cases, the 2014 money-based poverty measure focusing on one factor alone, i.e. income, presents high correlation neither with contemporary alternative multidimensional poverty measures, nor with past ones. By construction, there is a very high correlation between the IPT Total and the poverty rate in 2014. After that, the highest pairwise correlation relates IPM Total and IPM rural in 2014, followed by the same measures in 2004. This reinforces the idea that poverty in Morocco is primarily a rural phenomenon.

Table 2. Summary Statistics

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
IPM Total (2014)	75	3.895	3.081	0.306	17.563
IPM Urban (2014)	75	0.906	0.472	0.000	3.417
IPM Rural (2014)	75	6.968	4.877	0.000	32.910
IPM Total (2004)	75	43.203	2.183	37.948	47.502
IPM Urban (2004)	75	4.202	1.484	0.000	7.400
IPM Rural (2004)	75	18.283	7.447	0.000	34.522
Poverty rate (2014)	75	9.467	6.803	0.861	34.541
Monetary poverty (2014)	75	4.194	3.311	0.326	16.123

Table 3. Partial Correlations between the Indicators

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1)	**IPM Total (2014)**	1							
(2)	IPM Urban (2014)	0.499	1						
(3)	IPM Rural (2014)	**0.802**	0.341	1					
(4)	IPM Total (2004)	0.773	0.465	0.680	1				
(5)	IPM Urban (2004)	0.329	0.636	0.243	0.352	1			
(6)	IPM Rural (2004)	0.646	0.360	0.740	0.802	0.291	1		
(7)	Poverty rate (2014)	**0.994**	0.516	0.764	0.797	0.346	0.670	1	
(8)	Monetary poverty (2014)	0.443	0.400	0.253	0.443	0.284	0.172	0.446	1

3.2. The Different Dimensions of Poverty in 2014

The IPM is constructed using variables to measure the manifestation of poverty or factors of its social reproduction. These variables concern access to basic services, such as education, health and housing conditions (Table 1). In Morocco in 2014, education deficits explained just over half of multidimensional poverty (56.4%). Deprivation of access to basic social infrastructure (electricity) explained 17.9% of multidimensional poverty. Finally, 13.7% of the IPM were explained by deprivations in terms of health, and the remaining 12.0% for housing conditions (Table 4). Notice that the education and health dimensions are inversely related to the Total IPM (Table 5).

Table 4. Partial Correlations between the Indicators

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
IPM Total (2014)	75	3.895	3.081	0.306	17.563
Education	75	56.449	5.903	44.028	69.120
Health	75	13.668	6.235	3.379	32.112
Electricity	75	17.918	5.632	5.943	29.941
Housing	75	11.965	5.699	2.110	24.716

Table 5. Partial Correlations between the Dimensions

		(1)	*(2)*	*(3)*	*(4)*	*(5)*
(1)	IPM Total (2014)	1				
(2)	Education	-0.499	1			
(3)	Health	-0.714	0.402	1		
(4)	Electricity	0.625	-0.706	-0.791	1	
(5)	Housing	0.681	-0.777	-0.728	0.609	1

3.3. The Geography of Poverty in 2014

The mapping of multidimensional poverty also provides indicators of social deprivation by geographic areas. This spatial dimension makes it possible to locate the regions with the highest levels of overall poverty, in addition to providing similar estimates for urban and rural areas (Figure 2). Poverty is mainly concentrated in the provinces of Driouch, Figuig, Guercif, Jerada, Taourirt (Oriental region), Azilal, Khenifra (Beni Mellal-Khenifra region), Chichaoua, Essaouira, Youssoufia (Marrakech-Safi region), and Taounate (Fes-Meknes region), due to the high level of rural poverty in these provinces.

The province with the highest level of urban poverty is Moulay Yacoub (Fes-Meknes region).

Figure 3 shows the poverty decomposition by source of deprivation in 2014. The provinces with the relative worst performance in the education dimension are in the region of Grand Casablanca-Settat, Marrakech-Safi, Guelmim-Oued Noun, Laayoune-Sakia El Hamra, and Dakhla-Oued Eddahab. The provinces of Rabat, Casablanca, Es-Semara, and Laayoune are where the health dimension presents the highest contribution to poverty. The main structural problems related to access to electricity are concentrated in provinces located in the regions of Oriental and Fès-Meknès. While provinces in the regions of Oriental, Drâa-Tafilalet, and Souss-Massa have the worst performances related to housing conditions.

Figure 2. IPM (2014)

(a) Total *(b) Urban* *(c) Rural*

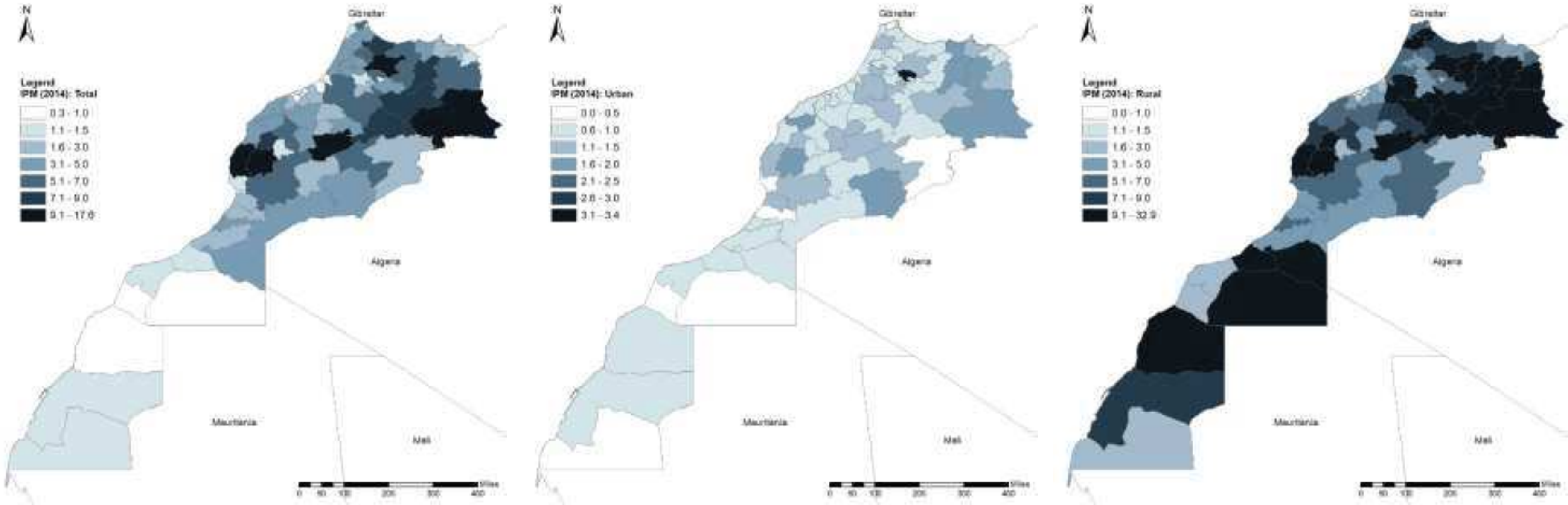
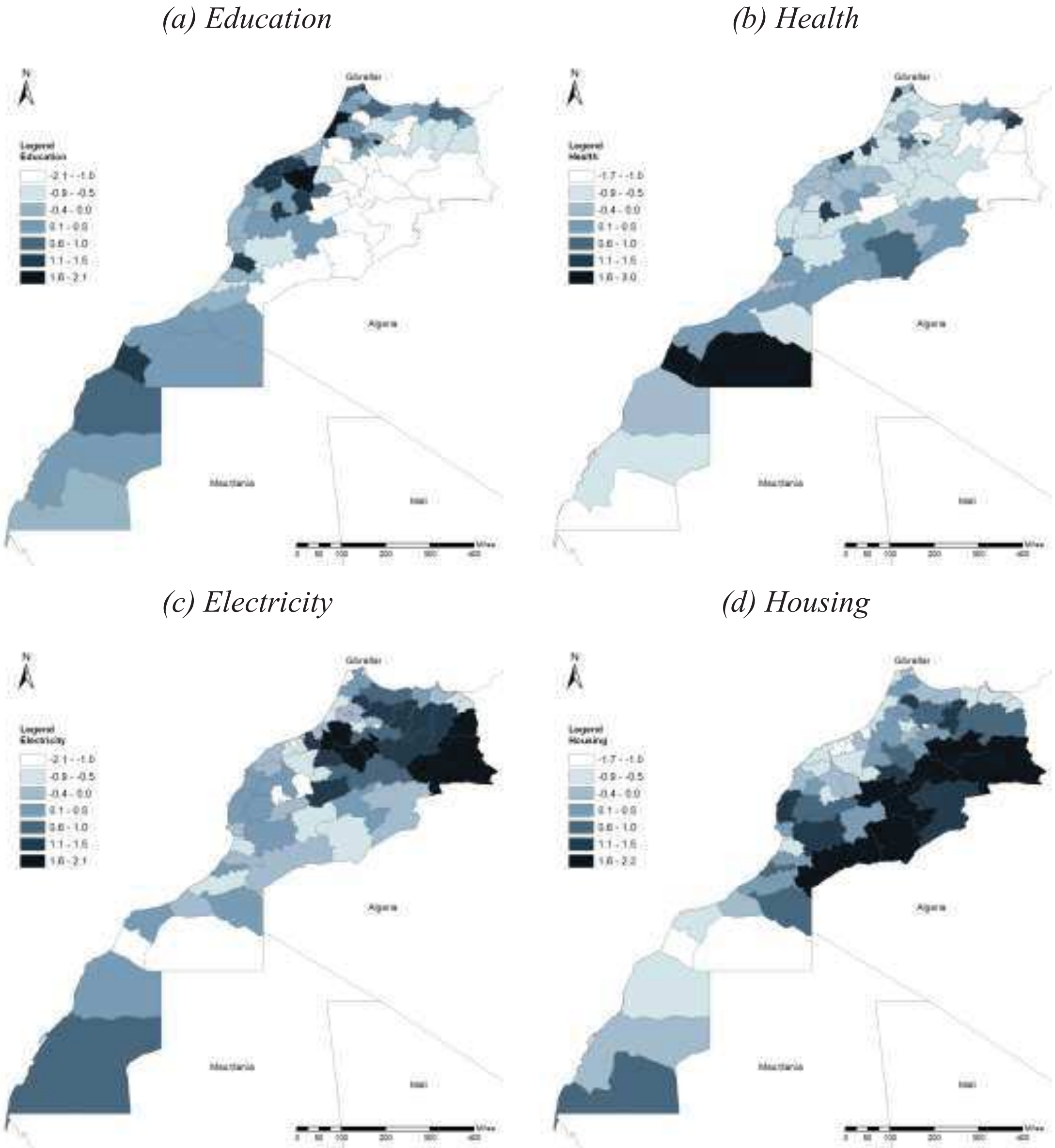


Figure 3. IPM (2014): Dimensions of Poverty, by Province



Obs. We have standardized the values on the maps (number of standard deviations above and below the mean = zero).

4. Results

4.1. Exploratory Spatial Analysis

Table 6 presents the global measure of spatial autocorrelation (Moran's *I* statistic) for the IPM. All the Moran's *I* statistics are positive and statistically significant (except IPM Urban, 2004) which suggests that the spatial dimension is relevant in the distributions of all variables. The positive and statistically significant global Moran's I indicate a positive spatial autocorrelation – that is, Moroccan provinces with high (low) IPM, for example, are located near other provinces with high (low) IPM.

Table 6. Moran's *I* test for Spatial Autocorrelation

Variable	*Moran's I*	*z-value*	*Prob.*
IPM Total (2014)	0.302	4.155	0.001
IPM Urban (2014)	0.116	1.714	0.050
IPM Rural (2014)	0.261	3.772	0.002
IPM Total (2004)	0.289	3.942	0.001
IPM Urban (2004)	-0.064	-0.662	0.260
IPM Rural (2004)	0.228	3.052	0.006
Growth IPM Total (2004-2014)	0.305	4.193	0.001
Growth IPM Urban (2004-2014)	0.070	1.424	0.071
Growth IPM Rural (2004-2014)	0.182	3.216	0.011
Poverty rate (2014)	0.321	4.332	0.001
Monetary poverty (2014)	0.475	6.619	0.001

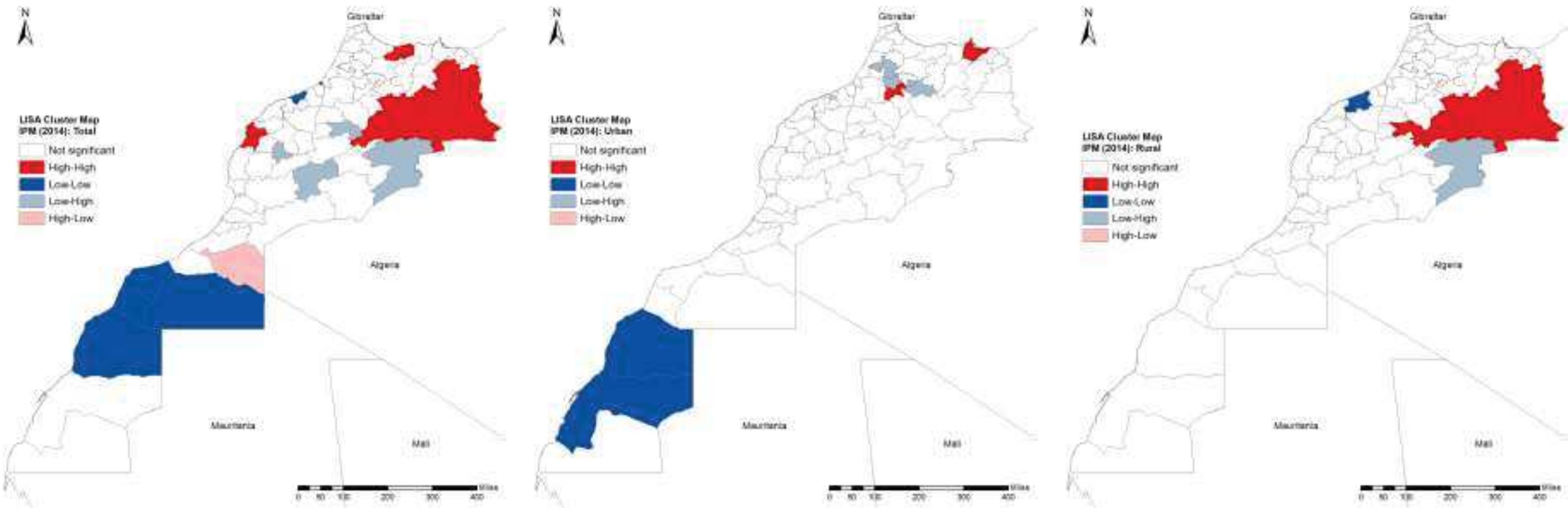
Note: The Queen spatial weights matrix was used in the spatial analysis.

The local Moran's *I* statistic is used to compare the values of each index in each specific location with values in neighboring locations. Figure 4 presents the patterns of local spatial association decomposed into four categories, High-High, Low-Low, High-Low, and Low-High. The IPMs have a spatial dimension, which allows us to understand the spatial heterogeneity within the country. Local Moran's *I* statistics identify the agglomeration of provinces around common characteristics. The High-High cluster in IPM Total, for instance, formed by 5 provinces geographically closely located (Figuig, Jerada, Taourirt, Boulemane, Midelt), have a relatively high level of poverty incidence. These provinces concentrate 2.8% of the population in Morocco. Additionally, two other cores of "hot spots" of poverty are related to Al Hoceima and Safi, and an additional spatial outlier located in Assa Zag.

While for rural poverty there is a clear cluster of high poverty in parts of the Oriental and Drâa-Tafilalet regions, in the northeast part of the country, clusters of urban poverty are territorially more restricted. The latter are associated with two different provincial cores, namely Nador and EL Hajeb.

Figure 4. IPM (2014): Local Spatial Autocorrelation – LISA Cluster

(a) Total *(b) Urban* *(c) Rural*



Note: The Queen spatial weights matrix was used in the spatial analysis.

4.2. Regional Poverty Convergence

We estimated the spatial convergence model according to Equation (4) following the Florax, Folmer and Rey (2003) script to analyze the evolution of the IPM in the period 2004-2014. We considered the three versions of the indicator, namely, total, urban and rural. For robustness check, we used different spatial weights matrices. Results for the three indicators are presented in Tables 7-9. In the three sets of estimations, the preferred specifications included a spatially lagged dependent variable. The idea of the spatial lag model to understand convergence of poverty across Moroccan provinces is that spatial effects matter to understanding the evolution of poverty in the country.

More specifically, the existence of a spatial correlation in the data suggests that the level of poverty in a region relates to the level of poverty in neighboring regions. There may be spatial spillovers resulting from structural characteristics or even policies with a broader regional focus. We also expect most of this spatial effect to occur in nearby provinces geographically, with a decline in its magnitude as it moves to higher order neighbors. We can see the importance of modeling special dependency in the analysis of convergence of the poverty indicators in Morocco through the positive and statistically significant coefficient of the spatially lagged dependent variable (W_IPM_{2014}/IPM_{2004}) in the models for total, urban and rural poverty.

Not in all models, however, the results show significant results for the test of absolute β-convergence of poverty in the period under analysis. The estimated coefficient, β, was positive and significant for two of the models, namely those for total and rural poverty. This result suggests that poorer regions presented slower reductions in the multidimensional poverty indicators, for IPM Total and IPM Rural. The estimated β-coefficients for each of these models are positive and highly significant, suggesting that there was spatial divergence of total and rural poverty in the period. Nonetheless, the evolution of urban poverty, as measured by the IPM Urban, seemed to show neither convergence nor divergence across the provinces.

This result reveals the importance of understanding the phenomenon in different levels of spatial aggregation. While looking at bigger regions (Figure 1) suggested convergence of poverty indicators in the country, finer spatial aggregation shows the results go in the other direction. This is particularly important for the refinement of the design of spatially targeted social policies.

Table 7. Regression Results for Regional Poverty Convergence: IPM Total

Dependent variable: IPM_{2014}/ IPM_{2004} (Total)

	OLS	Spatial Econometrics: SAR Model			
		Queen 1	Queen 2	Queen 1 and 2	Inverse Distance
	(1)	(2)	(3)	(4)	(5)
IPM Total (2004)	0.021***	0.020***	0.021***	0.020***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
W_ IPM_{2014}/ IPM_{2004} (Total)		0.166*	0.192*	0.238**	0.187**
		(0.093)	(0.112)	(0.117)	(0.088)
Constant	-0.836***	-0.783***	-0.833***	-0.791***	-0.797***
	(0.080)	(0.082)	(0.077)	(0.079)	(0.078)
Dummy Outlier	Yes	Yes	Yes	Yes	Yes
Observations	75	75	75	75	75
R-squared	0.741				
Pseudo R2		0.741	0.749	0.745	0.757

Note: Standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Regression Results for Regional Poverty Convergence: IPM Urban

Dependent variable: IPM_{2014}/ IPM_{2004} (Urban)

	OLS	Spatial Econometrics: SAR Model			
		Queen 1	Queen 2	Queen 1 and 2	Inverse Distance
	(1)	(2)	(3)	(4)	(5)
IPM Urban (2004)	0.002	0.002	0.002	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
W_ IPM_{2014}/ IPM_{2004} (Urban)		0.120	0.368***	0.344***	0.089
		(0.073)	(0.127)	(0.115)	(0.055)
Constant	0.196***	0.172***	0.119***	0.127***	0.179***
	(0.017)	(0.022)	(0.031)	(0.028)	(0.020)
Dummy Outlier	Yes	Yes	Yes	Yes	Yes
Observations	75	75	75	75	75
R-squared	0.818				
Pseudo R2		0.815	0.818	0.817	0.820

Note: Standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Regression Results for Regional Poverty Convergence: IPM Rural

Dependent variable: IPM_{2014}/IPM_{2004} (Rural)

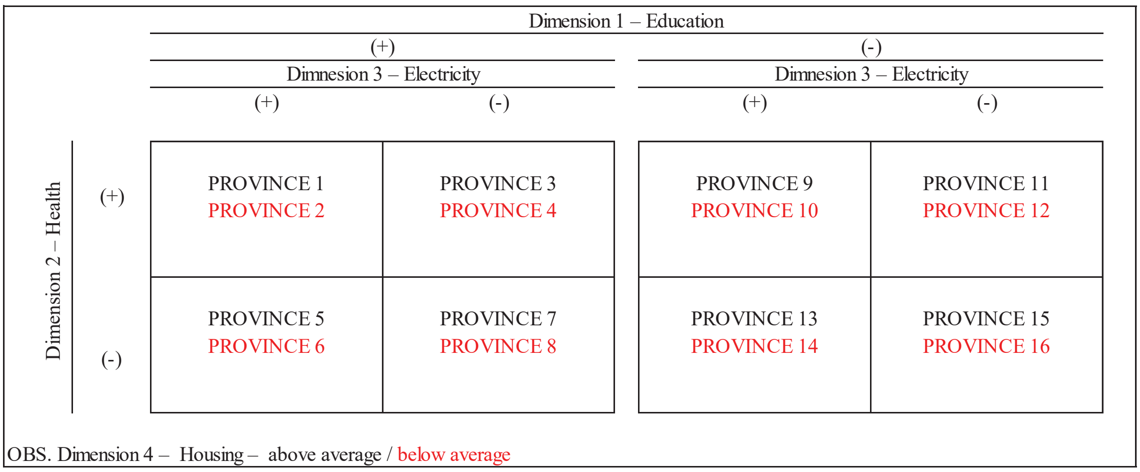
	OLS	Spatial Econometrics: SAR Model			
		Queen 1	Queen 2	Queen 1 and 2	Inverse Distance
	(1)	(2)	(3)	(4)	(5)
IPM Rural (2004)	0.005***	0.004**	0.005***	0.004***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
W_ IPM_{2014}/IPM_{2004} (Rural)		0.225***	0.158	0.334***	0.120
		(0.076)	(0.100)	(0.105)	(0.094)
Constant	0.247***	0.176***	0.186***	0.129***	0.221***
	(0.037)	(0.041)	(0.052)	(0.050)	(0.041)
Dummy Outlier	Yes	Yes	Yes	Yes	Yes
Observations	75	75	75	75	75
R-squared	0.783				
Pseudo R2		0.806	0.791	0.810	0.783

Note: Standard errors in parentheses. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3. Typology

We classified the regions using a typology created from the different dimensions of the IPM. Figure 5 shows the regional typology considering four poverty dimensions: education, health, electricity, and housing. We consider the values below or above the average score in each dimension, which gives us up to 16 typologies when combined.

Figure 5. Schematic Typology



Source: Adapted from Haddad et al. (2017).

Figure 6 shows the distribution of the provinces in Morocco among the 16 typologies while Figure 7 shows their spatial distribution. Specific information for each province provides the opportunity to improve targeting and fight poverty in its different forms. While some provinces where low socioeconomic conditions prevail may face poverty more strongly associated to lack of access to labor markets, other areas where access to infrastructure is more limited relate more to another poverty dimension. There are also provinces where different dimensions may be critical at the same time. Thus, there is no unique recipe for fighting poverty in Moroccan provinces.

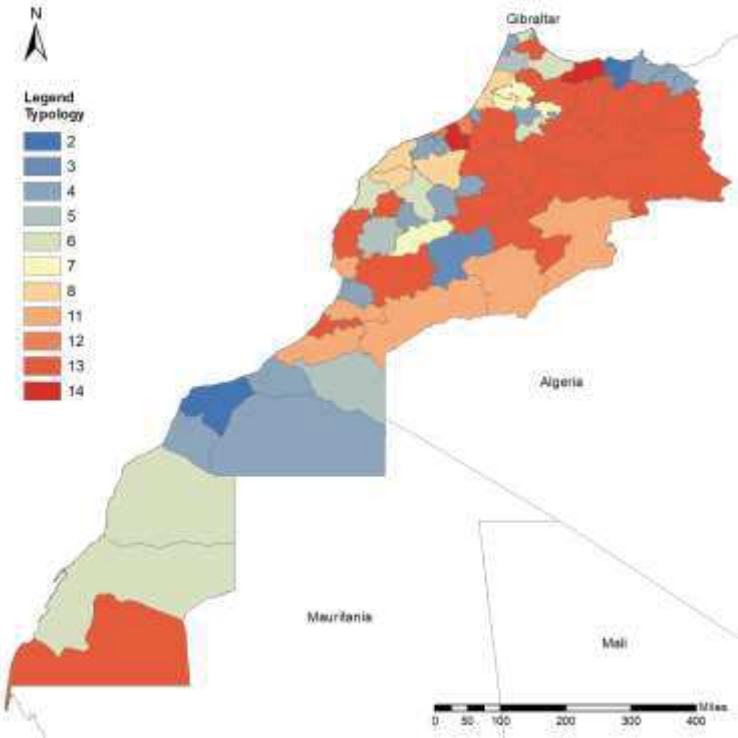
Figure 6. Typology of Moroccan Provinces

	Dimension 1 – Education			
	(+)		(-)	
	Dimnesion 3 – Electricity		Dimnesion 3 – Electricity	
Dimension 2 – Health	(+)	(-)	(+)	(-)
(+)	Driouch, Tarfaya	Ouarzazate Tanger-Assilah, Mdiq-Fnideq, Berkane, Nador, Oujda-Angad, Meknès, Fès, Salé, Fquih Ben Salah, Berrechid, Mediouna, Nouaceur, El Kelaa des Sraghna, Marrakech, Chtouka-Ait Baha, Inezgane Ait Melloul, Tan-Tan, Es-Semara, Laayoune		Errachidia, Zagora, Agadir Ida Ou Tanane, Tata, Tiznit, Guelmim Rabat, Skhirate-Témara, Casablanca, Mohammadia
(-)	Larache, Chichaoua, Assa-Zag Chefchaouen, Fahs-Anjra, El Hajeb, Rehamna, Safi, Boujdour, Oued-Ed-Dahab	Moulay Yacoub, Sidi Kacem, Sidi Slimane, Al Haouz Kénitra, El Jadida, Settat, Sidi Bennour	Ouezzane, Tétouan, Figuig, Guercif, Jerada, Taourirt, Boulemane, Ifrane, Sefrou, Taounate, Taza, Khémisset, Azilal, Béni Mellal, Khénifra, Khouribga, Essaouira, Youssoufia, Midelt, Tinghir, Taroudannt, Sidi Ifni, Aousserd Al Hoceima, Benslimane	

OBS. Dimension 4 – Housing – above average / below average

Note: Spatial aggregation: 75 provinces' Morocco.

Figure 7. Typology: Spatial Distribution of Moroccan Provinces

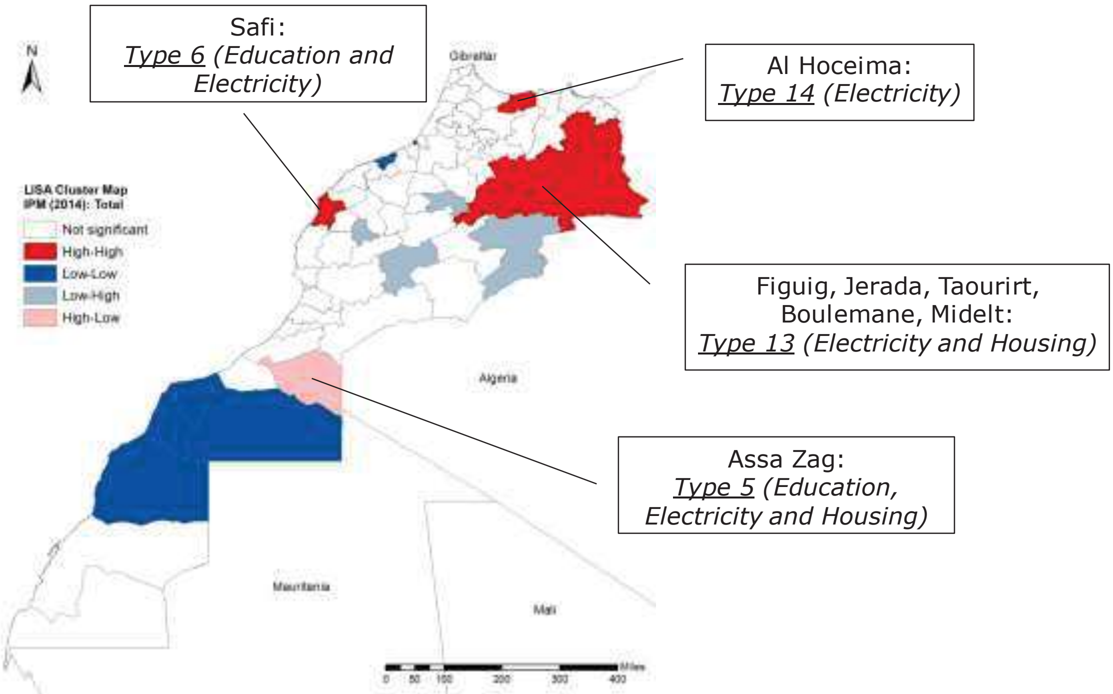


5.4. Summary

How important for understanding poverty is the spatial dimension in Morocco? We return to the cluster map of IPM Total (Figure 4) and combine it with information from Figure 7. This allows us to identify the main drivers of poverty in provinces where its incidence is relatively higher.

Considering the main hot spots, we see that provinces fall into four of the typologies defined in Figure 8. In the High-High cluster in the northeast, with the largest territorial extension and more strongly associated with rural poverty, the type-13 provinces of Figuig, Jerada Taourit, Boulemane and Midelt face similar structural problems leading to a higher IPM. They all face relative poor access to infrastructure, namely electricity and housing. In another High-High poverty core, Al Hoceima (type 14), poverty is mainly associated with relative lower access of the local population to electricity. The same dimension (electricity) affects the local population in Safi (type 6), which also suffers from bad performance in educational indicators. Finally, there appears also an enclave located in Zag (type 5), where residents coexist with relative deprivation in three out of the four poverty dimensions: education, electricity and housing.

Figure 8. "Hot Spots": Main Drivers of Poverty in Moroccan Provinces



Note: Local spatial autocorrelation: Local Moran's I: Clusters. The Queen spatial weights matrix was used in the spatial analysis.

5. Factor Analysis

The precedent analysis of the IPM has provided important insights into the broader understanding of the spatial dimension of poverty in Morocco. Despite the use of *ad hoc* equal weights for the different poverty dimensions, the methodological approach used by HCP has many advantages, including the possibility of its comparability over time. Notwithstanding, we will test whether an alternative approach that generates endogenous weights for the poverty dimensions, using the same sources of data, could bring additional insights on this matter.

We use factor analysis (FA) to develop an alternative multidimensional poverty index for Morocco, using the 2014 census micro data. We then compare the FA index with the IPM to validate the results, highlighting the main differences between the two approaches.

5.1. Factor Analysis – Description of Variables

To identify poverty differences among Moroccan provinces in a multidimensional context, using factor analysis as an alternative approach to the IPM, we measure the latent variables of interest. We start by collecting observable variables that we consider likely indicators of the latent variables. Thereby, we collect data for Moroccan provinces related to 12 variables. We performed an exploratory factor analysis with this database with the following objectives. First, to identify the variables within a group that are highly correlated among themselves but have relatively small correlations with variables in a different group. Second, interpret each group of observed variables as representations of a single underlying construct, or factor, from the definition of each variable.

After exploratory factor analysis, we confirmed the 12 variables that can potentially form latent variables for the construction of a poverty indicator. These variables are defined in Table 10 and the partial correlation between them is presented in Table 11. Based on these variables, we performed a confirmatory factor analysis. In the context of confirmatory factor analysis[6], we pre-selected the initial variables considering four potential dimensions underlying different poverty facets, namely education, health, electricity, and housing.

[6] The use of factor analysis is confirmatory when you want to test specific hypothesis about the structure or the number of dimensions underlying a set of variables (i.e. in your data you may think there are three dimensions and you want to verify that).

Table 10. Description of Variables

Variable	*Description*
X1	Literacy rate, adult total (% of people ages 15 and above without education level)
X2	The inverse of the population with a university degree (% of people ages 25 and above)
X3	The inverse of the number of health workers by population
X4	Number of households without a portable phone (% in relation to total households)
X5	Number of households without internet access (% in relation to total households)
X6	Number of households without a computer (% in relation to total households)
X7	Number of households with the main roofing material of the residence: reclaimed wood, bamboo or other recovered materials (% in relation to total households)
X8	Number of households with the floor material of the residence: bare soil or soil covered with earthen materials or similar (% in relation to total households)
X9	Number of households with the main walls material of the residence: stones sealed with earth; raw earth bricks; reclaimed wood, tin, grass, bamboo (% in relation to total households)
X10	Number of households without bathrooms (% in relation to total households)
X11	Number of households with the sewage system dumped into nature (% in relation to total households)
X12	Number of households without electricity (% in relation to total households)

Table 11. Matrix of Partial Correlations

	X1	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*	*X11*	*X12*
X1	1											
X2	0.6490	1										
X3	0.6609	0.8344	1									
X4	0.7526	0.6544	0.6663	1								
X5	0.8791	0.6647	0.7144	0.7051	1							
X6	0.9020	0.7208	0.7567	0.7682	0.9763	1						
X7	0.6724	0.4563	0.6170	0.5911	0.6589	0.6386	1					
X8	0.6801	0.4841	0.6702	0.6840	0.6484	0.6612	0.9141	1				
X9	0.6909	0.4283	0.6102	0.6006	0.6530	0.6339	0.9738	0.9356	1			
X10	0.6047	0.1915	0.2620	0.5109	0.5110	0.4890	0.4755	0.4558	0.4672	1		
X11	0.7858	0.4158	0.4803	0.7094	0.6784	0.6866	0.6259	0.6344	0.6172	0.9138	1	
X12	0.4665	0.1736	0.1556	0.4627	0.3695	0.3605	0.3416	0.2705	0.2846	0.6564	0.6089	1

Note: Number of observations: 72 Moroccan provinces.

5.2. Factor Analysis – Results

The Poverty Index (PI) is constructed using the 12 observed variables described in Table 10. The factor loadings and specific variances presented in Table 12 have been estimated based on the principal factor method. Instead of the intended four initial factors, the confirmatory factor analysis was performed with three factors that have a higher eigenvalue greater than unity.

Table 12: Factor analysis: Unrotated

Factor	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Factor1	**7.6913**	**6.3062**	**0.7290**	**0.7290**
Factor2	**1.3851**	**0.3638**	**0.1313**	**0.8603**
Factor3	**1.0213**	**0.6923**	**0.0968**	**0.9571**
Factor4	0.3290	0.1736	0.0312	0.9882
Factor5	0.1553	0.0522	0.0147	1.0030
Factor6	0.1031	0.0523	0.0098	1.0127
Factor7	0.0508	0.0593	0.0048	1.0175
Factor8	-0.0085	0.0090	-0.0008	1.0167
Factor9	-0.0175	0.0044	-0.0017	1.0151
Factor10	-0.0220	0.0367	-0.0021	1.0130
Factor11	-0.0587	0.0198	-0.0056	1.0074
Factor12	-0.0785	.	-0.0074	1.0000

Note: Method: principal factors (unrotated). LR test: independent vs. saturated: chi2(105) = 1254.87 Prob>chi2 = 0.0000. Number of observations: 72 provinces' Morocco.

To simplify the interpretation of the factors, we rotated the solution from the principal factor method by the orthogonal varimax rotation (Table 13). The resulting factors explain 95.71% of the total variance of the model (Factor 1: 37.25%, Factor 2: 31.71%, and Factor 3: 26.75%).

Table 13. Factor Analysis: Rotated

Factor	*Eigenvalue*	*Difference*	*Proportion*	*Cumulative*
Factor1	3.9296	0.5838	0.3725	0.3725
Factor2	3.3458	0.5237	0.3171	0.6896
Factor3	2.8221	.	0.2675	0.9571

Note: Method: principal factors (rotated: orthogonal varimax). LR test: independent vs. saturated: chi2(66) = 1278.03 Prob>chi2 = 0.0000. Number of observations: 72 provinces' Morocco.

The rotated factor loadings and uniqueness (specific variances) are presented in Table 14. The uniqueness indicates that the three factors account for a large percentage of the sample variance of each variable. The variables are grouped by their correlations in the three factors. That is, all variables within a particular group are highly correlated among themselves but have relatively small correlations with variables in a different group. Then it is conceivable that each group of variables represents a single underlying construct, or factor, that is responsible for the observed correlations.

According to the subset of variables more highly correlated with each factor, the first factor (F1) would represent general economic conditions and might be labelled as "socioeconomic dimension". The second factor (F2) concentrates the variables related to the housing conditions, so that it could be named as "housing dimension". The third factor (F3) represents the variables more related to access to infrastructure and could be labelled as "infrastructure dimension".

The endogenously weighted factor (Poverty Index), a synthetic factor, is constructed using the variance explained by each factor as weights:

$$\text{Poverty Index} = \left(\frac{0.3725}{0.9571}\right) * \text{F1} + \left(\frac{0.3171}{0.9571}\right) * \text{F2} + \left(\frac{0.2675}{0.9571}\right) * \text{F3} \tag{6}$$

Table 15 shows the descriptive statistics for the three-factor solution and the synthesis factor, that is, the Poverty Index. Figure 9 shows the Kernel density estimates. Lastly, Figure 10 presents the spatial distribution of the three poverty dimensions and the synthesis factor.

Table 14. Factor Loadings (Pattern Matrix) and Unique Variances

Variable	*Factor1*	*Factor2*	*Factor3*	*Uniqueness*
X1	**0.6801**	0.3934	0.4950	0.1377
X2	**0.8415**	0.2158	0.0235	0.2447
X3	**0.7772**	0.4286	0.0249	0.2116
X4	**0.6323**	0.3669	0.4162	0.2924
X5	**0.7748**	0.3630	0.3670	0.1332
X6	**0.8350**	0.3382	0.3482	0.0672
X7	0.2930	**0.8954**	0.2539	0.0480
X8	0.3635	**0.8539**	0.2209	0.0900
X9	0.2833	**0.9198**	0.2309	0.0205
X10	0.1235	0.2439	**0.9071**	0.1025
X11	0.3572	0.3657	**0.8163**	0.0724
X12	0.1289	0.1006	**0.7008**	0.4822

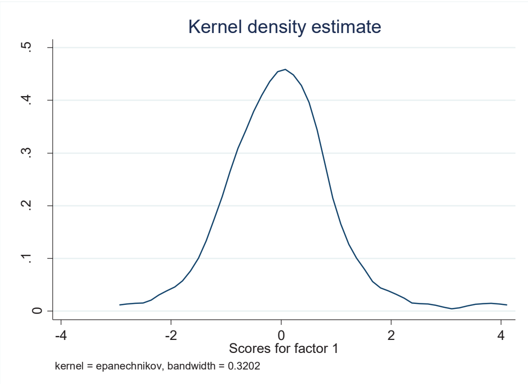
Note: Kaiser-Meyer-Olkin measure of sampling adequacy: 0.8162.

Table 15. Factor Analysis: Summary Statistics

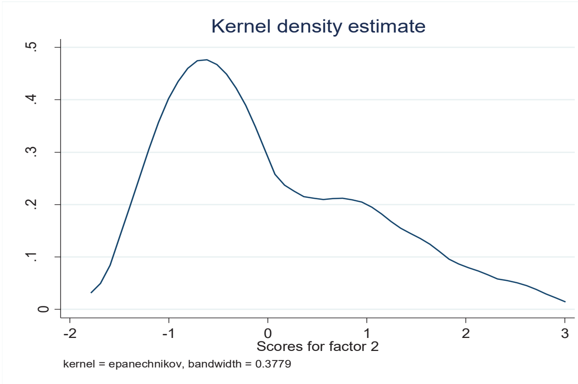
	Obs.	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Factor 1	72	0.0000	0.9766	-2.6214	3.7853
Factor 2	72	0.0000	0.9877	-1.4098	2.6284
Factor 3	72	0.0000	0.9686	-1.2679	3.5691
Poverty Index	72	0.0000	0.5798	-1.2687	1.2345
Poverty Index - normalization from a range of [0, 1]	72	0.5068	0.2316	0.0000	1.0000

Figure 9. Factor Analysis: Kernel Density Estimate

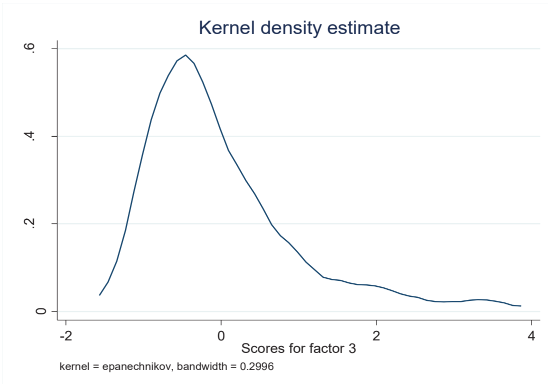
Factor 1: "Socioeconomic"



Factor 2: "Housing"



Factor 3: "Infrastructure"



FA Index: Poverty Index

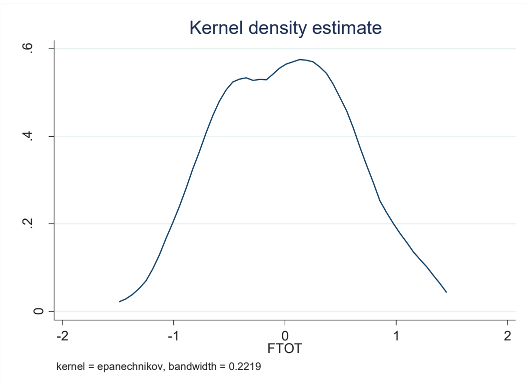
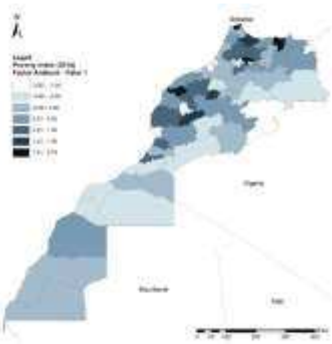
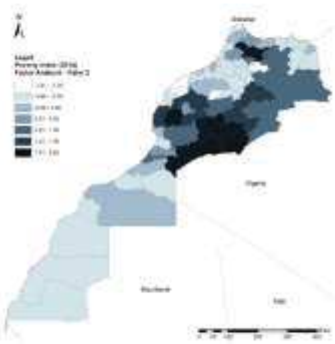


Figure 10. Factor Analysis: Spatial Distribution of Poverty Dimensions

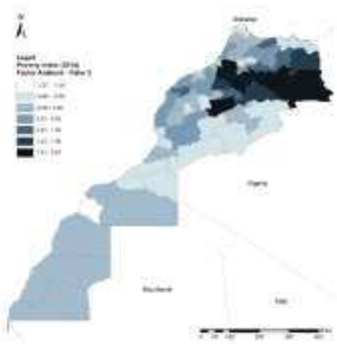
Factor 1: "Socioeconomic"



Factor 2: "Housing"



Factor 3: "Infrastructure"



5.3. IPM versus PI-FA Index

How does the poverty index constructed using factor analysis (PI-FA) correlate with other relevant indicators for measuring poverty in Morocco? In this sub-section, we compare the hierarchy of the provinces through the PI-FA with the IPM Total. Although incomplete, it seems pertinent to make such comparison on a complementary basis that addresses some of the missing dimensions in each indicator. Figure 11 shows the spatial distribution of the IPM Total (2014) and PI-FA Index (2014). The simple correlation between both indicators is 83.3%. Figure 12 adds to this analysis the graphical relationship between them, using a scatter plot.

Figure 11. IPM Total *versus* PI-FA Index: Spatial Distribution

IPM Total, 2014 *PI-FA Index, 2014*

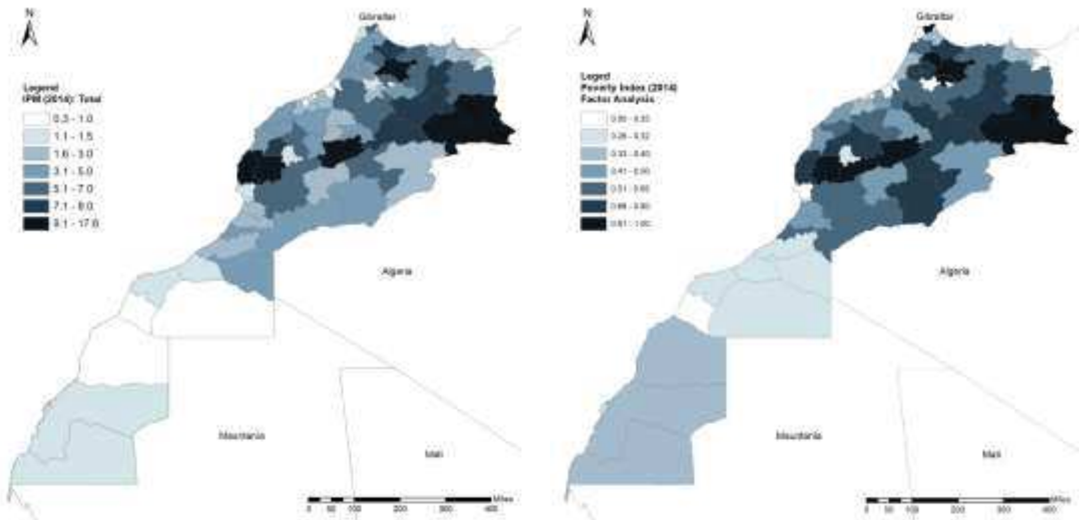
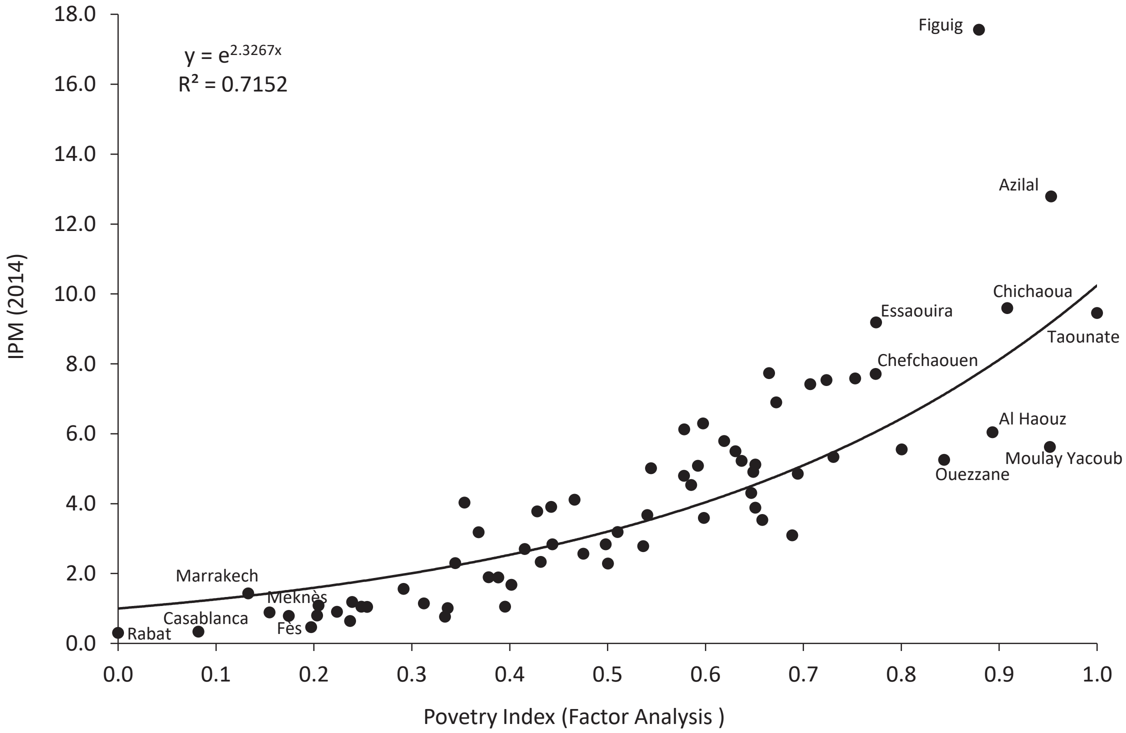


Figure 12. Relationship between IPM Total (2014) and Poverty Index



6. Final Remarks

The first goal of the 2030 Agenda for Sustainable Development recognizes that ending poverty in all its forms everywhere is the greatest global challenge facing the world today and an indispensable requirement for sustainable development. In Morocco, a remarkable progress reducing poverty over the last decade has been made owing to economic growth and macroeconomic stability, together with the slowing population growth. Even though, subjective poverty remains at a high level, especially in rural areas, it remains a major cause for concern. There are different economic and social reasons that lead to the marginalization of social groups that suffer from poverty and vulnerability.

One of the key issues that should matter to policymakers is the spatial dimension of poverty. Despite progress on economic growth in a range of countries, disparities between regions and areas represent a prominent trend. According to our ESDA, there is a spatial concentration of poor provinces in Morocco. The convergence analysis, in turn, sought to answer whether this concentration had increased or decreased over the analyzed period. What has become clear through the convergence analysis is that, roughly speaking, this spatial concentration remained relatively stable from 2004 to 2014, despite significant reductions in poverty across the board.

We were able to classify the provinces in regional typologies. These typologies ranked the provinces according to the contributions of different dimensions to poverty. The identification of provinces in each typology reflects some of the structural features that characterize spatially distinct productive structures, social performance, and access to infrastructure. This mapping is particularly important for the design of development policies targeted at the specific needs of each population group in different areas of the country. As pointed by Daoudim (2016), maps can be of great interest in national effort towards Sustainable Development Goals attainment.

Finally, we proposed an alternative to the IPM using factor analysis. This robustness exercise assessed the sensibility of results to different weights (exogenous versus endogenous) within a given technique and across methods. We concluded that the HCP approach is preferable given its flexibility to be consistently updated and to include, *ex ante*, a desirable number of dimensions suggested by theory and data availability.

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