Spatial Econometric Analysis of Household Poverty in Mauritania

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Abstract

In this paper, I analyze the determinants of poverty in Mauritania using a spatial econometric approach. I show the presence of significant spatial dependence in the household's welfare; thus, the classical techniques of regression are not appropriate for identifying the determinants of poverty. I empirically show that the classic approach leads to erroneous conclusions about the statistical significance of the impact of belonging to some socio-economic groups on poverty as well as the impact of primary education in urban areas, technical high school, and alphabetization in rural areas. I provide precise estimates of these determinants of poverty with more accurate statistical inference using spatial error models.

1 Introduction

In 1999 Mauritania was declared eligible to join the Heavily Indebted Poor Countries debt initiative, which led to a Poverty Reduction Strategy Paper (PRSP) being adopted. Three plans of this strategy have been implemented in the period 2001-2015, during which poverty has significantly decreased. However, the objective of reducing the poverty headcount to 16.9% in 2015 has not been accomplished. The

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Poverty Reduction Strategy has been superseded by a new national strategy of accelerated growth and shared prosperity, which covers the period 2016 to 2030. However, combating poverty continues to be a principal objective in the new strategy.

The National Office of Statistics (ONS) has undertaken a series of permanent surveys on household living condition (EPCV). On the basis of these surveys, the action plans of the national strategies are built and updated by several government agencies and their partners.

Given the importance of public decision aid systems in fighting poverty, the econometric tools upon which the decision is made must be very accurate and suitable for the data. Otherwise, the adopted policies may be based on erroneous conclusions.

One of the tools used by the ONS to identify the determinants of household poverty is the traditional regression analysis (ONS 2009). Given the availability of the Global Positioning System (GPS) coordinates of households in the EPCV2014, the traditional approach can be extended to include spatial dependence in household welfare.

The similarity of economic agents' behavior within a connected group has been incorporated in micro-economic demand models (Gaertner 1974 and Pollak 1976). Gaertner (1974) proposed a dynamic model of interdependence of consumer behavior in which he considers that the individual's demand pattern does not only depend on his own past consumption decisions but also on the past consumption behavior of individuals to whom he is related. According to the author, the related individuals could be neighbors, relatives, friends, colleagues, members of the same social class, etc. In this paper, the interdependence among households' expenditures is limited in the spatial proximity dimension. In other words, the interdependence is only modeled among neighbors.

The empirical analyses have attempted to distinguish three causes of similarity in agents behaviors: i) the endogenous interactions according to which the behavior of an agent varies depending on the behavior of his group; ii) the contextual interactions wherein the agent's behavior varies depending on the exogenous group members characteristics; iii) the correlated effects according to which the similarity of the group members' behavior is caused by the similarity of their individual characteristics or the similarity of the institutional environments that they face together (Manski 2000).

In the literature, the traditional regression analysis is the most widespread approach to identify and evaluate the main contributors to poverty. In general, the determinants of poverty are specified by estimating the influences of household, regional, and individual characteristics as marginal effects on the income or expenditure per capita. The drawback of this approach is that the classic non-spatial model suffers from bias and inefficiency issues when ignoring spatial effects that are present in the underlying data generating process. The OLS estimator becomes biased and inconsistent when the omitted spatial effects are present in the spatially lagged dependent variable. If the ignored spatial effects are present as spatial dependence in the disturbance term, the OLS estimator remains unbiased, but it becomes inefficient (Anselin 1988b and Anselin and Bera 1998). The spatial dependence in the disturbance term implies that the classic estimators of the standard error will be biased, which may be misleading in a decision support setting (Anselin and Lozano-Garcia 2008).

In my paper, I show the existence of a significant spatial dependence in the Mauritanian households' welfare. This spatial correlation is basically detected in the error terms of the households' earning model at the national level and in both rural and urban sectors. The spatial dependence in the error terms may be produced by spatially correlated unobserved variables like soil quality, climate, or the availability of substitute goods that are not included in the data (Case 1991).

This finding is a sufficient reason to avoid using a non-spatial approach to estimate the determinants of household poverty in Mauritania. Furthermore, it confirms the need to employ spatial econometric techniques that accurately estimate these determinants.

Given the fact that poverty is more deep-rooted in rural areas than urban areas, I analyze the determinants of poverty in rural areas, and I compare them with those of urban poverty. The specification tests show the presence of a significant spatial process in both sectors. I use spatial weight matrices based on the k-nearest neighboring households. The optimal numbers of neighbors that maximize the log-likelihood functions of spatial models are 17 at the national level and 18 and 17 for rural and urban sectors, respectively.

The findings of this paper show that the non-spatial model mistakenly concludes the statistical insignificance of the impact of some socio-economic groups and educational attainments on poverty. In contrast, the spatial error model affirms that the returns to the primary school level in urban areas are statistically significant. It indicates, contrary to the classical approach that the returns to the technical high school and alphabetization in rural areas are statistically significant. Also, it confirms that the standards of living of the household-aid socio-economic group in urban areas and private-sector employees at the national level are inferior to those of the public-sector employees.

The remainder of this paper is organized as follows. Section 2 presents the data and gives a background on poverty in Mauritania. Section 3 briefly reviews the spatial economic techniques used for modeling spatial dependence. In section 4, I present the specification of the regression model and the spatial weight matrix. Section 5 reports the empirical results. Section 6 concludes.

2 Data and Background on Poverty in Mauritania

2.1 Data

In this paper, I use three waves of the EPCV survey conducted by the national office of statistics (ONS) in 2004, 2008, and 2014. In addition to the information on households economic, social, and demographic characteristics, the latter survey contains the GPS coordinates of households, which permit conducting a spatial econometric analysis of poverty.

2.2 Measurements

The most frequently used measurements of poverty are the FGT indexes introduced by Foster et al. (1984). I use these indexes to provide a descriptive analysis of poverty evolution in Mauritania.

$$P_\alpha(z) = \int_0^z \left(\frac{z-y}{z}\right)^\alpha f(y)dy, \quad \hat{P}_\alpha(z) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha, \tag{1}$$

where z is the poverty line, y_i the income (or expenditure) of household i, α is the sensitivity parameter (the sensitivity of the index to the poverty line), and $q = \max_i i1(y_i < z)$ is the rank of the least poor household among the poor.

The first measure $P_0(z)$ is the headcount ratio, which calculates the proportion of the population living below the poverty line. This is the simplest and the most popular index of poverty. The limit of this measure is that it does not provide any information about the severity of poverty. For instance, this index does not change if the poor individuals become poorer.

The poverty gap index $P_1(z)$ measures the depth of poverty by assessing the extent to which the poor fall below the poverty line. It is defined as:

$$\hat{P}_1(z) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right). \tag{2}$$

This index represents the mean gap between the poverty line and the income of the poor, expressed as a percentage of the poverty line.

The squared poverty gap index $P_2(z)$ measures the severity of poverty by giving more weight to the poorest. It represents the mean squared gap between the poverty line and the income of the poor, normalized by the poverty line. Squaring the poverty gap implies that the depth of poverty is weighted by the distance between the poor's income and the poverty line. Thus, the poorer individuals become, the more the impact on the squared poverty gap index is amplified.

$$\hat{P}_2(z) = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right)^2 . \tag{3}$$

The FGT indexes are additively decomposable. The variation of the FGT measures can be divided into a growth component resulting from rising average income and an inequality component due to the changes in the distribution of income.

2.3 The poverty line

The poverty line is the minimum expenditure required to cover basic needs. Individuals whose annual expenditure falls below this line are considered as poor. The ONS uses the absolute poverty line set by the World Bank for developing countries, which corresponds to one dollar per day per capita using 1985 purchasing power parity.

Table 1: Evolution of the poverty line

	1988	**1996**	**2000**	**2004**	**2008**	**2014**
Poverty line	32800	58400	72600	94600	129600	169445
Extreme poverty line	24800	44150	54880	71550	96400	126035

Source: SCAPP2016-2030. The units are MRO per year and per capita.

From one period to another, the poverty line is updated for inflation, and in order to ensure comparability among households in different areas, the data are harmonized.

2.4 Pattern and dynamics of poverty in Mauritania

The analysis of the evolution of poverty at the national level shows a sustained decrease in the headcount ratio, which fell from 56.6% in 1990 to 31% in 2014. However, the number of poor was increasing with the exception of the period 2008 to 2014, where the number of poor decreased for the first time from 1.4 million to less than 1.1 million. (MDEF 2017). It should also be mentioned that the incidence of poverty observed in 2014 was far from the 16.9% target set by the Poverty Reduction Strategy Paper (PRSP) for 2015 (MDEF 2001).

All the EPCV surveys produced by the Mauritanian National Statistics Office (ONS) show that poverty is more prevalent in rural areas both in terms of headcount ratio and the severity of poverty.

When comparing the dynamics of poverty in rural and urban areas between 2000 and 2014, we notice a downward trend in poverty indicators. Nevertheless, the reduction in poverty incidence was not stable. For instance, poverty decreased in rural areas from 66.2% in 2000 to 59% in 2004. Meanwhile, it increased in urban areas from 28.5% to 28.9%. Between 2004 and 2008, the headcount ratio decreased in cities from 28.9% to 20.8%, whereas it increased in rural areas from 59% to 59.4%. However, the incidence of poverty did decrease in both rural and urban areas between 2008 and 2014.

The trends of extreme poverty reduction at the national, urban, and rural levels are similar to those of poverty. This demonstrates significant progress in poverty reduction, with the exception of the increase in the extreme poverty headcount ratio observed in rural areas between 2004 and 2008.

Table 2: Evolution of the poverty in Mauritania

	Headcount P0				**Poverty gap P1**				**Poverty severity P2**			
	2000	**2004**	**2008**	**2014**	**2000**	**2004**	**2008**	**2014**	**2000**	**2004**	**2008**	**2014**
National	51	46.7	42	31	19.3	15.3	14.5	9.4	9.6	6.9	6.9	4.1
Rural	66.2	59	59.4	44.4	-	20.6	22.3	14	-	9.6	11.1	6.3
Urban	28.5	28.9	20.8	16.7	-	7.6	4.9	4.3	-	3	1.7	1.8
					Extreme poverty							
National	31.4	27.9	25.9	16.6	11.1	7.7	7.7	4.5	4.9	3.1	3.4	1.8
Rural	47.8	37.8	40.8	25.1	-	-	-	6.9	-	-	-	2.8
Urban	13.6	13.3	7.7	7.5	-	-	-	1.8	-	-	-	0.7

Source: SCAPP2016-2030 (MDEF 2017)

Household poverty

Table 3 shows the evolution of household poverty by the household-head gender, area of residence, socio-economic group of the household head, and the household-head's level of education and region of residence[1]. The dynamics of household poverty shows a decrease in the headcount ratio, poverty gap, and poverty severity over the period 2004-2014. Between 2004 and 2008, the incidence of household poverty index decreased from 40.78% to 35% with an annual rate of 1.45% at the national level.

[1] Mauritania is administratively divided into 15 regions, 55 departments, and 218 communes. Although the capital Nouakchott is subdivided into three administrative regions, they are presented in the data as a single region.

Moreover, the annual reduction rate of household poverty rose to 2.1% in the period 2008-2014.

Furthermore, the poverty gap and the severity of poverty indexes have been halved over the period 2004-2014 at the national level. As shown in Table 3, these indexes decreased from 13% to 6.35% and 5.8% to 2.67%, respectively, over the same period.

The poverty incidence is lower in female-headed households compared to male-headed households. However, the depth and the severity of poverty are quite similar in households headed by a male and those headed by a female.

As it can be seen, household poverty is predominantly a rural phenomenon in terms of the concentration of poor in rural areas and in terms of the depth and severity of poverty in these areas compared to the urban zones. Table 3 shows that household poverty has not been reduced between 2004 and 2008 in rural areas. However, we observe in the same period a significant decrease in poverty indexes in the urban zones. In this period, the urban-rural expenditure gap has widened despite the high growth rates of the GDP. Nevertheless, poverty has been reduced significantly between 2008 and 2014 in both rural and urban areas.

The analysis of the poverty incidence index by the education level of the household head shows that poverty is more widespread among households headed by an illiterate person, 52% in 2004 and 28.5% in 2008, and households headed by a person having completed a literacy program, 47.8% in 2004 and 29.5% in 2014. Poverty is less prevalent among households headed by a person with tertiary and secondary education. It can be seen that household poverty is deeper and more severe in households headed by an illiterate person than other households.

In regards to the socio-economic group of the household head, we notice that the least poor group is public employees. Furthermore, the best achievement in poverty reduction was recorded among households headed by this socio-economic group with a reduction rate attaining 73.9% over the study period. This performance can be explained by the salary increases in the public sector over this period. The evolution of the poverty indexes shows a significant reduction in poverty among all groups. However, the levels of poverty among households headed by independent farmers remain very high compared to other socio-economic groups.

Table 3: Evolution of household poverty in Mauritania

	Headcount P0			**Poverty gap P1**			**Poverty severity P2**		
	2004	**2008**	**2014**	**2004**	**2008**	**2014**	**2004**	**2008**	**2014**
National	40,78	34,96	22,31	13,03	11,74	6,35	5,82	5,5	2,67
Gender of HH									
Female	37,91	34,22	20,18	12,36	11,74	5,77	5,65	5,7	2,5
Male	41,45	35,18	23,24	13,19	11,74	6,61	5,86	5,44	2,75
Residence area									
Rural	50,52	50,46	33,67	16,99	18,17	10,21	7,8	8,85	4,45
Urban	25,32	14,87	10,25	6,77	3,4	2,27	2,69	1,16	0,78
Education of household head									
Illiterate	52	50,2	28,46	17,56	17,98	8,62	8,13	8,68	3,86
Primary	29,57	20,95	17,7	8,74	5,41	4,48	3,63	2,19	1,66
Secondary	16,87	9,45	7,82	4,14	2,45	1,71	1,43	0,95	0,69
Technical secondary	12,4	7,33	6,34	3,61	3,29	0,73	1,32	1,53	0,12
Tertiary	9,19	7,86	3,17	1,63	2,66	0,87	0,6	1,37	0,3
Traditional	33,27	30,73	25,85	9,47	9,46	7,47	3,9	4,24	3,14
Alphabetization	47,82	34,89	29,55	16,19	9,2	4,54	7,11	3,36	1,02
Socio-economic group of household head									
Public sector	24,82	15,46	6,46	6,99	4,2	1,31	2,8	1,73	0,4
Private sector	41,56	32,32	20,63	14,07	11,08	5,43	6,5	5,16	2,12
Self-employed agricultural	59,5	59,69	36,36	20,23	22,11	10,88	9,44	10,58	4,93
Self-employed non-agricultural	38,12	31,59	20,99	11,6	9,55	5,87	4,93	4,08	2,38
Unemployed	41,4	39,94	28,66	12,69	14,99	7,79	5,22	7,56	3,4
Household aids and other	43,97	37,42	26,54	14,03	12,32	7,06	6,34	5,9	2,76
Inactive	36,46	40,48	22,95	11,42	14,26	7	5,14	6,99	3,11
Region									
Hodh Charghy	43,24	52,69	21,25	12,39	20,97	5,86	5,22	10,92	2,2
Hodh El Gharby	41,72	41,15	31,97	13,18	12,88	8,93	5,61	5,57	3,68
Assaba	34,01	48,46	35,08	11,12	17	11,84	5,34	7,99	5,53
Gorgol	60,39	57,22	30,75	20,87	19,49	7,98	9,63	9,14	3
Brakna	56,85	53,52	30,79	19,13	19,49	9,54	8,75	9,56	4,22
Trarza	45,29	28,7	22,5	15,38	9,12	8,24	7,05	4,23	4,14
Adrar	36,29	48,52	28,45	10,2	15,63	6,5	4,06	7,09	2,59
Nouadhibou	12,78	12,59	7,75	2,92	2,58	1,72	1,01	0,62	0,49
Tagant	62,24	62,16	41,67	23,75	24,49	8,74	11,56	12,75	3,25
Guidimagha	56,23	42,99	30,29	20,09	13,81	9,17	9,22	6,27	4,05
Tirs Zemour	25,55	12	12,86	5,86	3,72	1,07	2,06	1,6	0,24
Inchiri	38,86	22	14,71	9,15	6,5	2,45	3,1	2,23	0,56
Nouakchott	20,7	10,59	9,11	4,97	2,11	2,02	1,89	0,63	0,68

At the regional level, the incidence of household poverty has fallen in all regions between 2004 and 2014 with the exception of Assaba. Given the performance in poverty reduction between 2004 and 2014, we can distinguish three groups of regions. The first group represents the regions where household poverty has been reduced with a rate greater than 50%. Those regions are Inchiri, Nouakchott, Hodh Chargui and Trarza. The second group contains the regions whose poverty reduction rates are between 30% and 50%, which are Tiris Zemour, Gorgol, Guidimagha, Brakna, Nouadhibou and Tagant. The third group encompasses the regions with a poverty reduction rate below 30%. The latter regions are Hodh El Gharby and Adrar.

3 Review of Spatial Methods

3.1 Spatial Weights

The famous Tobler's first law of geography postulates that nearby things are more related than distant things (Tobler 1979). This idea translates into the concept of distance or spatial proximity, which are used to formally express the neighbor structure between observations in terms of spatial weights.

The spatial weights are pivotal in modeling spatial interaction between individuals, regions, or any other spatial units. They are represented in an N by N positive matrix W. Each element w_{ij} of this matrix specifies whether or not location j impacts location i. The spatial weights matrix W allows the building of the spatially lagged values of the dependent and explanatory variables. Conventionally, the elements of the main diagonal of the spatial weights matrix are set to zero.

The spatial weights matrices are often standardized in line such that the sum of the elements of a row is equal to one, and their values lie between 0 and 1. The elements of a standardized matrix W^s are calculated as follows:

$$w_{ij}^s = \frac{w_{ij}}{\sum_j w_{ij}}.$$

This standardization allows the comparison between the spatial parameters of different models of many spatial stochastic processes. Also, it facilitates the interpretation of the coefficients. For instance, the standardization allows borrowing a natural interpretation to the autoregressive parameter ρ as a "correlation" coefficient (Ord 1975). Furthermore, the standardization makes the operations with a spatial weights matrix more intuitive. For example, the element i of the spatially lagged variable resulting from multiplying the weights matrix by the dependent variable Wy is a weighted average $\sum_j w_{ij}^s y_j$ of the y values of i's neighbors.

3.2 Spatial Models

The spatial interactions between the observations are modeled by including spatially lagged variables in the regression. The specifications of classical spatial models take into account three types of spatial interaction effects: (i) endogenous spatial interaction effects by introducing the spatially lagged values of the dependent variable, (ii) spatial interaction effects among the disturbance terms, and (iii) exogenous spatial interaction effects among the regressors. The latter specification does not need any spatial econometric techniques to be estimated.

3.2.1 Spatial Lag Model

The spatial autoregressive model (SAR) describes the dependence between the outcome variable y and its lagged expression Wy, which represents a linear combination of neighboring values to each observation. When the spatial weight matrix is standardized, this linear combination represents weighted averages of the neighboring values. This model was introduced by Ord (1975) on the basis of the earlier work of Whittle (1954). The SAR model can be expressed as follows:

$$y = \rho W y + X\beta + u, \tag{4}$$

where y is an $N \times 1$ vector of the dependent variable, W is an $N \times N$ of spatial weights, Wy is the spatially lagged dependent variable, ρ is the spatial autoregressive parameter, X is an $N \times K$ matrix of exogenous regressors, β is a $K \times 1$ of unknown parameters, and u is an $N \times 1$ vector of disturbances.

Anselin (1988b) also proposed an extension of the spatial lag model labeled the spatial Durbin model. It introduces spatially lagged independent variables WX in order to identify the impact of neighbors' characteristics on the independent variable.

3.2.2 Spatial Error Models

The presence of spatial dependence in the error term violates the assumption of a spherical error covariance matrix. As a consequence, the OLS estimator becomes inefficient, and the traditional estimators of the standard error are biased. Therefore, the statistical tests (t- and F-statistics) and the coefficient of determination R^2 could lead to incorrect conclusions. These shortcomings can be overcome by employing an estimator that takes into account the special structure of the error covariance driven by the spatial process.

$$y = X\beta + u, \; u = \lambda W u + \varepsilon \tag{5}$$

The specification of the dependence in the error terms can be autoregressive (AR) like in the Eq.(5) or a moving average (MA).

3.2.3 The Kelejian-Prucha Model

This model[2] combines the specifications of the spatial lag model Eq. 4 and the spatial error model Eq. 5. In other words, it includes the spatially lagged dependent variable as well as a spatially autocorrelated disturbance term.

$$y = \rho W_1 y + X\beta + u, \quad u = \lambda W_2 u + \varepsilon \tag{6}$$

The weight spatial matrices W_1 and W_2 used for structuring the spatial autocorrelation in the endogenous variable and the error terms can be the same or different.

3.2.4 The Manski Model

The full spatial, general, nested model simultaneously introduces the three types of spatial interaction effects: endogenous spatial interaction effects, exogenous spatial interaction effects among the regressors, and spatial interaction effects among the disturbance terms. The Manski model can be expressed as follows:

$$y = \rho W y + X\beta + W X\gamma + u, \quad u = \lambda W u + \varepsilon. \tag{7}$$

It is not recommended to use this specification since it suffers from serious identification issues, which makes the distinction between the different spatial effects impossible.

3.3 Specification Tests

There are two distinct approaches in the spatial econometrics literature to find an appropriate econometric specification. The first is a forward stepwise strategy called the specific-to-general approach. It takes the classical linear model as a point of departure.

The second is a backward stepwise strategy called the general-to-specific approach (also called the Hendry strategy). It starts with a global model containing multiple spatially lagged variables and progressively simplifies the model by employing a sequence of tests.

[2]This model is known by several labels; for instance, Elhorst (2010) call it the Kelejian-Prucha model after the names of the authors who were the first to suggest an estimation technique for this model. However, these authors named it by the spatial Cliff-Ord-type model or the SARAR (acronym for Spatial AutoRegressive with an AutoRegressive error structure) model. LeSage and Pace (2009) denote this model by the term SAC. Anselin and Rey (2014) labelled it the combo model.

3.3.1 Lagrange Multiplier Tests

The classical approach starts by estimating the OLS[3] model and then tests the presence of a spatially autoregressive error term or spatially lagged endogenous interaction effects. The Moran's I and Lagrange Multiplier (LM) or Rao Score test statistics are the diagnostic tools employed to detect the presence of these spatial interaction effects.

Burridge (1980) proposed a Lagrange Multiplier test for detecting spatial autocorrelation in the disturbance terms. Formally, it tests the statistical significance of the parameter λ in Eq.5. The null hypothesis of this test is H0: $\lambda = 0$, and the alternative is $\lambda \neq 0$. Under the null hypothesis, the test statistic asymptotically converges to a chi-square distribution with one degree of freedom.

$$LM_\lambda = \frac{(e^{'}We/\hat{\sigma}^2_{ML})^2}{T} \sim \chi^2(1), \tag{8}$$

where e is the OLS residual, W is the spatial weight matrix, and T is a trace expression $= tr(WW + W^{'}W)$ and $\hat{\sigma}^2_{ML} = e^{'}e/N$.

To identify an omitted spatial lag in the dependent variable, Anselin (1988a) suggested a Lagrange Multiplier test based on the OLS model results. The null hypothesis of this test is H0: $\rho = 0$, and the alternative $\rho \neq 0$ is a spatial lag model (Eq.4). Like the latter statistical test, the LM_ρ is asymptotically chi-square distributed with one freedom degree.

$$LM_\rho = \frac{(e^{'}Wy/\hat{\sigma}^2_{ML})^2}{D} \sim \chi^2(1), \tag{9}$$

where e is the OLS residual, y is the dependent variable, $\hat{\sigma}^2_{ML} = e^{'}e/N$, and $D = (WX\hat{\beta})^{'}[I - X(X^{'}X)^{-1}X^{'}](WX\hat{\beta})/\hat{\sigma}^2_{ML} + T$, with $T = tr(WW + W^{'}W)$.

The joint null hypothesis of the absence of both a spatial lag and spatially correlated error ($\rho = \lambda = 0$) can be tested using a Lagrange Multiplier. This joint test statistic follows a chi-square distribution with two degrees of freedom.

$$LM_{\rho\lambda} = \frac{d^2_\lambda}{T} + \frac{(d_\lambda - d_\rho)^2}{D - T} \sim \chi^2(2) \tag{10}$$

with $d_\lambda = e^{'}We/\hat{\sigma}^2_{ML}$, $d_\lambda = e^{'}Wy/\hat{\sigma}^2_{ML}$, where T and D are the same as in the Eqs. 8 and 9, respectively.

[3]The classical linear model is frequently referred to as the OLS model since it is the most commonly used method to estimate the linear model.

3.3.2 Robust Lagrange Multiplier Tests

Anselin et al. (1996) demonstrate that LM_λ and LM_ρ given above are sensitive to the existence of a spatial lag and spatially correlated error, respectively. In other words, the LM_λ could mistakenly suggest a spatial error model, while the correct specification is a spatial lag model. Similarly, the LM_ρ test suffers from the same issue. To overcome this problem, Anselin et al. (1996) proposed a new generation of robustified LM-tests that have more power in indicating the true alternative.

The robust LM test statistic of the spatial error model can be expressed as follows:

$$RLM_\lambda = \frac{(d_\lambda - TD^{-1}d_\rho)^2}{[T(1-TD)]} \sim \chi^2(1), \tag{11}$$

and for the spatial lag model:

$$RLM_\rho = \frac{(d_\rho - d_\lambda)^2}{D-T} \sim \chi^2(1) \tag{12}$$

3.3.3 The Moran's I

Moran's I is the most commonly used test for global spatial autocorrelation. It was introduced by Moran (1950a,b) and extended by Cliff and Ord (1972) for testing the presence of spatial autocorrelation among regression residuals. It provides the degree of linear association between an outcome variable and its spatially lagged values. In other words, it formally indicates the extent to which observations' values are linearly correlated with the spatially weighted averages of neighboring values.

$$I = \frac{N}{S_0}\frac{e^{'}We}{e'e}, \tag{13}$$

where e is a vector of N residuals, $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all elements of the weight matrix W, used as a scaling factor. Consequently, this scaling factor S_0 is equal to the number of observations if the spatial weight matrix is standardized. Accordingly, the expression Eq.13 simplifies and becomes the following:

$$I = \frac{e^{'}We}{e'e}. \tag{14}$$

The analytic expressions of the mean and the variance of the Moran's I statistic are obtained under two different hypotheses (Cliff and Ord 1981). The first hypothesis is that the values of the outcome variable independently and identically follow a normal distribution. The second hypothesis is that the distribution of the outcome variable is unknown.

The theoretical mean of the Moran's I under the null hypothesis of absence of spatial dependence is the same in both hypotheses (Eq.15). This theoretical mean is not null; however, it tends to zero for large samples.

$$\mathbb{E}[I] = -\frac{1}{N-1}. \tag{15}$$

The realizations of the Moran's I statistic vary between -1 and 1, and the spatial autocorrelation is positive when I is greater than its mathematical expectation under the null hypothesis. By contrast, the autocorrelation is negative if I is less than the mathematical expectation.

The variance of the Moran's I under the normality assumption can be expressed as follows:

$$\mathbb{V}[I] = -\frac{N^2 S_1 - N S_2 + 3S_0^2}{S_0^2(N^2-1)} - (\mathbb{E}[I])^2, \tag{16}$$

where N is the number of observations, S_0, S_1 and S_2 are calculated from the spatial weights as follows: $S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}$, $S_1 = 1/2\sum_{i=1}^{N}\sum_{j=1}^{N}(w_{ij}+w_{ji})^2$, $S_2 = \sum_{i=1}^{N}(\sum_{j=1}^{N} w_{ij} + \sum_{j=1}^{N} w_{ji})^2$.

The variance of Moran's I under the non-normality hypothesis is:

$$\mathbb{V}[I] = \frac{N[(N^2-3N+3)S_1 - NS_2 + 3S_0^2] - b[(N^2-N)S_1 - 2NS_2 + 6S_0^2]}{[(N-1)(N-2)(N-3)S_0^2]} - (\mathbb{E}[I])^2, \tag{17}$$

where S_0, S_1 and S_2 are the same as in the Eq.(16), and $b = m_4/m_2^2$, where m_2 and m_4 are, respectively, the second and the fourth moments of the outcome variable.

To test the significance of Moran's I, we can use the $\mathbb{I}_z$ statistic, which asymptotically follows a distribution that is approximated by the standard normal distribution:

$$\mathbb{I}_z = \frac{I - \mathbb{E}(I)}{\sigma(I)} \sim N(0,1). \tag{18}$$

The Moran's I is a non-constructive test because the alternative hypothesis does not indicate a specific model. When the null hypothesis is rejected, the underlying model could be a spatial error model, a spatial lag model, or a model with heteroskedastic error terms (Anselin and Rey 1991, 2014).

In addition to its role as a spatial autocorrelation test, the Moran's I can be used as an exploratory spatial data analysis tool (Anselin 1996 and Ertur and Koch 2006).

For instance, the Moran scatterplot permits visualizing the individuals according to their welfare and that of their neighbors as well as the outliers.

4 Model Specification and Spatial Weights Matrix

4.1 Model Specification

The non-spatial specification used to model household welfare is based on a Mincer (1974) earnings equation type in which the log of Total Household Expenditure per capita (THEC) is used as a proxy of income. The regressors are the age of the household head and the size of the household (number of persons living in the household). The household-head gender (1: female, 0: male), area of residence (0: Urban, 1: Rural), and education of the household head which contains six levels primary, secondary, tertiary, traditional and Illiterate are used as a reference group. The household-head's socio-economic group variable contains seven groups: private-sector employees, self-employed agricultural, self-employed non-agricultural, household aids and others, unemployed, and inactive. These groups are compared to the reference group (public-sector employees).

4.2 Spatial Weights Matrix Specification

To capture the dependence structure between neighboring households in Mauritania, I use a spatial weight matrix based on the k-nearest neighbors computed from the distance between households using the GPS coordinates of their housing.

The structure of the k-nearest neighbors weight matrix $W(k)$ can be formally expressed as follows:

$$\begin{cases} w^*_{ij} = 0 & \text{if} \quad i = j \\ w^*_{ij} = 1 & \text{if} \quad d_{ij} \leq d_i(k) \\ w^*_{ij} = 0 & \text{if} \quad d_{ij} > d_i(k) \\ w_{ij}(k) = & w^*_{ij}(k) / \sum_j w^*_{ij}(k), \end{cases}$$

where $d_i(k)$ is a critical cut-off distance defined for each household i in a manner that ensures that every household has exactly k neighbors. In this paper, I use a spatial weight matrix based on the 17 nearest neighboring households, standardized in line. The choice of k was made according to the recommendations of Stakhovych and Bijmolt (2009). In this paper, they show, using a Monte-Carlo experience, that the probability of finding the correct specification of the weight matrix increases when the selection procedure relies on 'goodness-of-fit' criteria. I apply this approach by estimating 40 spatial error models with different k-nearest neighbors spatial weight matrices, and I compare them using the log-likelihood function value, which is the most commonly used criterion (Elhorst 2010). I choose the specification based on the 17 nearest neighbors weight matrix because it exhibits the highest log-likelihood function value, as shown in the graphic (a) of Figure 1. Using the same method for urban and rural sectors gives similar results, 17 nearest neighbors for the urban households and 18 for their rural counterparts.

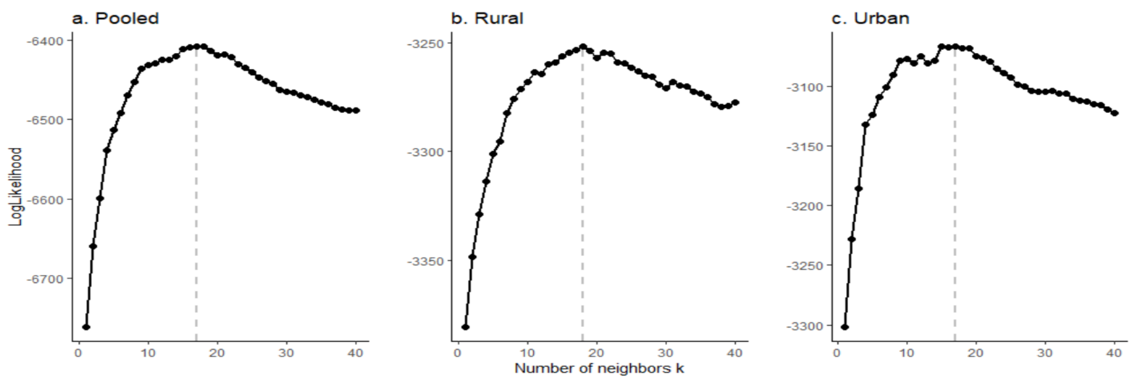

Figure 1: Log Likelihood function values

One can argue that the most appropriate spatial weight matrix for modeling spatial interaction between households is an inverse distance matrix with a cut-off. This could be true for households that are geographically dispersed in a homogeneous manner, which is definitely not the case for Mauritanian households. Indeed, I analyze the spatial dependence in both rural and urban areas, where the geographic dispersion of households is very different. In addition, there are many remote households in the data set. This makes the choice of an appropriate cut-off distance extremely difficult. For instance, if we want to make an analysis without excluding any households, we need to choose a cut-off point equal to 57 kilometers. To reduce the cut-off to a reasonable distance of five kilometers, I have to exclude 60 households from the analysis, and yet the structure of neighborhoods remains very asymmetric regarding the number of neighbors for each household.

Another reason for choosing a spatial weight matrix based on the k-nearest neighbors $W(k)$ is that the GPS position error has an impact on the inverse distance weights. Contrary to the case of polygons proximity, the accuracy of the household's GPS position is very important when the weight matrix is based on the inverse-distance. However, the spatial weight matrix based on the k-nearest neighbors $W(k)$

is much less affected by GPS position error.

Another difficulty arises when the inverse distance weight matrix is row-standardized since it loses its economic interpretation in terms of distance decay (Elhorst 2001). In other words, the spatial weights of distant observations will be similar to those of more centrally located observations in an independent manner on their locations. For instance, we consider two remote households, where each of them has only one neighbor, but the distance between the first household and its neighbor is 10 kilometers, and the distance of the second household and its neighbor is 40 meters. Standardizing the inverse distance matrix will give the near and remote neighbors the same weight as in the case of spatial weight matrix based on the k-nearest neighbors. In addition, the standardized inverse distance matrix will very likely become asymmetric. This implies that the impact of household i on household j will not be the same as the impact of household j on household i.

4.3 Spatial Dependence among Households

The Moran scatter plot in Figure 2 shows a positive linear association between Household Expenditure on the horizontal axis and its spatially lagged values on the vertical axis.

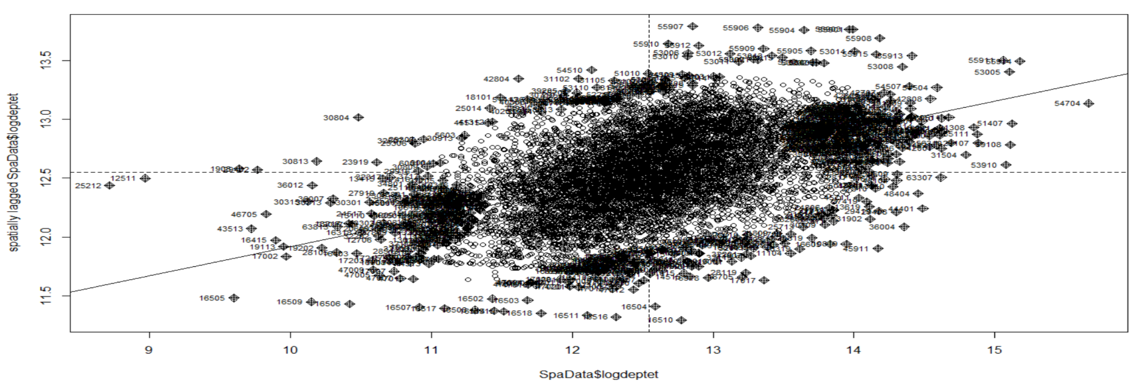

Figure 2: Moran scatter plot of residuals

To test the presence of spatial dependence in the households' welfare, I start with the Moran's I test on the OLS residuals. The results of this test exclude the null hypothesis of spatial independence, as shown in Table 7. The Moran's correlogram (Fig.3) shows that the null hypothesis is rejected for 99 different specifications of the k-nearest spatial weight matrix ($k = 2$ to 100).

Given the non-constructive nature of the Moran's I test, I apply a sequence of Lagrange Multiplier tests, which allows the identification of the exact specification of the spatial dependence.

The specification test results reported in Table 7 indicate that the realizations of the Lagrange Multiplier statistics for the spatial lag LM_ρ and spatial error LM_λ are both significant. This is valid for the different specifications of the spatial weight matrices $W(k)$ within a range from two to 20 neighbors.

The classic specific-to-general approach without the Robust Lagrange Multiplier (RLM) test suggests estimating the specification identified by the more significant LM test (Florax et al. 2003), which is the LM_λ test in this case. Accordingly, the best specification is the SEM model presented in Eq.5.

As mentioned above, the LM tests could mistakenly exclude the correct model because of their sensitivity to local misspecifications.

The results of Robust Lagrange Multiplier tests for spatial dependence in the error term (RLM_λ) indicate a highly significant autocorrelation that is robust to the number of neighbors considered in the spatial weight matrix $W(k)$. However, the RLM_ρ test indicates a spatial lag that is not robust to the number of neighbors and is less significant than the RLM_λ. According to the decision rule of choosing the model with the most significant RLM test (Anselin and Rey 2014), the appropriate specification is the spatial error model presented in Eq.5:

$$y = X\beta + u,\ u = \lambda W u + \varepsilon.$$

The specification search using the classic approach leads to choosing the same model for urban and rural sectors. The results of the LM tests for the urban sector reported in 8 are similar to those of the pooled regression with the exception of the result of the RLM_ρ, which is significant for the different specifications of the spatial weight matrix. However, it still less significant than the RLM_λ, which confirms the choice of a spatial error model for urban households. The specification tests for the rural sector presented in Table 9 indicate that the RLM_ρ is not significant; consequently, the appropriate specification is also a spatial error model.

5 Empirical Results

The spatial dependence tests indicate the presence of a significant spatial autocorrelation in the error term for the pooled, urban and rural regressions. This implies that the classical linear regression results cannot be trusted because the OLS estimator is inconsistent in the presence of spatial autocorrelation in the error term. To overcome this and obtain more accurate estimates of poverty determinants, I use a spatial error model indicated by the robust Lagrange Multiplier tests as the best model.

Table 4 shows the results of the OLS and spatial error model estimations. To assess the models' fit, I use the Akaike Information Criterion (AIC)[4], the value of which is lower in the spatial error model than in the OLS model. This means that the spatial model fits the data better than the non-spatial model.

Comparing the SEM and the non-spatial regression results at the national level shows that the OLS model erroneously indicates that the impact of being a private-sector employee on poverty is not different from that of being a public-sector employee.

The estimates of the socio-economic groups' coefficients are interpreted with reference to the public-sector employees. Therefore, a non-significant estimate for a socio-economic group coefficient suggests that being a member of this group has the same impact on poverty as being a member of the reference group (public-sector employees). The classical linear model shows that the private sector, inactive persons, and the self-employed non-agricultural groups' coefficients are not statistically significant at the national level. Nevertheless, the spatial error model results highlight that the coefficients of these groups are statistically significant.

The diagnostics for spatial dependence using the specific-to-general test strategy have indicated that the most suitable model for both rural and urban sectors is a spatial error model. This is confirmed by the AIC criteria, which yields lower values for the spatial models in both sectors. These results confirm that the non-spatial OLS model estimators are not consistent and that the spatial error model fits the data better than the OLS model.

[4]The coefficient of determination cannot be used to compare spatial models since it gives equal weights for all squared residuals. Therefore, it does not take into account the underlying spatial autocorrelation (Anselin and Rey 2014).

Table 4: Classical and Spatial Regressions Results

	OLS	Spatial Error Model
Intercept	$13,19621^{***}$	$13,23625^{***}$
	(0,036824)	(0,037374)
Rural	$-0,35715^{***}$	$-0,34549^{***}$
	(0,012613)	(0,022965)
Age	$0,000781^{*}$	$0,001094^{***}$
	(0,000442)	(0,000410)
Female	$-0,00073$	$-0,01169$
	(0,015191)	(0,014108)
Household size	$-0,10382^{***}$	$-0,10720^{***}$
	(0,001719)	(0,001678)
Primary	$0,107689^{***}$	$0,099052^{***}$
	(0,024899)	(0,023066)
General secondary	$0,247080^{***}$	$0,197598^{***}$
	(0,026416)	(0,024547)
Technical high school	$0,342977^{***}$	$0,285195^{***}$
	(0,089272)	(0,081784)
Tertiary	$0,381974^{***}$	$0,301078^{***}$
	(0,036004)	(0,033750)
Traditional	$0,070890^{***}$	$0,047420^{***}$
	(0,019671)	(0,018274)
Alphabétisation	$0,176027$	$0,184979$
	(0,126815)	(0,116369)
Private sector	$-0,04136$	$-0,05919^{**}$
	(0,026681)	(0,024806)
Self-employed agricultural	$-0,04821^{*}$	$-0,03226$
	(0,029149)	(0,027313)
Self-employed non-agricultural	$-0,02763$	$-0,04312^{**}$
	(0,022919)	(0,021382)
Familial aids and other	$-0,05914^{**}$	$-0,05969^{**}$
	(0,029217)	(0,027368)
Unemployed	$-0,19650^{***}$	$-0,20695^{***}$
	(0,059674)	(0,054748)
Inactive	$-0,01653$	$-0,04481^{*}$
	(0,026184)	(0,024233)
λ		$0,609619^{***}$
		(0,015276)
AIC	14015	12854
Sample size	9179	9179

Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

The results of the OLS and SEM model estimations reported in Table 5 show that the non-spatial model spuriously leads to the conclusion that the primary school level of urban household-heads has no significant impact on poverty, while the SEM model confirms that the impact of this educational level on poverty is statistically significant at 5%. Another mistaken conclusion of the non-spatial model in the urban areas is that it indicates that belonging to the household-aids socio-economic group has the same impact on poverty as belonging to the public-sector employees group. Meanwhile, the spatial model shows that at a 10%, level of significance, the standard of living of the household-aids group is inferior to that of the public-sector employees group in urban areas.

Table 5: OLS and SEM results for urban and rural households

	Urban		Rural	
	OLS	SEM	OLS	SEM
Intercept	$13,258^{***}$	$13,283^{***}$	$12,880^{***}$	$12,949^{***}$
	(0,0494)	(0,0479)	(0,0787)	(0,0759)
Age	0,0005	0,0006	$0,0012^{*}$	$0,0015^{**}$
	(0,0006)	(0,0005)	(0,0006)	(0,0006)
Female	$-0,051^{***}$	$-0,050^{***}$	$0,1126^{***}$	$0,0680^{***}$
	(0,0181)	(0,0166)	(0,0276)	(0,0261)
Household size	$-0,106^{***}$	$-0,110^{***}$	$-0,098^{***}$	$-0,101^{***}$
	(0,0022)	(0,0021)	(0,0027)	(0,0026)
Primary	0,0693	$0,0977^{**}$	$0,1526^{***}$	$0,1147^{***}$
	(0,0451)	(0,0409)	(0,0388)	(0,0364)
General secondary	$0,1888^{***}$	$0,1773^{***}$	$0,3410^{***}$	$0,2496^{***}$
	(0,0448)	(0,0406)	(0,0552)	(0,0522)
Technical high school	$0,2860^{***}$	$0,2481^{***}$	0,4956	$0,5236^{*}$
	(0,0946)	(0,0854)	(0,3220)	(0,2983)
Tertiary	$0,3306^{***}$	$0,2871^{***}$	$0,4353^{***}$	$0,2596^{**}$
	(0,0507)	(0,0463)	(0,1115)	(0,1042)
Traditional	0,0218	0,0308	$0,1564^{***}$	$0,1001^{***}$
	(0,0438)	(0,0396)	(0,0273)	(0,0259)
Alphabétisation	$-0,012$	0,0279	0,2540	$0,2665^{*}$
	(0,2209)	(0,2014)	(0,1610)	(0,1491)
Private sector	0,0083	$-0,022$	$-0,271^{***}$	$-0,266^{***}$
	(0,0282)	(0,0258)	(0,0711)	(0,0669)
Self-employed agricultural	0,0169	0,0638	$-0,238^{***}$	$-0,223^{***}$
	(0,0531)	(0,0486)	(0,0677)	(0,0639)
Self-employed non-agricultural	0,0076	$-0,014$	$-0,237^{***}$	$-0,231^{***}$
	(0,0233)	(0,0214)	(0,0663)	(0,0625)
Familial aids and other	$-0,056$	$-0,060^{*}$	$-0,242^{***}$	$-0,234^{***}$
	(0,0356)	(0,0328)	(0,0700)	(0,0662)
Unemployed	$-0,119^{*}$	$-0,126^{**}$	$-0,449^{***}$	$-0,453^{***}$
	(0,0695)	(0,0629)	(0,1159)	(0,1079)
Inactive	0,0163	0,0063	$-0,222^{***}$	$-0,250^{***}$
	(0,0288)	(0,0262)	(0,0681)	(0,0640)
λ		$0,6483^{***}$		$0,5851^{***}$
		(0,0198)		(0,0240)
AIC	6922.8	6168.9	6976.4	6539.6
Sample size	4980	4980	4199	4199

Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

The spatial error model results affirm that returns to technical high school and alphabetization levels of rural household-heads are statistically significant at 10%, contrary to the non-spatial model that erroneously concludes that these returns are not significant.

6 Conclusions

This paper makes use of spatial econometric techniques to empirically analyze the poverty determinants in Mauritania using micro-level data. This analysis is based on the spatial dependence in the households' expenditures, which is structured using the spatial proximity between households. The spatial interactions are modeled with the k-nearest neighbors spatial weight matrices, which are more appropriate to the geographic dispersion of Mauritanian households.

The spatial dependence in household welfare is detected among the error terms for the pooled, urban, and rural regressions. This implies that the classical model estimators are inconsistent; therefore, I use a spatial error model, which overcomes the limitations of the classical linear model.

The empirical findings confirm that the classical approach provides misleading conclusions about the statistical significance of the effects of belonging to some socio-economic groups and educational attainment on poverty. The presence of significant spatial dependence on household welfare recommends using the spatial econometric methods in the process of monitoring and evaluating action plans aimed at reducing poverty.

The spatial model results highlight the negative effects of belonging to certain socio-economic groups on household welfare. This demonstrates the need for promoting the economic and financial empowerment of vulnerable groups.

Given the significant reward of the alphabetized household-heads by rural markets, I suggest maintaining and strengthening adult literacy programs in rural areas. The same applies to the technical high school level, which is not statistically significant in the classic model but is significant in the spatial model.

Despite the decrease in the return to the primary education from 2004 to 2014, the spatial model shows that it remains statistically significant in both urban and rural areas. However, the general decline in marginal effects of educational levels reduces the impact of development policies aiming at eradicating poverty. This issue can be surmounted by adopting a more competency-based education system that permanently responds to the needs of the market.

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A Appendices

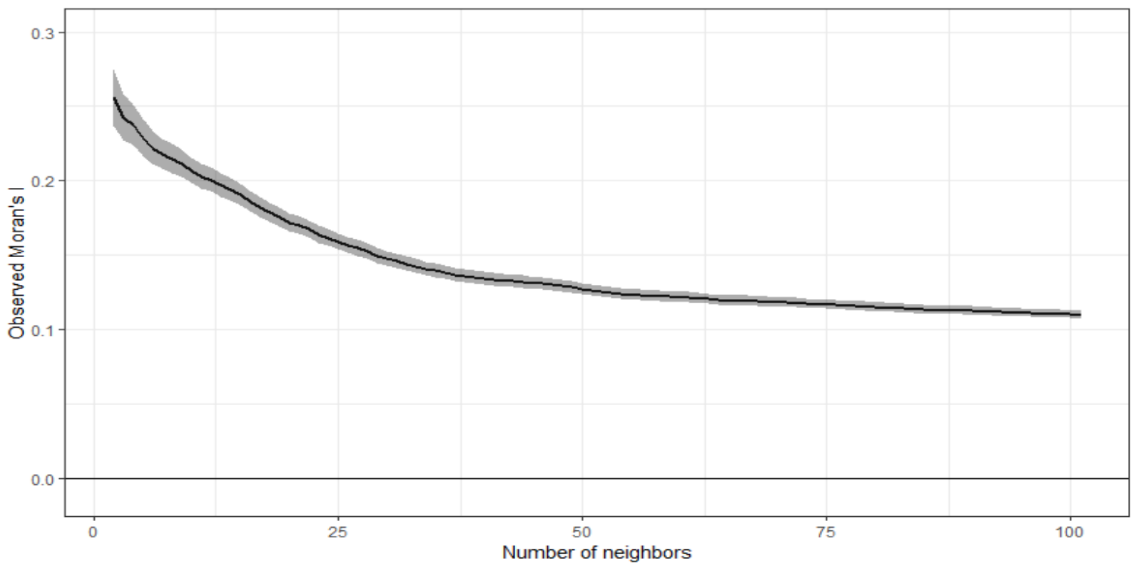

Figure 3: Moran's I correlogram as a function of k nearest neighbors

Table 6: The cut-off distance

		Statistics on households connectivity					
$\bar{d}$ (km)	isolated	Min	Q1	Median	Mean	Q3	Max
56.84	1	3	213	341	756.5	588	2214
26.08	2	2	53	118	628.6	579	2176
24.87	3	2	48	112	624.6	579	2172
23.59	4	1	44	105	620.1	579	2169
15.47	5	1	27	62	591.1	579	2153
15.3	6	1	27	61	590.2	579	2153
14.61	7	1	24	58	586.1	579	2153
11.53	9	1	15	44	555.1	579	2138
11.21	10	1	15	44	549.7	579	2138
10	13	1	14	44	518.6	579	2138
9	17	1	14	44	480.1	565	2093
8	19	1	14	43	433.4	565	2019
7	29	1	14	41	379.4	565	1870
6	43	1	13	30	320.8	539.2	1624
5	60	1	12	29	265.3	465	1294
4	76	1	12	29	207.1	355	1020
3	99	1	10	28	153.5	294	746
2	168	1	8	17	98.75	186	416
1	304	1	7	14	42.81	64	271

Table 7: Moran's I and Lagrange Multiplier Tests

NB of neighbors k	Moran's I	LM_{λ}	RLM_{λ}	LM_{ρ}	RLM_{ρ}	$LM_{\rho\lambda}$
2	0.2556*** (<2e−16)	712.65*** (<2e−16)	208.93*** (<2e−16)	507.83*** (<2e−16)	4.1119** (0,0425)	716.76*** (<2e−16)
3	0.2425*** (<2e−16)	946.28*** (<2e−16)	284.84*** (<2e−16)	665.13*** (<2e−16)	3.6881* (0,0548)	949.97*** (<2e−16)
4	0.2374*** (<2e−16)	1195.9*** (<2e−16)	409.06*** (<2e−16)	796.03*** (<2e−16)	9.1624*** (0,0024)	1205.0*** (<2e−16)
5	0.2290*** (<2e−16)	1380.9*** (<2e−16)	485.56*** (<2e−16)	904.28*** (<2e−16)	8.8701*** (0,0028)	1389.8*** (<2e−16)
6	0.2221*** (<2e−16)	1549.9*** (<2e−16)	564.49*** (<2e−16)	994.06*** (<2e−16)	8.6588*** (0,0032)	1558.5*** (<2e−16)
7	0.2178*** (<2e−16)	1731.5*** (<2e−16)	662.51*** (<2e−16)	1076.6*** (<2e−16)	7.6016*** (0,0058)	1739.1*** (<2e−16)
8	0.2146*** (<2e−16)	1910.6*** (<2e−16)	754.33*** (<2e−16)	1164.3*** (<2e−16)	8.0258*** (0,0046)	1918.6*** (<2e−16)
9	0.2116*** (<2e−16)	2076.3*** (<2e−16)	844.96*** (<2e−16)	1237.8*** (<2e−16)	6.3768** (0,0115)	2082.7*** (<2e−16)
10	0.2067*** (<2e−16)	2186.9*** (<2e−16)	930.68*** (<2e−16)	1263.0*** (<2e−16)	6.7670*** (0,0092)	2193.7*** (<2e−16)
11	0.2024*** (<2e−16)	2284.0*** (<2e−16)	1007.7*** (<2e−16)	1283.5*** (<2e−16)	7.3161*** (0,0068)	2291.3*** (<2e−16)
12	0.2004*** (<2e−16)	2417.3*** (<2e−16)	1103.8*** (<2e−16)	1321.9*** (<2e−16)	8.4092*** (0,0037)	2425.7*** (<2e−16)
13	0.1967*** (<2e−16)	2498.1*** (<2e−16)	1161.5*** (<2e−16)	1344.0*** (<2e−16)	7.4262*** (0,0064)	2505.5*** (<2e−16)
14	0.1941*** (<2e−16)	2603.9*** (<2e−16)	1230.8*** (<2e−16)	1380.8*** (<2e−16)	7.7124*** (0,0054)	2611.6*** (<2e−16)
15	0.1905*** (<2e−16)	2718.8*** (<2e−16)	1277.2*** (<2e−16)	1447.5*** (<2e−16)	5.9447** (0,0147)	2724.7*** (<2e−16)
16	0.1860*** (<2e−16)	2793.7*** (<2e−16)	1314.1*** (<2e−16)	1483.5*** (<2e−16)	3.9316** (0,0473)	2797.7*** (<2e−16)
17	0.1822*** (<2e−16)	2877.0*** (<2e−16)	1390.1*** (<2e−16)	1490.3*** (<2e−16)	3.4549* (0,0630)	2880.4*** (<2e−16)
18	0.1788*** (<2e−16)	2950.9*** (<2e−16)	1447.5*** (<2e−16)	1506.0*** (<2e−16)	2.6344 (0,1045)	2953.6*** (<2e−16)
19	0.1753*** (<2e−16)	3009.5*** (<2e−16)	1506.4*** (<2e−16)	1504.7*** (<2e−16)	1.7037 (0,1918)	3011.2*** (<2e−16)
20	0.1715*** (<2e−16)	3042.8*** (<2e−16)	1534.9*** (<2e−16)	1508.8*** (<2e−16)	0.9538 (0,3287)	3043.7*** (<2e−16)

P-values in parentheses. Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

Table 8: Moran's I and Lagrange Multiplier Tests - Urban areas

NB of neighbors k	Moran's I	LM_λ	RLM_λ	LM_ρ	RLM_ρ	$\text{LM}_{\rho\lambda}$
2	0.2774*** (<2e−16)	456.91*** (<2e−16)	180.58*** (<2e−16)	284.69*** (<2e−16)	8.3694*** (0.0038)	465.28*** (<2e−16)
3	0.2668*** (<2e−16)	622.82*** (<2e−16)	257.93*** (<2e−16)	376.27*** (<2e−16)	11.388*** (0.0007)	634.21*** (<2e−16)
4	0.2672*** (<2e−16)	822.20*** (<2e−16)	364.41*** (<2e−16)	476.63*** (<2e−16)	18.851*** (<1.4e−)	841.05*** (<2e−16)
5	0.2550*** (<2e−16)	927.74*** (<2e−16)	407.25*** (<2e−16)	535.16*** (<2e−16)	14.672*** (0.0001)	942.42*** (<2e−16)
6	0.2472*** (<2e−16)	1039.7*** (<2e−16)	460.32*** (<2e−16)	592.94*** (<2e−16)	13.514*** (0.0002)	1053.2*** (<2e−16)
7	0.2405*** (<2e−16)	1142.7*** (<2e−16)	538.46*** (<2e−16)	618.06*** (<2e−16)	13.772*** (0.0002)	1156.5*** (<2e−16)
8	0.2361*** (<2e−16)	1251.9*** (<2e−16)	614.87*** (<2e−16)	652.72*** (<2e−16)	15.661*** (<7.5e−)	1267.5*** (<2e−16)
9	0.2344*** (<2e−16)	1379.8*** (<2e−16)	679.73*** (<2e−16)	711.37*** (<2e−16)	11.269*** (0.0007)	1391.1*** (<2e−16)
10	0.2293*** (<2e−16)	1459.4*** (<2e−16)	736.07*** (<2e−16)	733.72*** (<2e−16)	10.377*** (0.0012)	1469.7*** (<2e−16)
11	0.2246*** (<2e−16)	1526.0*** (<2e−16)	783.83*** (<2e−16)	752.54*** (<2e−16)	10.367*** (0.0012)	1536.3*** (<2e−16)
12	0.2223*** (<2e−16)	1616.6*** (<2e−16)	853.46*** (<2e−16)	775.38*** (<2e−16)	12.156*** (0.0004)	1628.8*** (<2e−16)
13	0.2168*** (<2e−16)	1652.1*** (<2e−16)	878.28*** (<2e−16)	784.51*** (<2e−16)	10.602*** (0.0011)	1662.8*** (<2e−16)
14	0.2137*** (<2e−16)	1720.9*** (<2e−16)	902.96*** (<2e−16)	827.36*** (<2e−16)	9.3768*** (0.0021)	1730.3*** (<2e−16)
15	0.2126*** (<2e−16)	1839.7*** (<2e−16)	988.11*** (<2e−16)	861.88*** (<2e−16)	10.205*** (0.0014)	1849.9*** (<2e−16)
16	0.2081*** (<2e−16)	1895.7*** (<2e−16)	1021.7*** (<2e−16)	882.08*** (<2e−16)	8.1021*** (0.0044)	1903.8*** (<2e−16)
17	0.2048*** (<2e−16)	1962.9*** (<2e−16)	1096.0*** (<2e−16)	876.10*** (<2e−16)	9.1610*** (0.0024)	1972.1*** (<2e−16)
18	0.2012*** (<2e−16)	2015.4*** (<2e−16)	1135.8*** (<2e−16)	889.86*** (<2e−16)	10.253*** (0.0013)	2025.7*** (<2e−16)
19	0.1982*** (<2e−16)	2073.7*** (<2e−16)	1172.0*** (<2e−16)	910.96*** (<2e−16)	9.1973*** (0.0024)	2082.9*** (<2e−16)
20	0.1939*** (<2e−16)	2093.3*** (<2e−16)	1190.2*** (<2e−16)	911.59*** (<2e−16)	8.5333*** (0.0034)	2101.8*** (<2e−16)

P-values in parentheses. Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

Table 9: Moran's I and Lagrange Multiplier Tests - Rural areas

NB of neighbors k	Moran's I	LM_λ	RLM_λ	LM_ρ	RLM_ρ	$LM_{\rho\lambda}$
2	0.2314*** (<2e−16)	266.44*** (<2e−16)	51.677*** (<6.5e−)	214.76*** (<2e−16)	0.0001 (0.9908)	266.44*** (<2e−16)
3	0.2156*** (<2e−16)	341.20*** (<2e−16)	63.282*** (<1.7e−)	278.45*** (<2e−16)	0.5314 (0.4660)	341.74*** (<2e−16)
4	0.2053*** (<2e−16)	409.26*** (<2e−16)	92.260*** (<2e−16)	317.06*** (<2e−16)	0.0687 (0.7931)	409.32*** (<2e−16)
5	0.1995*** (<2e−16)	479.66*** (<2e−16)	118.42*** (<2e−16)	361.24*** (<2e−16)	0.0009 (0.9758)	479.66*** (<2e−16)
6	0.1918*** (<2e−16)	529.45*** (<2e−16)	139.26*** (<2e−16)	390.19*** (<2e−16)	6.9353 (0.9933)	529.45*** (<2e−16)
7	0.1905*** (<2e−16)	606.68*** (<2e−16)	166.79*** (<2e−16)	439.90*** (<2e−16)	0.0213 (0.8838)	606.70*** (<2e−16)
8	0.1883*** (<2e−16)	673.96*** (<2e−16)	189.72*** (<2e−16)	484.26*** (<2e−16)	0.0263 (0.8711)	673.98*** (<2e−16)
9	0.1842*** (<2e−16)	720.06*** (<2e−16)	212.51*** (<2e−16)	507.59*** (<2e−16)	0.0500 (0.8229)	720.11*** (<2e−16)
10	0.1803*** (<2e−16)	758.80*** (<2e−16)	242.06*** (<2e−16)	516.75*** (<2e−16)	0.0116 (0.9139)	758.81*** (<2e−16)
11	0.1780*** (<2e−16)	802.63*** (<2e−16)	271.21*** (<2e−16)	531.49*** (<2e−16)	0.0788 (0.7788)	802.71*** (<2e−16)
12	0.1756*** (<2e−16)	840.37*** (<2e−16)	301.51*** (<2e−16)	539.17*** (<2e−16)	0.3146 (0.5748)	840.68*** (<2e−16)
13	0.1738*** (<2e−16)	879.45*** (<2e−16)	325.92*** (<2e−16)	553.89*** (<2e−16)	0.3748 (0.5403)	879.82*** (<2e−16)
14	0.1714*** (<2e−16)	912.96*** (<2e−16)	355.93*** (<2e−16)	557.83*** (<2e−16)	0.8004 (0.3709)	913.76*** (<2e−16)
15	0.1675*** (<2e−16)	949.59*** (<2e−16)	373.87*** (<2e−16)	576.57*** (<2e−16)	0.8482 (0.3570)	950.44*** (<2e−16)
16	0.1632*** (<2e−16)	975.58*** (<2e−16)	389.21*** (<2e−16)	587.32*** (<2e−16)	0.9549 (0.3284)	976.54*** (<2e−16)
17	0.1600*** (<2e−16)	1008.6*** (<2e−16)	405.21*** (<2e−16)	604.08*** (<2e−16)	0.6679 (0.4137)	1009.2*** (<2e−16)
18	0.1574*** (<2e−16)	1041.4*** (<2e−16)	427.94*** (<2e−16)	613.97*** (<2e−16)	0.4469 (0.5037)	1041.9*** (<2e−16)
19	0.1545*** (<2e−16)	1065.5*** (<2e−16)	459.81*** (<2e−16)	606.26*** (<2e−16)	0.5071 (0.4763)	1066.0*** (<2e−16)
20	0.1504*** (<2e−16)	1067.6*** (<2e−16)	463.80*** (<2e−16)	604.28*** (<2e−16)	0.4600 (0.4976)	1068.0*** (<2e−16)

P-values in parentheses. Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

Table 10: OLS Regression of log Total Household Expenditure

	EPCV 2004	EPCV 2008	EPCV 2014
Intercept	12, 19795***	12, 84546***	13, 19621***
	(0,034520)	(0,028871)	(0,036824)
Rural	−0, 28638***	−0, 50605***	−0, 35715***
	(0,013359)	(0,010756)	(0,012613)
Age	0, 001064**	0, 001129***	0, 000781*
	(0,000489)	(0,000394)	(0,000442)
Female	−0, 07344***	−0, 06093***	−0, 00073
	(0,016967)	(0,013424)	(0,015191)
Household size	−0, 10019***	−0, 11712***	−0, 10382***
	(0,002212)	(0,001816)	(0,001719)
Primary	0, 291872***	0, 244633***	0, 107689***
	(0,023501)	(0,017109)	(0,024899)
General secondary	0, 480057***	0, 429970***	0, 247080***
	(0,023869)	(0,018322)	(0,026416)
Technical high school	0, 638094***	0, 582242***	0, 342977***
	(0,079199)	(0,069488)	(0,089272)
Tertiary	0, 850451***	0, 678105***	0, 381974***
	(0,035316)	(0,027315)	(0,036004)
Traditional	0, 254055***	0, 239695***	0, 070890***
	(0,014781)	(0,011932)	(0,019671)
Alphabétisation	0, 049731	0, 208608***	0, 176027
	(0,056400)	(0,068454)	(0,126815)
Private sector	−0, 06784***	−0, 06940***	−0, 04136
	(0,022989)	(0,019679)	(0,026681)
Self-employed agricultural	−0, 09038***	−0, 17646***	−0, 04821*
	(0,026123)	(0,024684)	(0,029149)
Self-employed non-agricultural	0, 019012	−0, 03991**	−0, 02763
	(0,021427)	(0,018247)	(0,022919)
Familial aids and other	−0, 02426	−0, 12428***	−0, 05914**
	(0,027650)	(0,021144)	(0,029217)
Unemployed	0, 008580	−0, 15466***	−0, 19650***
	(0,045125)	(0,030366)	(0,059674)
Inactive	−0, 01543	−0, 06620***	−0, 01653
	(0,024195)	(0,019216)	(0,026184)
Adjusted R-Square	0.326	0.4527	0.3797
Sample size	9161	11663	9179

Standard errors in parentheses. Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1.

Table 11: Maximum Likelihood and GMM Estimates of the SEM Model

	SEM-ML	SEM-GMM
Intercept	$13,23625^{***}$	$13,23627^{***}$
	(0,037374)	(0,037209)
Rural	$-0,34549^{***}$	$-0,34684^{***}$
	(0,022965)	(0,022439)
Age	$0,001094^{***}$	$0,001090^{***}$
	(0,000410)	(0,000411)
Female	$-0,01169$	$-0,01151$
	(0,014108)	(0,014138)
Household size	$-0,10720^{***}$	$-0,10715^{***}$
	(0,001678)	(0,001680)
Primary	$0,099052^{***}$	$0,099224^{***}$
	(0,023066)	(0,023118)
General secondary	$0,197598^{***}$	$0,198353^{***}$
	(0,024547)	(0,024600)
Technical high school	$0,285195^{***}$	$0,286191^{***}$
	(0,081784)	(0,081981)
Tertiary	$0,301078^{***}$	$0,302348^{***}$
	(0,033750)	(0,033819)
Traditional	$0,047420^{***}$	$0,047743^{***}$
	(0,018274)	(0,018314)
Alphabétisation	$0,184979$	$0,184903$
	(0,116369)	(0,116644)
Private sector	$-0,05919^{**}$	$-0,05900^{**}$
	(0,024806)	(0,024860)
Self-employed agricultural	$-0,03226$	$-0,03260$
	(0,027313)	(0,027369)
Self-employed non-agricultural	$-0,04312^{**}$	$-0,04293^{**}$
	(0,021382)	(0,021427)
Household aids and other	$-0,05969^{**}$	$-0,05973^{**}$
	(0,027368)	(0,027424)
Unemployed	$-0,20695^{***}$	$-0,20692^{***}$
	(0,054748)	(0,054880)
Inactive	$-0,04481^{*}$	$-0,04447^{*}$
	(0,024233)	(0,024288)
λ	$0,609619^{***}$	$0,594895^{***}$
	(0,015276)	(0,066668)
Sample size	9179	9179

Standard errors in parentheses. Standard errors in parentheses. Significance Codes, *** : 0.01; ** : 0.05; * : 0.1. Note: The comparison of the results of ML and GMM shows that both estimation methods yield similar estimates with a diffrence in the asymptotic standard error of the prameter λ, which does not impact its statistical significance.