<u>HIGHER NATIONAL SCHOOL OF MANAGEMENT</u>

Dissertation of obtaining the Master's Degree in Industrial Economics of Infrastructure and Networks

<u>3rd promotion</u>

Theme:

_LOCAL STRUCTURE EFFECTS ON MUNICIPALITY HUMAN DEVELOPMENT INQUALITIES

<u>Presented by</u>:

SEHILI Sihem

<u>Framed by:</u>

Mr. BELARBI Yacine, Director of dissertation, Research Director at CREAD

Mr. TOUMACHE Rachid, Headmaster at ENSSEA

<u>Session: 2014/2015</u>

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Thanking

Praise be to Allah for giving me the courage and the patience to do my research

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My sincere thanks are for my dear parents, my brothers and sisters, my fiancé and all my family.

Thanks to all my friends

ABSTRACT:

In This research work we estimate human development index, at a thin disaggregated level using census municipal-based data. However, for the absence of information at the municipal income per capita data reasons, we use another assets index of household infrastructure, and ownership of certain durable assets.

We suggest an estimating human development index indicators at municipal level to unveil their distribution with unprecedented geographical coverage and detail. Then we specify which spatial model is appropriate to our human development spreads into municipalities.

RESUME:

Dons ce travail de recherche, nous estimons l'indice de développement humain, à un niveau désagrégé très fin en utilisant la base de données municipal du recensement, nous examinons après en absence d'informations sur le revenu par habitant le recours à l'utilisons d'un indice des actifs concernant les infrastructures des ménages, et la propriété de certains biens durables.

Nous proposons une estimation indicatrice des droits de l'indice de développement au niveau municipal pour éclairer leur distribution avec une avec des cartes géographique. Ensuite, nous spécifions le modèle spatial appropriée à notre indice de développement humain.

ملخص:

هذا البحث في محاولة لإعطاء تقدير لمؤشر التنمية البشرية على المستوى التفصيلي جدا باستخدام قاعدة بيانات التعداد البلدي ونظرا لغياب المعلومات عن نصيب الفرد من الدخل سوف نقوم باستخدام مؤشر آخرو هو عبارة عن مؤشر الأصول للبنية التحتية ألمنزلية والسلع المعمرة.

نقترح تقدير مؤشر التنمية البشرية على مستوى البلديات للكشف عن كيفية توزيعها عن طريق التغطية الجغرافية ثم بتحديد نموذج المكاني وملائمة لمؤشر التنمية البشرية لدينا

Key words: human development index, spatial dependence, Gini index, municipal based, inequality adjusted.

Les mots clés: Indice de développement humain, la dépendance spatiale, l'indice de Gini, base communale, les inégalités ajustés.

الكلمات الرئيسية: مؤشر التنمية البشرية، الاعتماد المكاني، مؤشر جيني، قوائم البلديات ، تعديل عدم المساواة

ABBREVIATION LIST:

- **HDI**: human development index
- **E:** education
- **H:** health
- **W:** wealth
- **AYS:** average years schooling
- **EYS:** expected years schooling
- **Pmax:** maximum probability
- **Pmin:** minimum probability
- **GNI:** gross national income
- **SAR:** spatial autoregressive
- **SEM:** spatial error model

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GENERAL INTRODUCTION

After the first introduction of human development index as a measure of the welfare of a society in human development report (1990, 1991, 1992, 1993, 1994, 1995…2014) this index has become an important alternative helped to expend the focus of economic development to include wider questions of human development well-being and quality of life. The exact choice of this socioeconomic indicator in order to summary and measure human development achievements, and to show the deprivation of the aspect of resources and opportunities.

Few scholars argued that development should be seen as creating the condition for realization of human potentiality (seers 1972). Other suggested the satisfaction of basic needs as a replacement for purely macroeconomic objectives (Hicks and Streeten, 1979), the most recent attempt in constructing a measure of human development index (HDI) by the UNDP, while the HDI measures achievements in basic commodity, knowledge, and life opportunities, the mean of opportunities is to express a freedom to achieve estimable ends in life (Amartya Sen 1994)

This HDI is constructed on the basic of household surveys, however, this more detailed spatial information is crucial for a variety of purposes ranging from academic research to the design of development policies.

In the three composite of human development such as **education**, seen as people choices to acquire knowledge, **health** indicate ability of person's to live a long and healthy life, **wealth** seen instrumentally as means to acquire basic goods and services, indicating persons access to resources. So HDI based on this in three dimensions of life are also averages conceal widespread human disparities and inequality, but we can see deficiencies resulting from inequality which is significant for economic and ethical analysis. Inequality in health, education, and wealth deeply impact progress towards increasing human development our physical and social characteristics make us immensely diverse creatures, we differ in age, sex, physical, social, health, intellectual abilities, climatic circumstances, epidemiological, and many other respects. However these diversities are very hard, accommodate adequately in the usual evaluative framework of inequality assessment.

The conceptual difficulties is no consensus about how to measure inequality in the HD, and the lake of disaggregated data, is given as major obstacles for not adjusting the HDI, but generally the measuring of inequality have been developed in relation to the unequal distribution of income and wealth.

However the object of this research work, is trying to construct a municipal-based in order to estimate multidimensional HDI in 1541 municipalities in Algeria with geographical coverage, we constructs a Gini index in order to determine which type of spatial model is appropriate for the spread of our HDI, after that we measure inequalities between municipalities for the two dimensions wealth, and education we can't calculate the index and Gini index for the third dimension that is health, because of the lack of appropriate data at the municipal level. The results are combined with data from HDI to produce an Inequality-Adjusted human development index. Knowing that the principal tragedy in Algeria is the scarcity of census data, and the lack of access to the existing data, yet much of the micro data are not available for scientific or policy research.

In order to elucidate the importance of the human development index, we try to answer this following questions:

- **Does human development incorporate distributional inequalities of the three dimensions health, wealth, and education in municipalities of Algeria?**
- **How is the spatial distribution of the human development in municipalities of Algeria?**
- **How can inequality adjusted human development index IHDI adjusts the human development index within a country?**
- **Which type of spatial dependence exists between municipalities?**

To answer previous questions we suggest the following hypotheses:

- The municipalities of Algeria have a medium human development index
- There are significant inequality between the municipalities
- The lagged spatial model is the appropriate model of our HDI spread into municipalities

CHAPTER I:

THE HUMAN DEVELOPMENT INDEX

The first HD Report admit that development is much more than expansion of income, and wealth[1], and defines HD as the process of enlarging people's choices, HDI of country is defined as a measure of its human development along the three dimension, which are health, wealth, and education.

Human development can be shortly defined as a capability set expansion which increases individual's freedom to achieve valuable functioning. Functioning are a person's states of being, doing and becoming. In this chapter we present the methodological used to estimate and analysis data, we'll explain the choice of municipal- based as unit of analysis, finely the components and structure of HDI.

[1] The debate on the concept of development, however, continued. For example see Sen (1988;1990), Ambuj D. Sagar, Adil Najam (1998), Haq (1995)

SECTION1: APPROACH AND METHODOLOGICAL PRINCIPLES

In this section we present the methodology used to estimate human development index at municipal scale using census data. As is well known, the HDI has three components: health, education and standard of living. Rather than coarsely mimicking the original HDI and using exactly the same variables initially defined at the national level we find it more appropriate to adapt the methodology by picking other variables that are more meaningful at municipal level. On the positive side, the exhaustiveness of census data allows estimating the spatial distribution of human development levels with unprecedented geographical coverage of the municipalities of Algeria.

1.1 **Study objects:**

The reference term of research work is the elaboration of HDI map, in order to visualize how HD is propagated in Algeria, we choice the municipality as unit of analysis, in order to have indicators at the lowest possible aggregation level.

This present work has for object to knowing better as possible municipality’s population, to localize the one how have lowest, and highest human development index, to measure their health, wealth, and education welfare state.

Before every step of research we must know the three fundament questions of our study research, Can we construct HDI at the municipal level, with the official component published in HDR? , which spatial model is appropriate for our HDI spread? Does exist a significant inequality between municipalities, which we can adjust?

a. Which spatial model is appropriate for our HDI spread?

Act to draw up a spatial error model or spatial lagged model of our human development spread into municipalities

b. Can we construct HDI at municipal level, with the official component published in HDR?

The municipal human development index proposed in this dissertation, resembles the “classical” HDI, but these measures are not exactly the same because they are based on different indicators, so our municipal HDI, is not strictly comparable with the official HDI published in the HDRs

c. Does exist a significant inequality between municipalities, which we can adjust?

Given the differences which exist between the Algerian Municipalities, see education, health and standard of living, we assume that it will be a significate Inequality between 1541 this municipalities.

Objective[2]

The knowledge:

- State of HDI in some municipality.
- Reflecting capacity of organization and act.
- Condition of education and wealth in some municipalities.
- Significant inequality between municipalities

Aim to → the distribution of human development with geographical coverage in order to visualize the well-being of populations in Algeria , establish which spatial model the human development spread into municipalities of Algeria

2.1 Methodology:

a. approach:

Given the complexity of the phenomenon, and to respond to three questions that underlie the approach, investigations and analyzes were conducted on the basis of operation of investigations in two ways:

Territorial:

By identifying local causes inequality and highlighting the impact of the environment, whether natural, geographical or economic on the living conditions of the population residents, in assessing the capacity for action joint Development territories which they are responsible.

[2] United Nation & l’Agence Nationale d’Aménagement du Territoire, ‘’Etude d’affinement de la carte de la pauvreté de 2000 Communes pauvres : territoires, populations et capacités d’action’’, rapport de synthèse Mars 2006. Publication Ministère de la Solidarité Nationale, de la Famille et de la Communauté Nationale à l’Etranger

Study population:

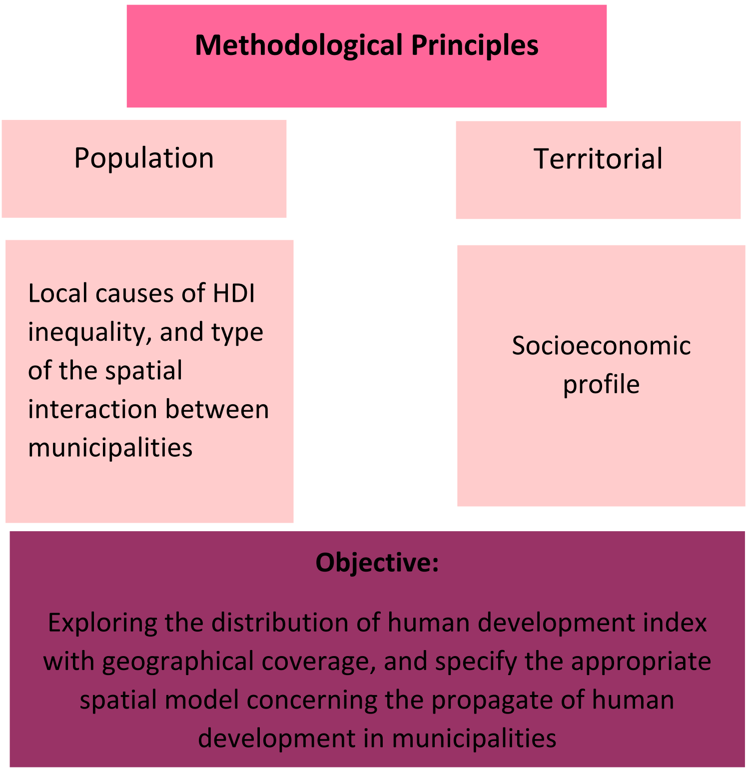
By refining the socioeconomic profile of municipalities, their condition of life, level of education, and their standard of living. And how we can adjusted inequality

b. tool of analysis:

We use two software for our geographical coverage and spatial model

-The first is ***MapInfo*** for the wealth, education, and HDI coverage

-The second is ***MATLAB*** for specifying which spatial model our index follow.



3.1 Scope of the study:

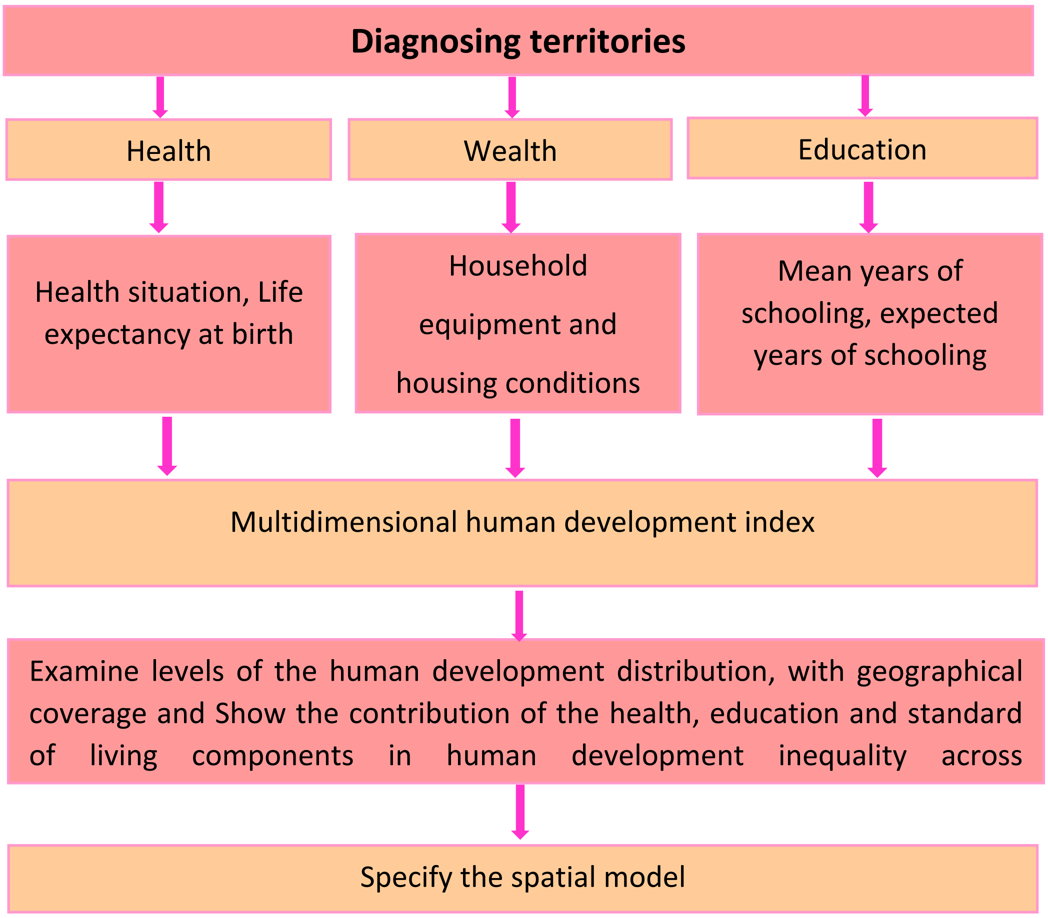
Our field of work will focus in 1541 Algerian Municipalities, which some of them have a very highest HDI " hydra", and some of them have a very lowest HDI "Tassadane"

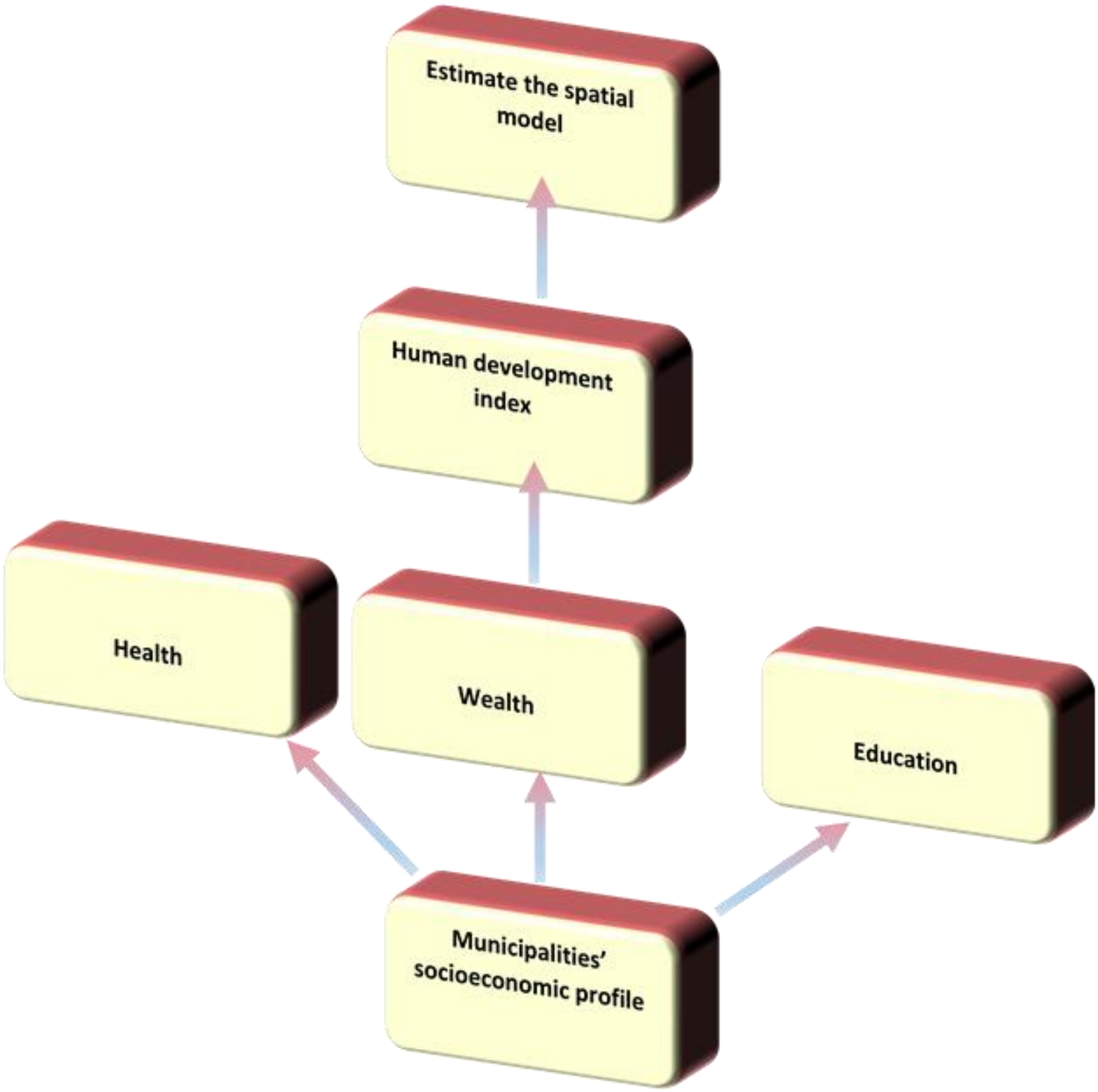
4.1 Analysis method:

- <u>Diagnosing territories</u>

The analysis was based on the collected data from different sources, in purposively and documented for their exploitation in "sheets communal "with the following topics:

1. Identification of the town;
2. household equipment and housing conditions;
3. Educational facilities, and level;




Estimate the spatial model
Human development index
Health
Wealth
Education
Municipalities' socioeconomic profile

SECTION 2: MUNICIPAL-BASED OF ALGERIA AS UNIT OF ANALYSIS

The choice of municipality[3] as unit of analysis has been basically determined by data constraints. Ideally, one would like to have indicators at the lowest possible aggregation level but census data have certain limitations in this respect. While it is possible to construct reasonably good education indicators at individual level and standard of living indicators at the household level, census data just allow constructing reasonably good health indicators at municipal level. An adverse implication of working at municipal level is that intra-municipal variability in human development is lost.

After computing the municipal-based health (Hi), education (Ei) and standard of living (Wi) components, their values are aggregated to obtain the corresponding municipal-based HDI. From 1990 to 2009, the HDI has been calculated using the arithmetic mean of its three subcomponents (Hi + Ei + Wi)/3) and from 2010 onwards, the HDI uses the Geometric mean

$\sqrt[3]{\mathrm{Hi} * \mathrm{Ei} * \mathrm{Wi}}$. Henceforth, the additive and multiplicative versions of the municipal-based HDI will be referred to as MHDIa and MHDIm, respectively. Both of them have their corresponding advantages and disadvantages. The multiplicative HDI does not allow for perfect substitutability between health, education and standard of living and penalizes those municipalities with unequal achievements across components. In other words: it rewards those municipalities with balanced distributions across components. In this regard, we consider that the choice of geometric means to average achievement levels is a step in the right direction as long as none of the components of the index can take a value of zero. When that happens, the whole HDI is dragged to zero. While some might find this to be a normatively attractive characteristic of the index, it appears exaggerated to conclude that human development is zero whenever one component equals zero (irrespective of the achievements in the other two). In general, this problem can be more acute when the units of analysis are very small (as it becomes increasingly possible that some of the components of the index equals zero). In fact, this problem has been encountered in the household-based HDI presented by Harttgen and Klasen (2011b), where many households contain adults with no education. As a consequence, the large inequality levels in human development might be an artifact of the way in which the HDI was constructed, so they

[3] Iñaki Permanyer, Albert Esteve-Palos, Joan Garcia, and Robert McCaa, 2013,'' Human Development Index-like Small Area Estimates for Africa computed from IPUMS-International integrated census microdata'', Equalitas.

might be distorted to a certain extent. It is worth emphasizing that when the new multiplicative HDI was presented in the 2010 Human Development Report, the aforementioned problem of the geometric mean at the boundaries of the domain was not encountered because country averages are always strictly greater than zero. In our empirical illustration for Mexico (see Section 3), the municipal averages of the different components are strictly positive, so the values of MHDIm are neither affected by that problem. The additive HDI allows for perfect substitutability between components, so a decrease of one unit in one component can be compensated by an increase of one unit in any other component. Therefore, MHDIa is insensitive to the extent to which achievements across components are balanced or not. These shortcomings motivated the construction of a multiplicative HDI in the 2010 Human Development Report. Despite these inconveniences there are two advantages of technical nature: an additive HDI does not have the boundary problems of the multiplicative HDI and it allows knowing the contribution of the different components to overall inequality in human development, an issue to which we now turn.

SECTION3: THE COMPONENTS AND STRUCTURE OF THE HDI

The human development index is compound of three indicators, they reflect the major dimension of human development: health, wealth, and education, these are to represent three of the essential choices ' for people to lead a long and healthy life, to have access to goods and services needed for a standard living, and to acquire knowledge.

These dimension are derived from the notion of human capabilities, Amartya Sen's[4] idea constitute the core principal of a development approach, this approach is a paradigm based on the concept of well-being that can help define public policy.

As such the process of economic human development can be seen as a process of expanding the capabilities, but we also admit that there are other dimensions which could be regarded as essential, such as law and order, peace, security freedom.

In this section we try to examine the components and structure of human development index.

1.1 The principal components of human development index are[5]:

a. Health:

Health is the most difficult component to estimate at the household level, there no health questions routinely collected in the census questionnaires that can serve the purpose of obtaining estimates in such detail.

At municipal level and for larger geographical units, there are indirect estimation techniques based on two questions[6] collected in census questionnaires which are (1) "how many children have you ever had?", (2) "how many of them are still alive?", that can be used to generate health estimates. These methods, developed by William Brass, basically use information on child survivorship to estimate probabilities of dying at age x, which can later transformed into life tables to estimate life expectancies, this is the method to estimate Life expectancy at birth, number of years a newborn infant could expect to live if prevailing

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[4] Sakiko, Fukuda-Parr, 2003, '' the human development paradigm: operationalizing Sen's idea on capabilities." Feminist economics

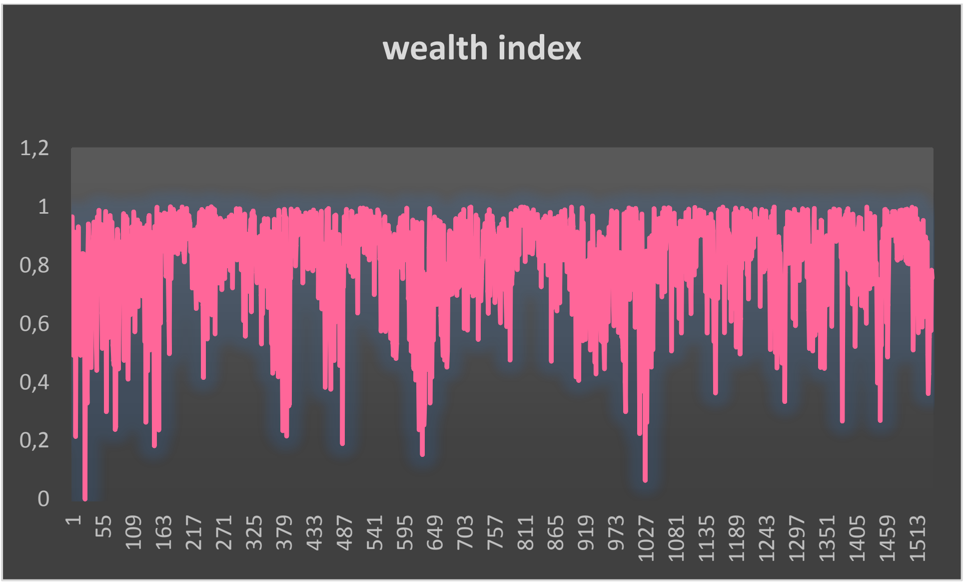
[5] Iñaki Permanyer, Albert Esteve-Palos, Joan Garcia, and Robert McCaa, 2013,'' Human Development Index-like Small Area Estimates for Africa computed from IPUMS-International integrated census microdata'', Equalitas.

[6] They have been included in the recommendation list that united nations issue in order to improve census quality

patterns of age-specific mortality rates at the time of birth stay the same throughout the infant's life

The health indicator for municipalities 'i' will be the percentage of surviving children born to women in that municipality between ages 20 and 39, which is denoted by P_i. After this the health component has to be normalized between zero and one. We define the municipal level normalized health index as, $H_i = (P_i – P_{max})/ (P_{max} – P_{min})$, where the P_{max}, P_{min} are the natural upper bound representing the case of maximal child survival, and the lowed bounds might be chosen.

Figure 1: distribution of wealth index in 1541 municipalities



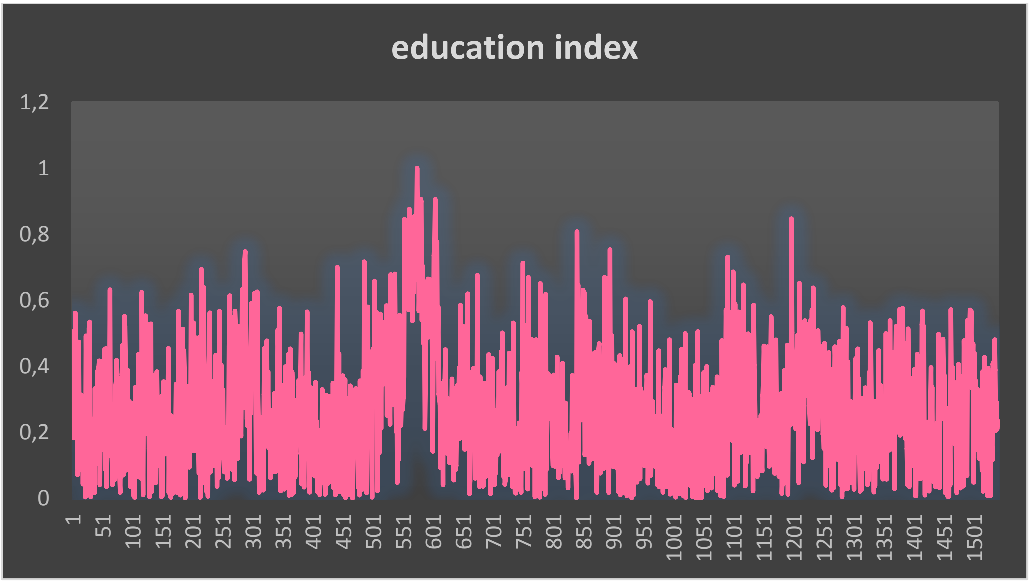
b. Education:

The education component can be estimated at municipal level using census data, for each municipality 'i' we can compute: (1) the average years of schooling of adults aged 25 and more(AYS), is the average number of years of education received by people ages 25 and older, converted from educational attainment levels using official durations of each level. (2) The expected years of education for children in schooling age (EYS), is the number of years of schooling that a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates persist throughout the child's life. Again this indicators must be normalized between zero and one so that they are commensurable with the other dimensions of the composite index, so we have P_{max}, P_{min} for each AYS and EYS

Therefore the normalization formulae are (AYS - P_{min}) / (P_{max} - P_{min}) and

(EYS - P_{min}) / (P_{max} - P_{min}), the education index for municipality 'i' is obtained as geometric mean, that is: $E_i = \sqrt{(AYSi/Pmax)(EYSi/Pmax)}/0.978$, the number 0.978 is a maximum normalizing factor of combined education index[7]. We agree with UNDP that the new variable average of schooling is better than the adult literacy rate, because this rate are already quite high in most part of the word.

Figure 2: the distribution of education index in 1541 municipalities of Algeria



c. Standard of living:

The standard of living dimension is estimated with the Gross National Income (GNI) per capita, estimated GNI per capita Derived from the ratio of female to male wage, female and male shares of economically active population and GNI however, when it comes to estimate any of those figures at municipal level many technical difficulties arise.

In order to fill this gap and to keep our methodology plain and easy we use the asset indices[8] are constructed at the household level (h). Analysts may thus prefer to use the

[7] United Nation (2011). Sustainability and Equity, Human development report. United nations publication
[8] Deon Filmer, Lant H.Pritchett, 2001, ''estimating wealth effects without expenditure data-or tears: an application to educational enrollments in states of India'', Demography, volume.38, No.1 , pp. 115-132

asset index as an explanatory variable or as a means of mapping economic welfare to other living standards and capabilities such as health and nutrition.

$$A_h = \frac{a_{h1} + \cdots \ldots\ldots + a_{hk}}{K} \qquad (1)$$

Where A_h is the asset index for household 'h' and the $a_{hj} \in \{0, 1\}$ refer to the absence/ presence of asset 'j' in household 'h'. A_h is normalized between zero and one, it equal to one if the household owns all assets.

In order to test the sensitivity of our results to the choice of alternative weighting schemes. After computing the asset index A_h for each household in the census, a wealth index W_i, is computed for each municipality 'i' as a weighted arithmetic mean of the asset incises of the households belonging to 'i'. Since the asset index A_h is normalized, W_i is automatically normalized.

Asset indices have been widely used in the literature, because reporting of household assets is less vulnerable to measurement errors than the GNI (McKenzie, 2005). Moreover, asset indices might be a better proxy for long-term living standards than current income because they are less vulnerable to economic shocks fluctuations over time than income or expenditure, something that seems to be in line with the conceptual foundations of asset indices as a proxy for material welfare (that is: income). More recently, Filmer and Scott (2012) attempt to validate the use of the outcomes of assets indices closely follow the results obtained with per capita expenditures. To sum up, even if their values should be taken with caution, asset indices seem a viable way of assessing material welfare.

Table 1 : benchmark values used to normalize the HDI components

Dimensions	indicators	minimum	maximum
Mean years of schooling	AYS	4.675	10.965
Expected years of schooling	EYS	1.355	15.615
wealth	Asset index	0	13

2.1 The structure of HDI:

The Human Development Index (HDI) is a summary measure of human development. It measures the average achievements in a country in three basic dimensions of human development: a long and healthy life, access to knowledge and a decent standard of living. The HDI[9] is the geometric mean of normalized indices measuring achievements in each dimension.

Steps to construct the Human Development Index[10]:

Step1: Having defined the minimum and maximum values, the sub-indices are calculated as follows:

$$\textbf{Dimension index} = \frac{\textbf{actual value} - \textbf{minimum value}}{\textbf{maximum value} - \textbf{minimum value}} \qquad \textbf{(2)}$$

Step2: Aggregating the sub-indices to produce the Human Development Index

The HDI is the geometric mean of the three dimension indices:

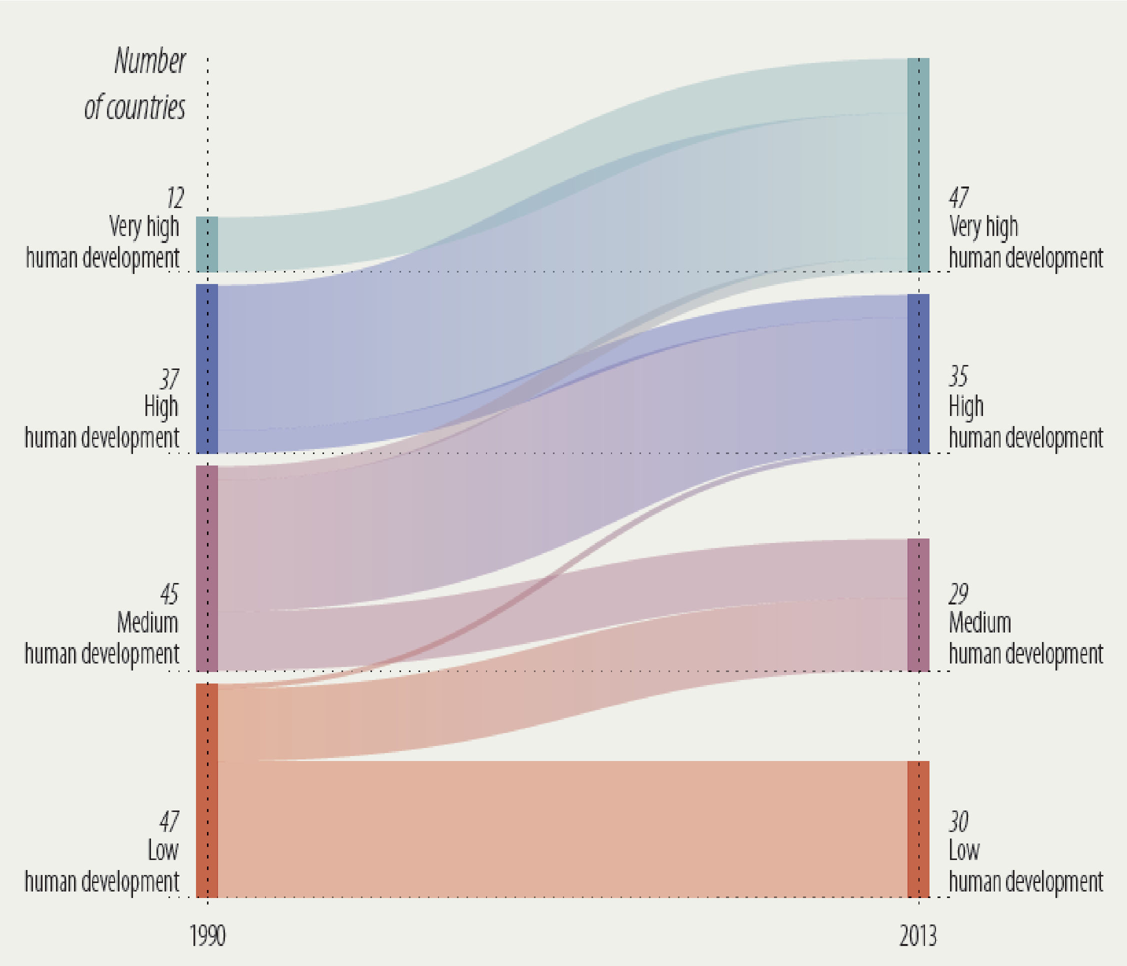
$$(\mathrm{I}\mathit{Life}\ 1/3 * \mathrm{I}\ \mathit{Education}\ 1/3 * \mathrm{I}\mathit{Income}\ 1/3) \qquad (3)$$

We can also calculate HDI as the average of X1, X2, and X3 the indices for standard of living, education, health. We can think of this as a weighted average where each index is weighted equally.

[9] Klugman, J., F. Rodriguez, and H. J. Choi. 2011. "The HDI 2010: New Controversies, Old Critiques." Human Development Research Paper 1.
[10] United Nation (2014). Sustaining Human Progress, Human development report. United nations publication

$$\text{HDI} = \frac{\alpha X1 + \beta X2 + \gamma X3}{\alpha + \beta + \gamma}, \text{ where } \alpha + \beta + \gamma = 1 \qquad (4)$$

Figure 3 : progress to higher human development groups since 1990



Source: Source: Human Development Report 2014

Concluding

We can say that the human development index, which is about expanding people's choices, builds on shared natural resources. Promoting human development requires addressing sustainability—locally, nationally and globally— and this can and should be done in ways that are equitable and empowering.

CHAPTER II:

ESTIMATE HUMAN DEVELOPMENT LEVELS AT MUNICIPAL SCALE

This chapter proposes an estimation of human development index and some of their components at the municipal level, after a small art revue about HDI his different approach and critics.

We use the results of estimation to give a geographical coverage of the HDI and his components, in order to identify geographic patterns, they are not very informative on the exact distribution, but very useful.

SECTION1: ART REVUE

In this section we try to show the different approach and critic of HDI do by another work research, their modification and some improvements on the components. In this approach, development is not defined as an increase in GNP per capita, or in consumption, health, and education measures alone, but as an expansion of capability. Well in the preview work research and human development report some rider criticized on the grounds of harshly curtailing income above a selected threshold and thereby not considering the income differential's, for those countries with relatively high incomes, adequately. This does not seem to be in line with the proposition that higher income would widen people's choice (Trabold-Nubler, 1991). It has also been suggested that there is no reason why the principles of diminishing returns would not be applicable to different components of the index (Kelly, 1991).

The HDI can be sensitive to the selected fixed ranges (min Fj and max Fj) for its components. The UNDP argues that these fixed ''normative'' values have been selected as the extreme values observed or expected over a long period. It may be argued that the expectations of the value of an indicator over a long period is very likely to be a subjective estimate. It may also be said that there are ranges of values for both min Fj and max Fj which may be equally acceptable on the same grounds. However, depending on the selected extreme values the results would be different for each component.

The problem is that as HDI is the average of the sum of three equally weighted indices, it follows that the absolute value of each component will affect the level of HDI. Hence the selected extreme values would affect the value of the index resulting in a change in the ranking order (Noorbakhsh, 1996a).

In general the simple addition of the components HDI has just little justification. To put the argument differently, as the three components of HDI are spread around different means with different variances, the simple averaging of these components for the purpose of building a composite index would be questionable. In addition the means and variances of different components would vary with respect to the selected extreme values for Fj.

Noorbakhsh (1996) suggests a modified human development index which takes into account some of the criticisms mentioned above. Namely by allowing a wider range for ε it allows for wider variations in the income component of the index (see Appendix 4). It also applies the principle of diminishing returns to the educational components. As for the structure of the index itself MHDI removes the scale effect by standardizing the data first. The standardized components would then constitute three vectors in a multidimensional vector space.

Conceptually this makes sense as any index for human development should be defined within the context of all countries. It is possible to demonstrate that the length of these vectors are equal (Noorbakhsh, 1996a).

The HDI has been criticized on the grounds of attaching equal weights to its selected components. Some researchers have argued that as an increase in income can increase people's choice and achieve improvements on other components, it should be given a higher weight (Kelly, 1991). Strictly speaking components of HDI do not carry equal weights. We mentioned before that the choice of max Fj and min Fj would result in different scaling of the components. As the index is the average of these differently scaled components in effect it would attach various weights to the components. This unintentional weighting, however, does not provide an answer to the criticism of equal weighting of components. On the contrary it questions the validity of the HDI.

One of the most frequently used composite indices for ranking a number of cases is the BORDA rule. This index provides a ranking order on the basis of the sum of rankings by individual components. First countries are ranked according to each component. Then these ranks are added in order to find the composite scores. Countries are then ranked on the basis of their composite scores. We used the BORDA rule for finding an alternative human development index and compared its results with other indices. We called this measure BORDA.

In our work research we chose to measure the multidimensional human development index, in reason of municipal-base that we have. Consider how ‘‘dimensions’’ might relate to one approach to development, namely Amartya Sen’s capability approach.

''It represents the various combinations of functioning (beings and doings) that the person can achieve.'' Capabilities may relate to things near to survival or those which are rather less central. The definition of capability does not delimit a certain subset of capabilities as of peculiar importance. Rather Sen argues that the selection of capabilities on which to focus is a value judgement that is to be made explicitly, and in many cases by a process of public debate.

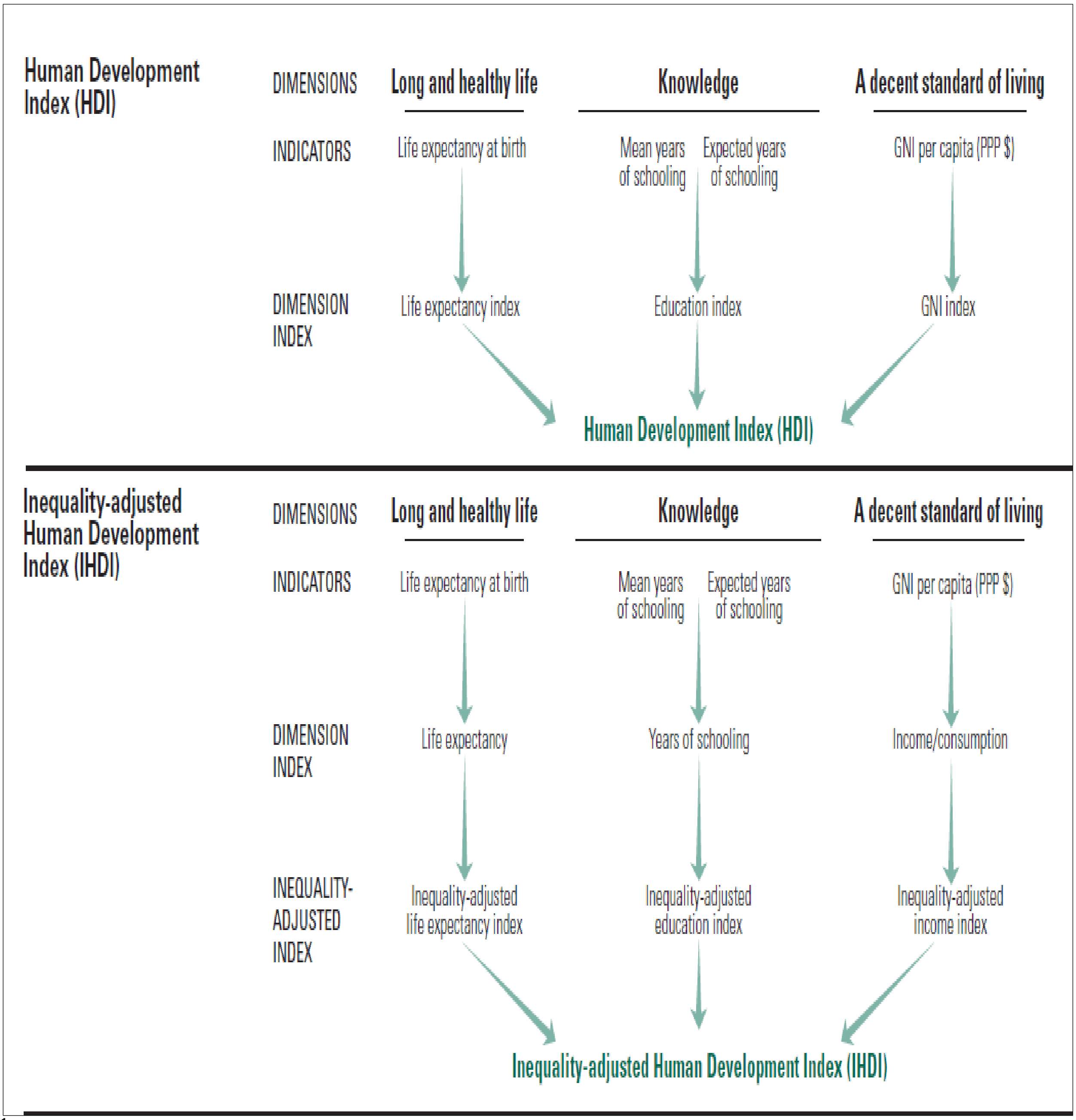
Dimensions of human development are nonhierarchical, irreducible, incommensurable and hence basic kinds of human ends. Dimensions do not derive from nor divide up an idea about what the good life is, but rather are values or ''reasons for action'' which people from different language groups and neighborhoods could recognize based on practical reason that is, on their own experience of figuring out what they are going to do, or on their observation of other people's experience.

Put differently, the dimensions of development are like the ''primary colors'' of values. An infinite range of shades can be made from our primary colors, and not every painting (or life or community or income generation project) uses all or even most shades.

SECTION2: THE ESTIMATION OF HDI

As we tell previously the two steps for estimating human development are, first Creating the dimension indices, by the Minimum and maximum values (goalposts) are set in order to transform the indicators into indices between 0 and 1. The maximums are the highest observed values in the time series (1998–2008). The minimum values can be appropriately conceived of as subsistence values. The minimum values are set at 21 years for life expectancy, at 0 years for both education variables and at $100 for per capita gross national income (GNI). The low value for income can be justified by the considerable amount of unmeasured subsistence and nonmarket production in economies close to the minimum, not captured in the official data.

Figure 4: Calculating the human development indices—graphical presentation



[1]

Source: United nations report 2011

[1] United Nation (2014). Sustaining Human Progress, Human development report. United nations publication

Table 2 : Goalposts for the Human Development Index[2]

Dimension	Observed maximum	Minimum
Life expectancy	83.4 (Japan, 2011)	20.0
Mean years of schooling	13.1 (Czech Republic, 2005)	0
Expected years of schooling	18.0 (capped at)	0
Combined education index	0.978 (New Zealand, 2010)	0
Per capita income (PPP $)	107,721 (Qatar, 2011)	100

Having defined the minimum and maximum values, the sub-indices are calculated as follows:

$$\textbf{Dimension index} = \frac{\textbf{actual value} - \textbf{minimum value}}{\textbf{maximum value} - \textbf{minimum value}}$$

For education, equation 1 is applied to each of the two subcomponents, then a geometric mean of the resulting indices is created and finally, equation 1 is reapplied to the geometric mean of the indices using 0 as the minimum and the highest geometric mean of the resulting indices for the time period unde7r consideration as the maximum. This is equivalent to applying equation 1 directly to the geometric mean of the two subcomponents. Because each dimension index is a proxy for capabilities in the corresponding dimension. Thus, for income the natural logarithm of the actual minimum and maximum values is used.

[2] United Nation (2014). Sustainability and Equity, Human development report. United nations publication

And second consist to aggregating the sub-indices to produce the Human Development Index.

Table 3 : Example of Alegria

Indicator	Value
Life expectancy at birth (years)	**71**
Mean years of schooling (years)	**7,6**
Expected years of schooling (years)	**14**
GNI per capita (PPP DA)	**12.55**

Life expectancy at birth: $\frac{71-20}{83.4-20}$ = 0.804

Mean years of schooling index: $\frac{7.6-0}{13.1-0}$ = 0.58

Expected years of schooling index: $\frac{14-0}{18-0}$ = 0.77

Education index: $\frac{\sqrt{0.58*0.77}-0}{0.978-0}$ = 0.683

Income index: $\frac{\ln(12.55)-\ln(100)}{\ln(107.721)-\ln(100)}$ = 0.276

Human Development Index: $\sqrt[3]{0.804*0.683*0.276}$ = 0.533

SECTION2: AN EMPIRICAL ILLUSTRATION

In this section we illustrate the usefulness of our methodology by examining the Municipal HDI values in years 2008 for the case of Algeria. Algeria is classified as a country with "High Human Development" according to UNDP's classification. Its country-level HDI values in the years 1990, 2000 and 2014 were equal to 0.55, 0.624 and 0.717, respectively (using the new HDI methodology), in our years of study, the number of municipalities in Algeria was 676, 703 and 1541 respectively. This increase in the number of municipalities has also been observed in all other countries in the region of Arab states. The congruity between municipalities over the different census rounds has been very high.

(a) Data and definitions:

In order to estimate the municipal-based HDI we have used census data from Centre de Recherches en Economie Applique pour le Développement (CREAD), the division of Human Development and Social Economic.

Since the population in Algeria in our year of study is 40 million individuals, respectively, the computation of our municipal-based HDIs required the manipulation of hundreds of millions of observations.

For the construction of the asset index A_h (see Eqn. (1)) we have used the following list of household assets: (1) Has piped water; (2) Has flush toilet; (3) Has quality floors; (4) Has quality walls; (5) Has quality roof; (6) Has electricity; (7) Has parabole; (8) Has TV; (9) Has refrigerator; (10) Has phone; (11); Has internet (12); Has car(13). Therefore, the normalizing factor k equals 13 in our empirical illustration (see Eqn. (1) and Table 1). Their inclusion would seriously compromise comparability over time, so we have preferred to keep the reduced list of assets. While this might probably give an overoptimistic impression of the "true" standard of living in

Algerian municipalities for the year 2008, we contend it still can be useful to monitor the levels of some basic human capabilities that are needed to lead a minimally decent life. In order to make comparisons over time meaningful, we have used the same normalizing benchmark values in all indicators for the three censuses (see Table 1).

The asset index presented in this dissertation has been constructed as a synthetic index using equal weights (EW). In order to check the robustness of our results to the choice of alternative weighting schemes we have performed some sensitivity analysis. For that purpose we have derived new sets of weights using Principal Component Analysis

(b) *Results:*

Figure 5 : density functions of the municipal human development index for years 2008 (Algeria). The mean values of the density functions are 0.65, our calculations using census data

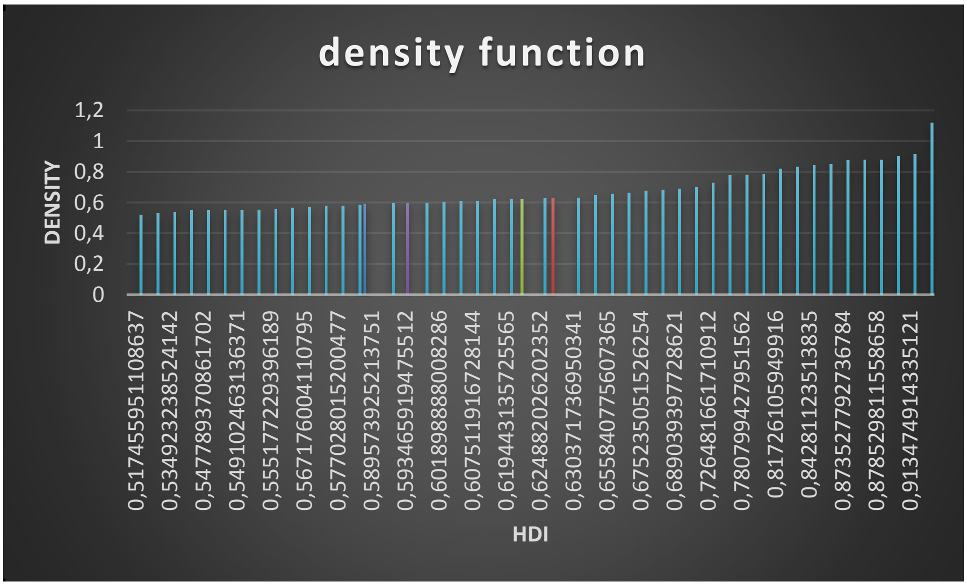
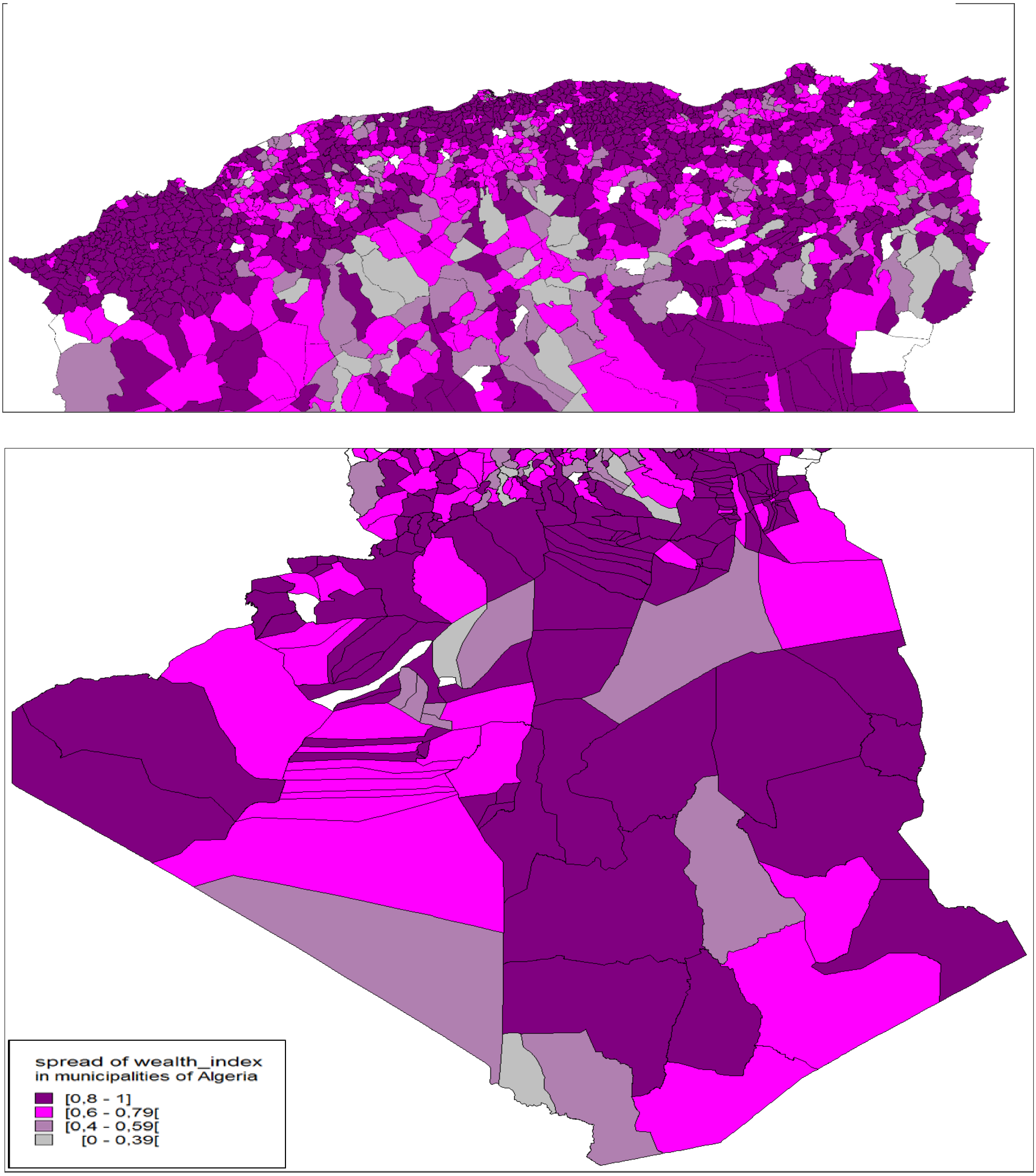


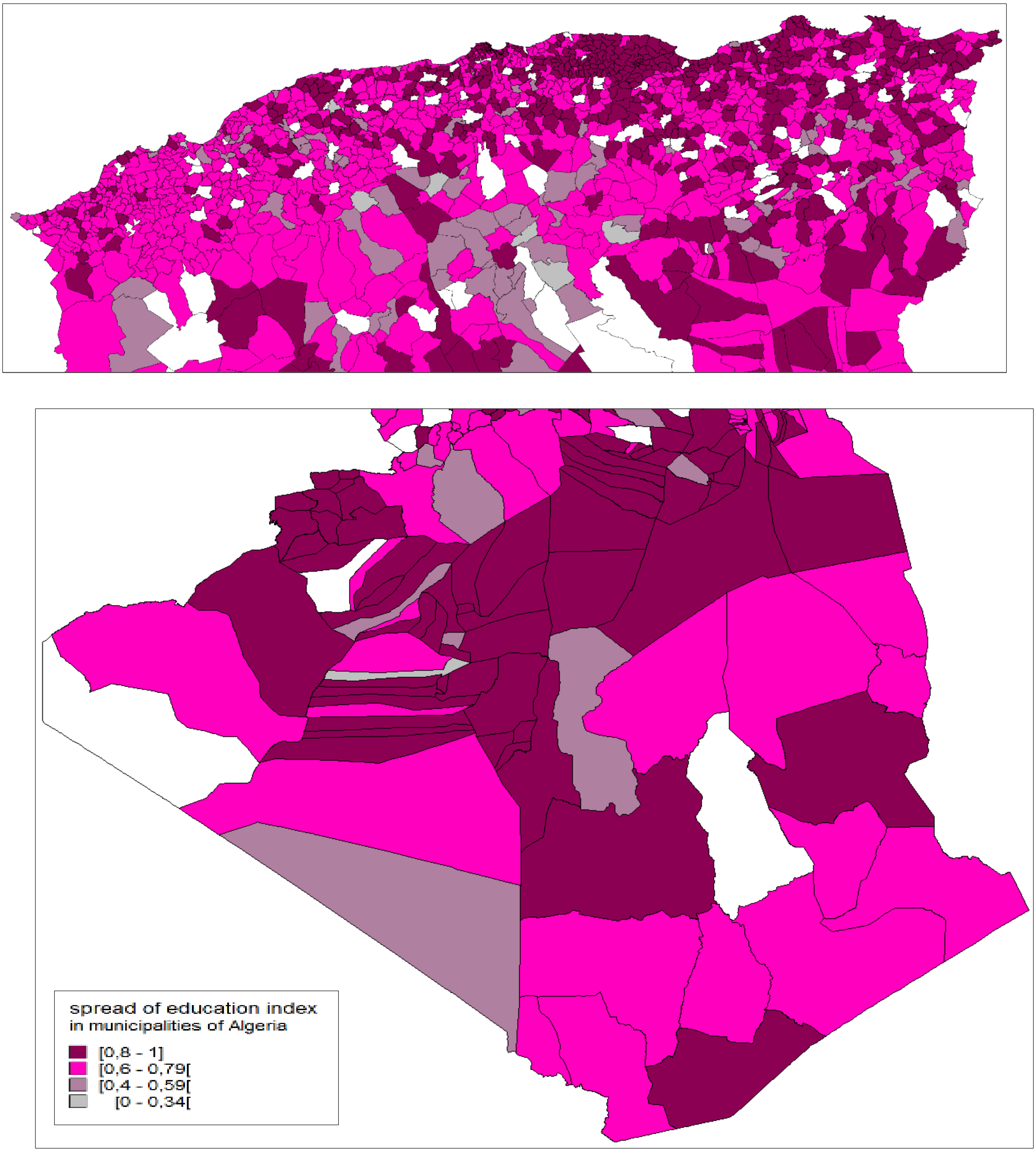
Figure2 shows the density functions of the HDI values corresponding to the census rounds 2008, respectively. These density functions indicate at least three things: (i) the average value of MHD has clearly the distributions become gradually skewed to the left. Overall, these are very encouraging results suggesting that the HDI distribution in Algeria has clearly improved over time and reduced inequality across municipalities in line with the impressions obtained from Figures 3, 4, 5 and 6. The implications of these results, however, need to be qualified and discussed in more detail.

Figure 6 : geographic coverage of wealth index in municipalities of Algeria



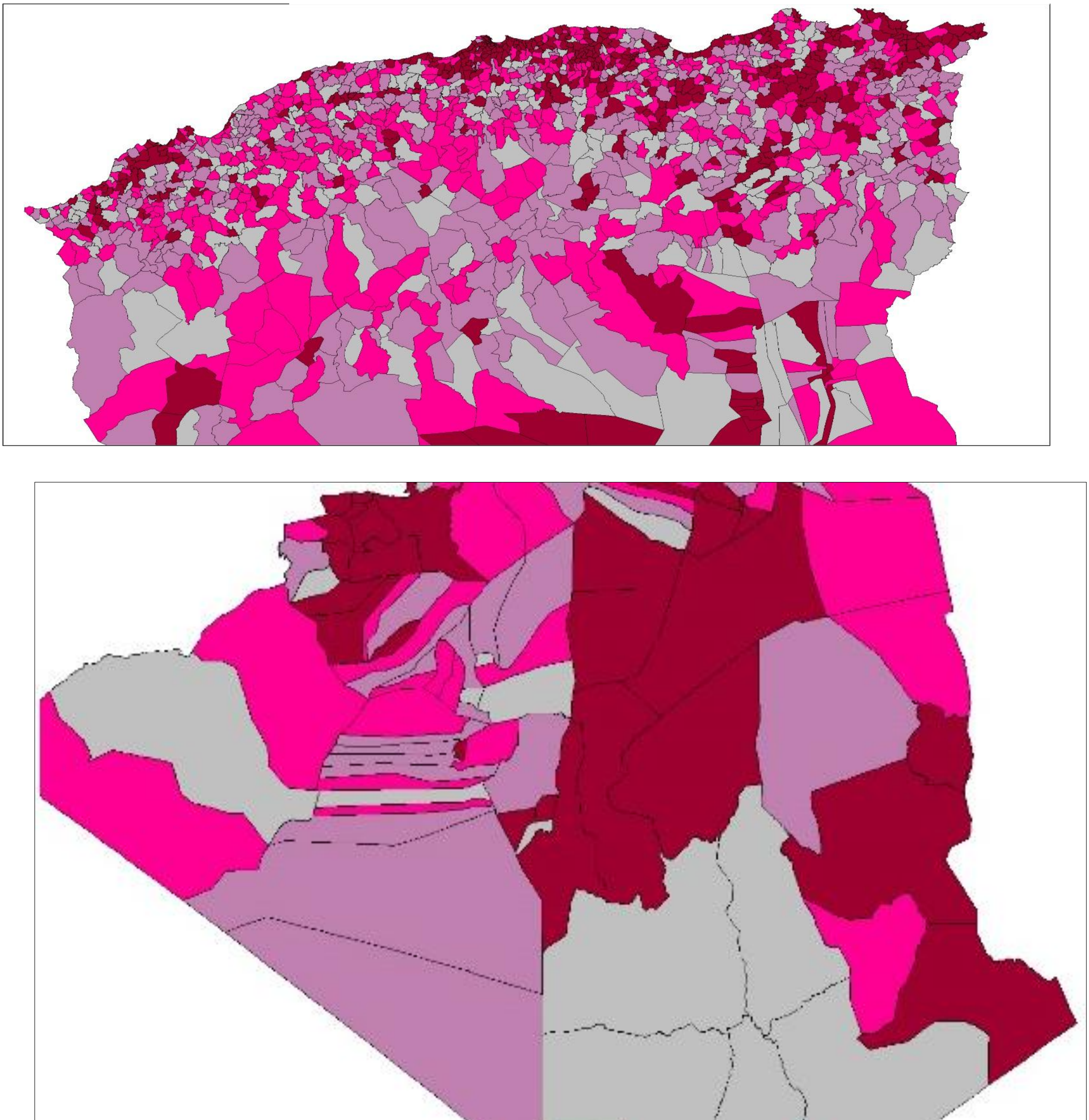
Source: established by ourselves, based on census data RGPH 2008

Figure 7 : geographic coverage of education index in municipalities of Algeria



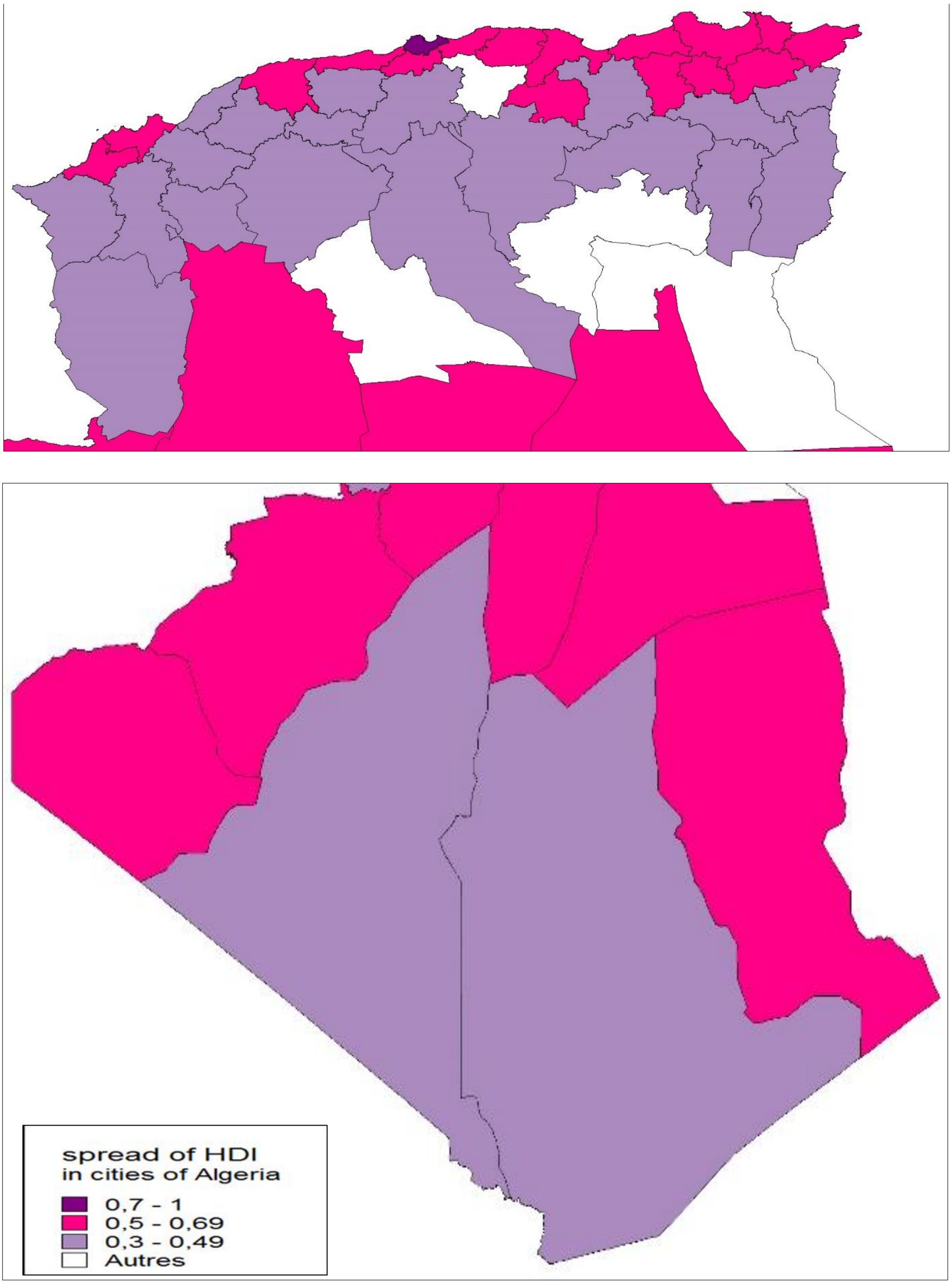
Source: established by ourselves, based on census data RGPH 2008

Figure 8 : geographic coverage of HDI in municipalities of Algeria



Source: Source: established by ourselves, based on census data RGPH 2008

Figure 9 : geographic coverage of HDI index in cities of Algeria



Source: Source: established by ourselves, based on census data RGPH 2008

Distribution of human development and its components

While the maps shown in Figures 3, 4, 5, and 6 are very useful to identify geographic patterns, they are not very informative on exact distribution of HDI, education, and wealth values across municipalities. One of the most attractive features of using census data is that they allow exploring with great detail the spatial distribution of our human development indicators. Figure 4 maps the values of MHD for the Algerian municipalities in 2008.

This map summarizes a wealth of information that is much more informative than the corresponding national-level average HDI. A glimpse at Figure 4 clearly shows that human development is not evenly distributed across the cities and that it seems to follow a spatial pattern where less developed municipalities tend to be surrounded by less developed municipalities as well and vice versa. It can be seen that large metropolitan areas like Algiers, Annaba, high human development levels, as opposed to what is observed in more rural areas of the country. Algiers, which is Algeria's largest metropolitan area, is surrounded by a ring of municipalities with substantially medium human development levels. Figure 4 maps the values of HDI years later. The patterns of inequality appear to be roughly the same after two decades: Large metropolitan areas tend to have higher human development levels than rural areas and Algiers City is surrounded by a ring of municipalities with relatively medium human development levels.

CONCLUDING:

In this chapter, we reviewed the measurement of human development index, and his components, with geographical coverage, in order to visualize how the HDI and his components spreads into municipalities. We discover that the majority of the Algerian's municipalities have a medium human development index, caused by the unfavorable quality of education. We conclude that the dimension are correlated, that's mean when one dimension increased it implicate that the other dimensions go better.

CHAPTERIII:

ESTIMATE HUMAN DEVELOPMENT LEVEAT MUNICIPAL SCALE

In this chapter we give a short explanation about the spatial models their estimation, specification test, and which type of spatial dependence our HDI spread into municipalities, the spatial dependence can be incorporated in two distinct ways: as an additional regressor in the form of a spatially lagged dependent variable (Wy), or in the error structure ($E[\varepsilon_i, \varepsilon_j] \neq 0$). The former is referred to as a spatial lag model and is appropriate when the focus of interest is the assessment of the existence and strength of spatial interaction. This is interpreted as substantive spatial dependence in the sense of being directly related to a spatial model. Spatial dependence in the regression disturbance term, or a spatial error model can take any of the forms and is referred to as nuisance dependence. This is appropriate when the concern is with correcting for the potentially biasing influence of the spatial autocorrelation, due to the use of spatial data.

SECTION1: THE SPATIAL DEPENDENCE

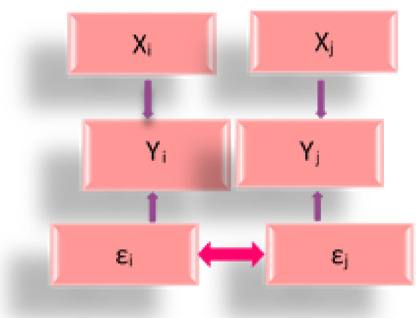
When a value observed in one location depends on the values observed at neighboring locations, there is a spatial dependence. And spatial data may show spatial dependence in the variables and error terms.

Why should spatial dependence occur? There are two reasons commonly given. First, data collection of observations associated with spatial units may reflect measurement error. This happens when the administrative boundaries for collecting information do not accurately reflect the nature of the underlying process generating the sample data.

A second and perhaps more important reason for spatial dependence is that the spatial dimension of social and economic may truly be an important aspect of a modeling. Based on the premise that location and distance are important forces at work, regional science theory relies on notions of spatial interaction and diffusion effects, hierarachies of place and spatial spillovers.

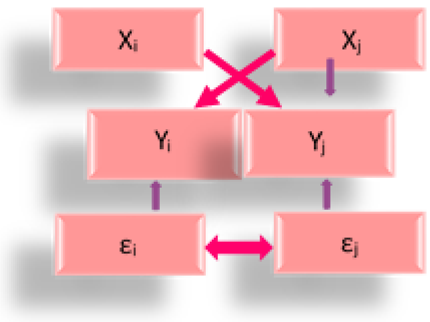
There are two primary types of spatial dependence:

- Spatial error: the error terms across different spatial units are correlated



With spatial error in OLS regression, the assumption of uncorrelated error terms is violated. As a result, the estimates are inefficient. Spatial error is indicative of omitted covariates that if left unattended would affect inference

- Spatial lag: the dependent variable Y in place i is affected by the independent variables in both place i and j.



With spatial lag in OLS regression, the assumption of uncorrelated error terms is violated; in addition, the assumption of independent observations is also violated. As a result, the estimates are biased and inefficient. Spatial lag is suggestive of a possible diffusion process, event in one place predict an increased likelihood of similar events in neighboring places.

- The various models:

(1) $y = X\beta + \varepsilon$ (OLS)

(2) $y = \rho Wy + X\beta + WX\theta + \mu$, $\mu = \lambda W\mu + \varepsilon$ (Maneski model)

*If $\theta = 0$ then Manski becomes te Kelejian Prucha Model

(3) $y = \rho Wy + X\beta + \mu$, $\mu = \lambda W\mu + \varepsilon$

*Or if $\lambda = 0$, we get the spatial Durbin model (SDM) Lesage & Pace

(4) $y = \rho Wy + X\beta + WX\theta + \varepsilon$ Spatial Durbin

* If $\rho=0$, then this becomes the spatially lagged X (SLX) model

(5) $y = X\beta + WX\theta + \varepsilon$

* If $\theta = 0$, then (4) degenerates into the spatial lag model

(6) $y = \rho Wy + X\beta + \varepsilon$ Spatial Lag, Spatial Autoregressive (SAR)

*If $\theta= -\rho\beta$, then (5) simplifies into the spatial error model (because $\lambda=\rho$ in this case).

$y=\rho Wy+X\beta+ WX[\theta=-\rho\beta]+\varepsilon$

$y=\rho\, W[X\beta+\varepsilon]+ X\beta+WX[-\rho\beta]+\varepsilon$

y=ρ WXβ+ρ Wε+ Xβ+ WX[$-\rho\beta$]+ε

(7) y = Xβ + μ, μ = λWμ + ε, where ε~ $i.i.d.$ Spatial error (SEM)

SECTION2: SPATIALLY LAGGED MODEL AND SPATIAL ERROR MODELS

In a cross-sectional setting with N observations, there is insufficient information to estimate the N by N covariance matrix directly from the data. Even asymptotic are not helpful since the number of covariance increases with, whereas the sample size only grows with N. In contrast, when repeated observations on the cross-section are available (as in a panel data setting), it may be possible to exploit the other dimension and obtain consistent nonparametric cross-sectional covariance matrix estimates.4 In general however, it will be necessary to impose a structure on the covariance.

There are three main approaches followed in the literature to address this issue: one based on the specification of a spatial stochastic process; a second on the direct parametric representation of the covariance structure; and a third where the covariance is left generally unspecified and treated in a non-parametric framework. I return to this issue in the next section. First, it is important to consider the important concepts of spatial weights and spatial lag operator.

A- SPATIALLY LAGGED MODEL

In parallel to time series analysis, spatial stochastic processes are categorized as spatial autoregressive (SAR) and spatial moving average (SMA) processes, although there are several important differences between the cross-sectional and time series contexts. Most importantly, in contrast to the unambiguous notion of a “shift” along the time axis, there is no corresponding concept in the spatial domain, especially when observations are located irregularly in space. Instead of the notion of shift, a spatial lag operator is used, which is a weighted average of random variables at “neighboring” locations. Essential in this concept is the definition of a neighborhood set for each location. This is obtained by specifying for each location i (as the row) the neighbors as the columns corresponding to non-zero elements in a fixed (non-stochastic) and positive N by N spatial weights matrix W. Formally, a spatial lag for y at i is then expressed as

$$\mathbf{Wy} = \sum_{j=1}^{N} W_{ij} . Y_j \qquad (1.1)$$

Where y is an N by 1 vector of observations on the random variable. Since for each i the matrix elements W_{ij} are only non-zero for those j ∈ S_j (where Sj is the neighborhood set), only the matching are included in the lag. For ease of interpretation, the elements of the spatial weights matrix are typically row-standardized, such that for each i, $\sum_j w_{ij} = 1$ Consequently, the spatial lag may be interpreted as a weighted average of the neighbors, or as a spatial smoother.

The spatially lagged y model is appropriate when we believe that the values of y in one unit i are directly influenced by the values of y found in I's neighbors. This influence is above and beyond other covariates specific to i. if we believe that y is not influenced directly by the value of y as such among neighbors, but rather that there is some spatially clustered feature that influences the value of y for i and its neighbors but is omitted from the specification we may consider an alternative model with spatially correlated errors, which we discuss subsequently. For the spatially lagged y model to appropriate, the dependent variable y must be considered as a continuous variable. In this monograph, we do not examine the generally more complicated case of binary dependent variables. These are more complicated since they often do not have a closed-form solution and must be estimated with iterative techniques outside the range of this volume (see Ward & Gleditsch 2002).

$$\mathbf{Y = \rho Wy + X\beta + \varepsilon} \qquad \mathbf{(1.2)}$$

Where ρ is a spatial autoregressive coefficient, ε is a vector of error terms, Wy is spatially lagged dependent variable unlike what holds for the time series counterpart of this model, the spatial lag term Wy is correlated with the disturbances, even when the latter are i.i.d. This can be seen from the reduced form of (1).

$$Y = (1 - \rho Wy)^{-1}\ X\beta\ + (1 - \rho Wy)^{-1}\ \varepsilon \qquad (1.3)$$

B- SPATIAL ERROR MODEL MODEL

A spatial error model is a special case of a regression with a non-spherical error term, in which the off-diagonal elements of the covariance matrix express the structure of spatial dependence. Consequently, OLS remains unbiased, but it is no longer efficient and the classical estimators for standard errors will be biased. As outlined in Section 2.3., the spatial structure can be specified in a number of different ways, and (except for the non-parametric approaches) results in an error variance covariance matrix of the form

$$E[\varepsilon \varepsilon'] = \Omega(\Theta)$$

Where Ө is a vector of parameters, such as the coefficients in a SAR or SMA error process. When the error process is SAR, the resulting model can also be expressed as a spatial lag specification, in the form of spatial Durbin or spatial common factor model. The SAR error model is

$$Y = X\beta + \varepsilon, \text{ and } \varepsilon = \lambda W\varepsilon + u \quad (1.4)$$

The spatially lagged dependent variable model sees spatial dependence as substance, in the sense that the Y_i is influenced by the value Y_j for other countries ($j \neq i$), the spatial error model treats spatial correlation primarily as a nuisance, much like statistical approaches often treat temporal serial correlation as something to be eliminated and solely as an estimation problem. This approach generally focuses on estimating the parameters for the independent variables of interest in the systematic part of the model, and essentially disregards the possibility that the observed correlation may reflect something meaningful about the data generation process. Instead of letting Y_i affect Y_j directly, the spatial error model assumes that the errors of a model are spatially correlated.

There are myriad ways in which this could be specified. We focus on a simple one that is based on a coding of the spatial regime in terms of spatial weights; other important approaches focus on geostatistical covariance structures, but we do not examine these in this monograph. Following the earlier notation, if we let W_i denote the vector of W indicating how close other units $j \neq i$, are to i, we can write the spatial error model as follows:

$$Y_i = X_i\beta + \varepsilon_i + \lambda w_i\xi_i$$

Here we have decomposed the overall error into two components, namely ε, a spatially uncorrelated error term that satisfied the normal regression assumption, and ξ, which is a term indicating the spatial component of error term. The parameter λ indicates the extent to which the spatial component of the errors ξ are correlated with one another for nearby observations, as given by the vector of connectivities W_i. Alternatively, we can state the spatial error model in matrix form, based on the terms previously defined in section1:

$$\begin{cases} \mathbf{Y = X\beta + \lambda W\xi + \varepsilon} \\ \mathbf{\varepsilon \sim \ N(0, \delta^2 I)} \end{cases}$$

If there is no spatial correlation between the errors for connected observations i and j, the spatial error parameter λ will be 0, and the model reduces to the standard linear regression model where the individual observations are independent of one another, and we can proceed to estimate the model by ordinary least squares in the conventional manner. However, if the spatial error parameter $\lambda \neq 0$, then we have a pattern of spatial dependence between the errors for connected observations. This could simply be coincidental, or it could reflect other kinds of mis-specifications in the systematic component of the model, in particular omitted variables that are spatially clustered. Social scientists typically expect to see positive spatial correlation. This implies the clustering of similar values, i.e., the errors for observation i tend to vary systematically in size with the errors for other, nearby observations j, so that smaller/larger errors for i would tend to go together with smaller errors for j. Such clustering of residuals violates the assumption that the error terms are independent of one another.

What are the consequences of spatial correlation among the error terms, and what are the implications if we run an OLS assuming that observations are independent? If $\lambda \neq 0$, then the OLS coefficient estimates ignoring the spatial correlation would still be unbiased. However, the standard errors of the coefficient estimates would be wrong. Recall that OLS relies on an estimate of the variance that assumes independent observations. If this is not correct, then the OLS estimate of the variance δ will tend to underestimate the actual variance, in a manner analogous to the case of serially correlated errors over time.

This occurs because the estimate of the variance disregards the correlation between the error terms for nearby observations. Moreover, the estimated coefficients are not necessarily efficient estimates or “close” to the true values of the impact of the features that we are interested in. We will return to estimation of the spatial error model later, but we first turn to its interpretation and relationship to the spatially lagged y model. The spatial error model and the spatially lagged y model may seem superficially similar, as each suggests spatial dependence between observations. However, the two model specifications actually have very different substantive implications. The spatially lagged y is a simultaneous model with feedback between the observations: the value of yi influences the value of yj—which will in turn influence the value of yk, which in turn influences the value of yi. As we saw in section1, different values of the independent variable for one observation i, will propagate through the connected observations, and the net impact will depend on the impact of these differences on other connected observations, via the spatially lagged y term. By contrast, in the spatial error model, dependence enters in the specification only through the error terms. The absence of the spatially lagged y term here implies that differences in the independent variables in i do not have effects on outcomes in observations connected to i. Thus, in a spatial error model specification, the observations are related only due to unmeasured factors that, for some unknown reason, are correlated across the distances among the observations.

SECTION3: ESTIMATION AND SPECIFICATION

a) Maximum Likelihood Estimation:

Maximum likelihood (ML) estimation of spatial lag and spatial error regression models was first outlined by Ord (1975). The point of departure is an assumption of normality for the error terms in (3.1) or in (3.4). The joint likelihood then follows from the multivariate normal distribution for y. Unlike what holds for the classic regression model, the joint log likelihood for a spatial regression does not equal the sum of the log likelihoods associated with the individual observations. This is due to the two-directional nature of the spatial dependence, which results in a Jacobian term that is the determinant of a full N by N matrix, e.g. $|I - \rho w|$, (spatial lag).

For the SAR error model, the log likelihood is based on the multivariate normal case, e.g., as used in the general treatments of Magnus (1978) and Breusch (1980). Since $\varepsilon \sim MVN(0, \Sigma)$, it follows that, with $\varepsilon = y - X\beta$ and $\Sigma = \sigma^2[(I - \lambda W)' (I - \lambda W)]^{-1}$

$$LnL = - (N/2) \ln (2\pi) - (N/2) \ln\sigma^2 + \ln|I - \lambda W| \quad (2.1)$$

$$- (1/2\sigma^2) (y - X\beta)' (I - \lambda W)' (I - \lambda W) (y - X\beta)$$

Closer inspection of the last term in (4.1) reveals that, conditional upon λ, a maximization of the log likelihood is equivalent to the minimization of the sum of squared residuals in a regression of a spatially filtered dependent variable $y^* = y - \lambda Wy$ on a set of spatially filtered explanatory variables $X^* = X - \lambda Wy$. The first order conditions for $\hat{\beta}$indeed yield the familiar generalized least squares estimator:

$$\widehat{\boldsymbol{\beta}}_{ML} = [(X - \lambda WX)'(X - \lambda WX)]^{-1} (X - \lambda WX)'(y - \lambda Wy) \quad (2.2)$$

And, similarly, the ML estimator for σ^2 follows as:

$$\widehat{\sigma^2}_{ML} = (e - \lambda We)' (e - \lambda We) / N \quad (2.3)$$

With $e = y - X\hat{\beta}_{ML}$. However, unlike the time series case, a consistent estimator for cannot be obtained from the OLS residuals and therefore the standard two-step FGLS approach does not apply. Instead, the estimator for λ must be obtained from an explicit maximization of a concentrated likelihood function[1].

The log-likelihood for the spatial lag model is obtained using the same general principles[2]and takes the form

$$\mathbf{LnL = -(N/2)\ ln\ (2\pi) - (N/2)\ ln\sigma^2 + ln|I - \lambda W|} \qquad \mathbf{(2.4)}$$

$$\mathbf{-(1/2\sigma^2)\ (y - \rho Wy - X\beta)'\ (y - \rho Wy - X\beta)}$$

The minimization of the last term in (8) corresponds to OLS, but since this ignores the log Jacobian ln|I - ρW|, OLS is not a consistent estimator in this model. As in the spatial error model, there is no satisfactory two-step procedure and estimators for the parameters must be obtained from an explicit maximization of the likelihood. This is greatly simplified since both $\hat{\beta}_{ML}$ and $\widehat{\sigma^2}_{ML}$ can be obtained conditional upon from the first order conditions:

$$\boldsymbol{\hat{\beta}}_{\mathbf{ML}} \mathbf{= (X'X)^{-1}\ X'\ (y - \lambda Wy)} \qquad \mathbf{(2.5)}$$

$$\boldsymbol{\hat{\beta}}_{\mathbf{ML}} \mathbf{= (X'X)^{-1}\ X'\ Y,\ \ e_0 = (Y - X}\boldsymbol{\hat{\beta}}_{\mathbf{0}}\mathbf{),\ (e_0 - p_L),}\ \boldsymbol{\hat{\beta}}_{\mathbf{L}} \mathbf{= (X'X)^{-1}\ X'Wy,\ e_L = Y - X}\boldsymbol{\hat{\beta}}_{\mathbf{L}}$$

$$\boldsymbol{\hat{\beta}}_{\mathbf{ML}} = \boldsymbol{\hat{\beta}}_{\mathbf{0}} - \rho\boldsymbol{\hat{\beta}}_{\mathbf{L}} \qquad \mathbf{(2.6)}$$

$$\widehat{\boldsymbol{\sigma}^2}_{\mathbf{ML}} \mathbf{= (e_0 - \rho e_L)'\ (e_0 - \rho e_L)\ /\ N} \qquad (2.7)$$

This yields a concentrated log-likelihood in a single parameter, which is straightforward to optimize by means of direct search techniques.

Both spatial lag and spatial error models are special cases of a more general specification that may include forms of heteroskedasticity as well. This also provides the basis for ML estimation of spatial SUR models with spatial lag or spatial error terms. Similarly, ML estimation of error components models with spatial lag or spatial error terms can be implemented as well. Spatial models with discrete dependent variables are typically not

[1] Anselin, L. and A. Bera (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In: A. Ullah and D. E. A. Giles, Eds., Handbook of Applied Economic Statistics, pp. 237–289. New York: Marcel Dekker

[2] Anselin, L. and D. Griffith (1988). Do spatial effects really matter in regression analysis. Papers, Regional Science Association 65, 11–34

estimated by means of ML, given the prohibitive nature of evaluating multiple integrals to determine the relevant marginal distributions[3].

Finally, it is important to note that models with spatial dependence do not fit the classical framework under which the optimal properties (consistency, asymptotic efficiency, and asymptotic normality) of ML estimators are established. This implies that these properties do not necessarily hold and that careful consideration must be given to the explicit formulation of regularity conditions. In general terms, aside from the usual restrictions on the variance and higher moments of the model variables, these conditions boil down to constraints on the range of dependence embodied in the spatial weights matrix. In addition, to avoid singularity or explosive processes, the parameter space for the coefficient in a spatial process model is restricted to an interval other than the familiar-1+1.

b) Specification:

- Moran's I:

The most commonly used specification test for spatial autocorrelation is derived from a statistic developed by Moran (1948, 1950a, 1950b) as the two-dimensional analog of a test for univariate time series correlation. In matrix notation, Moran's I statistic is

$$I = (N/S_0)\,(e'We/e'e) \qquad (3.1)$$

With 'e' as a vector of OLS residuals and $S_0 = \sum_i \sum_j w_{ij}$, a standardization factor that corresponds to the sum of the weights for the non-zero cross-products. The statistic shows a striking similarity to the familiar Durbin-Watson test. Inference for Moran's I is based on a normal approximation, using a standardized z-value obtained from expressions for the mean and variance of the statistic. Alternatively, as shown in Tiefelsdorf and Boots (1995), an exact test can be constructed based on numerical integration and the principles outlined in Imhof (1961) and Koerts and Abrahamse (1968).

Moran's I test has been shown to be locally best invariant [King (1981)] and consistently outperforms other tests in terms of power in simulation experiments [see, e.g., Bartels and Hordijk (1977), Anselin and Rey (1991), Anselin and Florax (1995b), Kelejian and Robinson (1998)]. Its application has been extended to residuals in 2SLS regression in Anselin and

[3] McMillen, D. P. (1992). Probit with spatial autocorrelation. Journal of Regional Science

Kelejian (1997), and to generalized residuals in probit models in Pinkse (1998, 1999). General formal conditions and proofs for the asymptotic normality of Moran's I in a wide range of regression models are given in Pinkse (1998) and Kelejian and Prucha (1999b). The consideration of Moran's I in conjunction with spatial heteroskedasticity is covered in Kelejian and Robinson (1998, 1999).

- ML Based tests:

When spatial regression models are estimated by maximum likelihood, inference on the spatial autoregressive coefficients may be based on a Wald or asymptotic t-test (from the asymptotic variance matrix) or on a likelihood ratio test[4]. Both approaches require that the alternative model (i.e., the spatial model) be estimated. In contrast, a series of test statistics based on the Lagrange Multiplier (LM) or Rao Score (RS) principle only require estimation of the model under the null. The LM/RS tests also allow for the distinction between a spatial error and a spatial lag alternative.

A LM/RS test against a spatial error alternative was originally suggested by Burridge (1980) and takes the form.

$$LM_{err} = [e'We/\ e'e/N]^2 / [tr(W^2+W'W)] \qquad (3.2)$$

This statistic has an asymptotic distribution and, apart from a scaling factor, corresponds to the square of Moran's I. From several simulation experiments [Anselin and Rey (1991), Anselin and Florax (1995b)] if follows that Moran's I has slightly better power than the test in small samples, but the performance of both tests becomes indistinguishable in medium and large size samples. The LM/RS test against a spatial lag alternative was outlined in Anselin (1988c) and takes the form

$$LM_{err} = [e'Wy/(e'e/N)]^2/D \qquad (3.3)$$

$$\text{Where } D = [(WX\beta)' (I\text{-}X (X'X)^{-1}X') (WX\beta)/\sigma^2] + tr\,(W^2 + W'W)$$

Asymptotic χ^2 (1) distribution.

Since both tests have power against the other alternative, it is important to take account of possible lag dependence when testing for error dependence and vice versa. This can be

[4] Anselin, L. and A. Bera (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In: A. Ullah and D. E. A. Giles, Eds., Handbook of Applied Economic Statistics, pp. 237–289. New York: Marcel Dekker

implemented by means of a joint test or by constructing tests that are robust to the presence of local misspecification of the other form. The LM/RS principle can also be extended to more complex spatial alternatives, such as higher order processes, spatial error components and direct representation models[5], to panel data settings[6], and to probit models. A common characteristics of the LM/RS tests against spatial alternatives is that they do not lend themselves readily to a formulation as an expression based on an auxiliary regression. However, as recently shown in Baltagi and Li (1998), it is possible to obtain tests for spatial lag and spatial error dependence in a linear regression model by means of Davidson and MacKinnon's (1984, 1988) double length artificial regression approach.

(c) Estimation of spatial model:

(i) Diagnostic for spatial dependence for the variable expected years of schooling:

By using MATLAB Software we obtained the following results

Table 4: the estimation of autoregressive model (SAR)

```
Spatial autoregressive Model Estimates
Dependent Variable = Exp years of schooling
R-squared          =    0.2657
Rbar-squared       =    0.2497
sigma^2            =    0.0150
Nobs, Nvars        =     48,     2
log-likelihood     =        48.595833
# of iterations    =     19
min and max rho    =   -1.0000,    1.0000
total time in secs =    0.1720
time for lndet     =    0.0310
time for x-impacts =    0.1090
# draws  x-impacts =      1000
Pace and Barry, 1999 MC lndet approximation used
order for MC appr  =     50
iter  for MC appr  =     30
***************************************************************
Variable              Coefficient  Asymptot t-stat    z-probability
const                    0.051919         0.473307         0.635994
wealth                   1.198077         3.051463         0.002277
rho                      0.367963         2.035865         0.041764

Direct                Coefficient           t-stat           t-prob         lower 01         upper 99
wealth                   1.256128         2.981814         0.004491         0.087979         2.303725

Indirect              Coefficient           t-stat           t-prob         lower 01         upper 99
wealth                   0.972469         0.395302         0.694372        -0.101267         7.032631

Total                 Coefficient           t-stat           t-prob         lower 01         upper 99
wealth                   2.228597         0.850672         0.399175         0.171255         8.981904
=================================================================================================
```

Source: obtained using Matlab software

[5] Anselin, L. (1999). Rao's score test in spatial econometrics. Journal of Statistical Planning and Inference (forthcoming).

[6] Anselin, L. (1988b). A test for spatial autocorrelation in seemingly unrelated regressions. Economics Letters 28, 335–341.

We can see that the wealth indicators, is positively related to the expected years of schooling, the result is completely logical, the increases of standard of living and well-being conduct to the increases of expected years of schooling.

The coefficient parameter **Rho** reflects the spatial dependence inherent in our sample data, measuring the average influence on observations by their neighboring observations it has positive effect and it is highly significant.

As a result the general model fit improved, as indicated in higher values of R-squares and log likelihood.

Table 5: Moran-I test for spatial correlation in residuals of exp years schooling

Moran I-test for spatial correlation in residuals	
Moran I	0.10681387
Moran I-statistic	1.60550479
Marginal Probability	0.10838276
mean	-0.02475226
standard deviation	0.08194690

Source: obtained using Matlab software

There are many tests performed to assess the spatial dependence of the model, but we will choice just the Moran's I test. First

⇨ Moran 'I score = 0.108, is highly significant, indicating strong spatial autocorrelation of the residuals.

In addition, the function reports the estimates of tests chosen among two statistics for testing spatial dependence in linear models. The statistics are the simple LM test for a missing spatially lagged dependent variable (Lagrange Multiplier (lag)), the simple LM test for error dependence (Lagrange Multiplier (error)).

Table 6: Moran-I test for spatial correlation in residuals of exp years schooling

LM error tests for spatial correlation in residuals	
LM value	1.46575952
Marginal Probability	0.22601594
chi(1) .01 value	17.61100000

LM error tests for spatial correlation in SAR model residuals	
LM value	0.36932251
Marginal Probability	0.54337379
chi(1) .01 value	6.63500000

Source: obtained using Matlab software

We can see both simple tests of the lag and error are significant, indicating presence of spatial dependence. LM they help us understand what type of spatial dependence may be at work.

LM (error) = 1.465

LM (lag) = 0.369

The both are significant, but when lagged dependent variable is present the error dependence disappears.

The appropriate model for this case is:

$y = \rho Wy + X\beta + \varepsilon$ Spatial Lag, Spatial Autoregressive (SAR), so our model becomes

$$\begin{cases} \textbf{Exp years} = \mathbf{0.367\ W\ Exp\ years + 1.198\ wealth} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon \sim N(0, \delta^2 I)} \end{cases}$$

(ii) Diagnostic for spatial dependence for the variable Mean years of schooling:

By using MATLAB Software we obtained the following results

Table 7: the estimation of autoregressive model (SAR) of mean years schooling

```
Spatial autoregressive Model Estimates
Dependent Variable = Mean years of schooling
R-squared          =    0.2635
Rbar-squared       =    0.2475
sigma^2            =    0.0151
Nobs, Nvars        =     48,     2
log-likelihood     =         48.579933
# of iterations    =     14
min and max rho    =   -1.0000,   1.0000
total time in secs =    0.1720
time for lndet     =    0.0470
time for x-impacts =    0.1090
# draws  x-impacts =      1000
Pace and Barry, 1999 MC lndet approximation used
order for MC appr  =     50
iter  for MC appr  =     30
***************************************************************
Variable                    Coefficient  Asymptot t-stat   z-probability
const                          0.057116         0.516693        0.605370
wealth                         1.211564         3.081838        0.002057
rho                            0.350969         1.917081        0.055228

Direct                      Coefficient           t-stat          t-prob        lower 01        upper 99
wealth                         1.266848         3.084617        0.003377        0.169605        2.268617

Indirect                    Coefficient           t-stat          t-prob        lower 01        upper 99
wealth                         0.806973         0.806827        0.423746       -0.189048        5.396197

Total                       Coefficient           t-stat          t-prob        lower 01        upper 99
wealth                         2.073821         1.728976        0.090241        0.276832        7.155265
```

Source: obtained using Matlab software

We can see that the wealth indicators, is positively related to the mean years of schooling, the same result as expected years schooling

The coefficient parameter **Rho = 0.350** reflects the spatial dependence inherent in our sample data, measuring the average influence on observations by their neighboring observations it has positive effect and it is highly significant. As a result the general model fit improved, as indicated in higher values of R-squares and log likelihood.

Table 8: Moran-I test for spatial correlation in residuals of mean years schooling

Moran I-test for spatial correlation in residuals	
Moran I	0.10681387
Moran I-statistic	1.60550479
Marginal Probability	0.10838276
mean	-0.02475226
standard deviation	0.08194690

There are many tests performed to assess the spatial dependence of the model, but we will choice just the Moran's I test. First

Moran 'I score = 0.106, is highly significant, indicating strong spatial autocorrelation of the residuals.

In addition, the function reports the estimates of tests chosen among two statistics for testing spatial dependence in linear models. The statistics are the simple LM test for a missing spatially lagged dependent variable (Lagrange Multiplier (lag)), the simple LM test for error dependence (Lagrange Multiplier (error)).

Table 9: Moran-I test for spatial correlation in residuals of mean years of schooling

LM error tests for spatial correlation in residuals	
LM value	1.46575952
Marginal Probability	0.22601594
chi(1) .01 value	17.61100000

LM error tests for spatial correlation in SAR model residuals	
LM value	0.36977781
Marginal Probability	0.54312541
chi(1) .01 value	6.63500000

We can see both simple tests of the lag and error are significant, indicating presence of spatial dependence. LM they help us understand what type of spatial dependence may be at work.

LM (error) = 1.465

LM (lag) = 0.369

The both are significant, but when lagged dependent variable is present the error dependence disappears.

The appropriate model for this case is:

$y = \rho Wy + X\beta + \varepsilon$ Spatial Lag, Spatial Autoregressive (SAR), so our model becomes

$$\begin{cases} \textbf{Mean years} = \textbf{0.350 W Mean years} + \textbf{1.211 wealth} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} \sim \textbf{N}(0, \delta^2 I) \end{cases}$$

CONCLUDING:

This chapter has been an attempt to present the salient issues pertaining to the methodology of spatial econometrics. It is by no means complete, but it is hoped that sufficient guidance is provided to pursue interesting research directions. Many challenging problems remain, both methodological in nature as well as in terms of applying the new techniques to meaningful empirical problems.

We estimate a spatial model for the expected years of schooling index and mean years of schooling index as dependent variables, knowing that the wealth index is taking as exogenous variable, we remark two things (i) the strong correlation between the three indexes, and (ii) the appropriate model for our indexes is the spatial lagged model. Which is completely expected and logical result.

CHAPTER IIII:

ESTIMATE INEQUALITY ADJUSTED HDI

SECTION1: THE CONCEPT OF INEQUALITY IN HDI (IHDI):

National human development data disaggregated by geographical or administrative units; by social groups according to gender, ethnicity or rural/urban divide; by economic surround on rich and poor; or by some sort of wealth quintile, may reveal significant disparities in HD within country as expressed by human development indices. These are disparities which have been labeled as categorical inequality, group inequality, or between-group inequality.

Conceptual difficulties[1], as well as a lack of appropriate disaggregated data, are customarily given as major obstacles for documenting inequality. In addition, there hasn't been a broad consensus about how to measure inequality in HDI distribution within a country.

Generally, methods for measuring inequality have been developed in relation to the unequal distribution of income and wealth across a population. Inequality in the distribution of other characteristics and resources is often recognized but rarely measured.

Conceptualizing and estimating the inequality of the three dimensions:

Most people around the world have seen major improvements in their lives over the last 40 years. But there are major problem of Inequalities in health, education, and income deeply impact progress towards increasing human development. It is clear that both inequalities in country-average HDIs and within-country HD inequality matter for the evaluation and analysis of HD achievements. To this end, measuring inequality is an important first step towards addressing inequality in HD. If we deal decisively with these challenges, we could be on the cusp of an era of historic equal opportunities for expanded choices and freedoms. But if we fail to act, future generations may remember the early 21st century as the time when the doors to a better future closed for most of the world's people.

The aim of this part of section is to estimate inequalities and to presents the Gini coefficient as a workable, though imperfect. Inequality measure for the purposes of this dissertation. A Gini coefficient will be employed in each of the spaces income, education, and health.

[1] DOUGLAS A. HICKS 1997. "The inequality-adjusted Human development index: A constructive proposal" world development, vol.25, No. 8, pp. 1283-1298, Elsevier.

Inequality determinations can be distinguished between descriptive and normative exercises. That is, we can distinguish between. Descriptive measures which make ***no explicit*** use of any concept of social welfare. And normative measures which are based on ***an explicit*** formulation of social welfare and the loss incurred from unequal distribution.

By this classification. The Gini coefficient is a descriptive measure. Widely used in considering distributions of income, it has a number of useful properties. The Gini coefficient is most easily seen geometrically, where the proportion of the ranked population is plotted against the population's cumulative holdings of a particular good. The Gini coefficient ranges from zero to one. With zero reflecting complete equality and one reflecting absolute inequality. Hence the greater Gini, mean the greater inequality. From one definition of the Gini coefficient it can be written as:

$$G = \frac{2}{n^2\, 3\mu_y} \sum_{i=1}^{n} \left(i - \frac{n+1}{2}\right) W_i + E_i + H_i$$

Where n is the number of municipalities and μ_y is the mean of the human development distribution, $W_i + E_i + H_i$ is the wealth, education, health index.

table 10 : exemple of gini index for adrar, chlef, and laghouat

Expected schooling index 08	Mean of schooling index	wealth index
GINI	GINI	GINI
ADRAR		
0,35731	0,4231653	0,27
CHLEF		
0,468706184	0,441942075	0,212151
LAGHOUAT		
0,487061839	0,421942075	0,232131
OUM EL BOUA		
0,468706184	0,419420748	0,192151

Source: established by ourselves, based on census data RGPH 2008

SECTION 2: ISSUES OF MEASUREMENT OF INEQUALITY IN THE SPACE OF W, E

The Inequality-adjusted Human Development Index (IHDI)[2] adjusts the Human Development Index (HDI) for inequality in the distribution of each dimension across the population. It is based on a distribution-sensitive class of composite indices proposed by Foster, Lopez-Calva, and Szekely (2005), which draws on the Atkinson (1970) family of inequality measures. It is computed as a geometric mean of geometric means, calculated across the population for each dimension separately.

The IHDI accounts for inequalities in HDI dimensions by "discounting" each dimension's average value according to its level of inequality. The IHDI equals the HDI when there is no inequality across people but falls further below the HDI as inequality rises. In this sense, the IHDI is the actual level of human development, while the HDI can be viewed as an index of the "potential" human development that could be achieved if there was no inequality. The "loss" in potential human development due to inequality is the difference between the HDI and the IHDI and can be expressed as a percentage.

1.1 Measuring the inequality adjusted HDI:

Computing the Inequality-adjusted Human Development Index There are three steps to computing the IHDI.

Step 1. Measuring inequality in the dimensions of the Human Development Index

The IHDI draws on the Atkinson (1970) family of inequality measures and sets the aversion parameter ε equal to 1. In this case the inequality measure is A = 1 – g/μ, where g is the geometric mean and μ is the arithmetic mean of the distribution. This can be written as:

$$A_x = 1 - \frac{\sqrt[n]{X_1 \ldots . X_n}}{\bar{X}} \qquad \textbf{(1)}$$

Where {X1 …, Xn} denotes the underlying distribution in the dimensions of interest. Ax is obtained for each variable (life expectancy, mean years of schooling and standard of

[2] Alkire, S., and J. Foster. 2010. "Designing the Inequality-Adjusted Human Development Index (IHDI)." Human, Development Research Paper 28.

living). The geometric mean in equation 1 does not allow zero values. For mean years of schooling one year is added to all valid observations to compute the inequality.

Table11: adjusting expected years schooling and wealth index for some cities

TIZI OUZOU	
Expected years schooling index	Wealth index
arith mean	arith mean
0,866802035	0,900881088
geo mean	geo mean
0,865676935	0,897350724
atkinston	atkinston
0,001297989	0,003918789
adjusted	adjusted
0,758965823	0,753693234
ALGER	
arith mean	arith mean
0,839183337	0,776918521
geo mean	geo mean
0,837104199	0,761403668
atkinston	atkinston
0,002477573	0,01996973
adjusted	adjusted
0,758069395	0,741548154
DJALFA	
arith mean	arith mean
0,573993188	0,599362586
geo mean	geo mean
0,553699553	0,551279691
atkinston	atkinston
0,035355185	0,080223384
adjusted	adjusted
0,733083981	0,69595672

Source: established by ourselves, based on census data RGPH 2008

STEP 2. ADJUSTING THE DIMENSION INDICES FOR INEQUALITY

The mean achievement in an HDI dimension,$\bar{X}$, is adjusted for inequality as follows:

$$\bar{X} * (1 - A_x) = \sqrt[n]{X_1 \ldots . X_n}$$

Thus, the geometric mean represents the arithmetic mean reduced by the inequality in distribution. The inequality-adjusted dimension indices are obtained from the HDI dimension indices, Ix, by multiplying them by (1 – Ax), where Ax, defined by equation 1, is the corresponding Atkinson measure:

$$\boldsymbol{I_x^* = (1 - A_x)}$$

The inequality-adjusted HDI for the three dimension is based on the unlogged wealth index. This enables the IHDI to account for the full effect of dimensions inequality.

Step 3. Combining the dimension indices to calculate the Inequality-adjusted Human Development Index

The IHDI is the geometric mean of the three dimension indices adjusted for inequality. First, the IHDI that includes the unlogged income index (IHDI*) is calculated:

$$\sqrt[3]{I^*_{education} . I^*_{life} . I^*_{wealth}}$$

$$\sqrt[3]{(1 - A_{life}). I_{life}. (1 - A_{educ}). I_{educ}. (1 - A_{wealth}). I_{wealth}}$$

$$HDI^* = \sqrt[3]{I_{life}. I_{educ}. I_{wealth}}$$

$$\text{Loss}=1 - \frac{IHDI^*}{HDI^*} = 1- \sqrt[3]{(1 - A_{life}). (1 - A_{educ}). (1 - A_{wealth}).}$$

Assuming that the percentage loss due to inequality in income distribution is the same for both average income and its logarithm, the IHDI is then calculated as:

$$IHDI = \frac{IHDI^*}{HDI} . HDI = \sqrt[3]{(1 - A_{life}).(1 - A_{educ}).(1 - A_{wealth})} . HDI$$

Table12 : dimensions indices and the HDI adjusted

wilaya	MEAN YEARS adjusted	Expected years adjusted	WEALTH adjusted	HDI adjusted
ADRAR	0,204999117	0,819900821	0,658284079	0,48007478
CHLEF	0,215353168	0,754337808	0,77276532	0,50071229
LAGHOUAT	0,239831744	0,720678471	0,710093848	0,49695987
OUM EL BOUAGHI	0,202181898	0,704405862	0,787184375	0,48218522
BATNA	0,192433996	0,756541283	0,780532239	0,48436017
BEJAIA	0,211935918	0,881082102	0,899660174	0,55178067
BISKRA	0,203208556	0,723925794	0,8290879	0,49592067
BECHAR	0,26811265	0,84261671	0,858977379	0,57895263
BLIDA	0,354435612	0,79799439	0,909210388	0,63591713
BOUIRA	0,183536478	0,800607761	0,831210132	0,49615534
TAMANGHASSET	0,184101749	0,694985975	0,746523314	0,45711532
TEBESSA	0,216784011	0,702802545	0,695215926	0,4731441
TLEMCEN	0,140579536	0,750714494	0,909410583	0,45784552
TIARET	0,172798849	0,691594871	0,76214999	0,44992938
TIZI OUZOU	0,289549866	0,866802035	0,900881088	0,60921453
ALGER CENTRE	0,60897275	0,839183337	0,776918521	0,73498204
DJELFA	0,31664017	0,573993188	0,599362586	0,47758879
JIJEL	0,239836475	0,811485674	0,745699744	0,52551691
SETIF	0,160091667	0,751209677	0,815799656	0,46121611
SAIDA	0,135880366	0,735273492	0,853082991	0,44008068
SKIKDA	0,23042273	0,794723924	0,806051038	0,5284875
SIDI BEL ABBES	0,174712609	0,721949509	0,926521143	0,48890987
ANNABA	0,366587175	0,817905563	0,885855627	0,64280778
GUELMA	0,219886842	0,801264335	0,857754851	0,53265509
CONSTANTINE	0,35181505	0,802565451	0,86021836	0,62392807
MEDEA	0,199560314	0,746362202	0,711574063	0,47323985
MOSTAGANEM	0,189089825	0,679840901	0,741348434	0,45677179
M'SILA	0,184419714	0,704529856	0,735337644	0,4571561

MASCARA	0,174339546	0,672726866	0,85990724	0,465474
OUARGLA	0,303618745	0,817054031	0,857022813	0,59683907
ORAN	0,297725327	0,718766857	0,912487457	0,58015438
EL BAYADH	0,229368406	0,714586255	0,771712152	0,50197397
ILLIZI	0,24682035	0,71797569	0,877135425	0,5376741
BORDJ BOU ARRERIDJ	0,204245768	0,798180843	0,83983233	0,51540542
BOUMERDES	0,330410374	0,783759204	0,883462391	0,61161031
EL TAREF	0,314520403	0,800023375	0,873727988	0,60354443
TINDOUF	0,332670906	0,777875175	0,949376332	0,62630764
TISSEMSILT	0,184889435	0,752964427	0,735528103	0,46783776
EL OUED	0,189931108	0,755913978	0,865720529	0,49905537
KHENCHELA	0,142630025	0,756478328	0,821806064	0,44592203
SOUK AHRAS	0,182371285	0,723257633	0,729514715	0,4582416
TIPAZA	0,28423802	0,77247796	0,871878675	0,57633471
MILA	0,207497019	0,791999036	0,84758039	0,51836914
AIN DEFLA	0,194289878	0,760606592	0,757133546	0,48186744
NAAMA	0,220257022	0,658894343	0,809495033	0,48976368
AIN TIMOUCHENT	0,198103566	0,732443398	0,918663212	0,51082745
GHARDAIA	0,325241531	0,84108318	0,89598296	0,62581826
RELIZANE	0,211793241	0,724357791	0,751678237	0,48674228

CONCLUDING:

High inequality in any dimension should lower the index value for that dimension, and hence its contribution to the HDI. Although the idea of the Gini-corrected HDI is rather intuitive it has not been widely used due to the difficulties of calculating Gini indices from the grouped data. They suggested a two-step Procedure assuming that data are available at the municipal level.

Conclusion

As Amartya Sen's approach, Human development is the expansion of people's freedoms and capabilities to lead lives that they value and have reason to value. It is about expanding choices, freedom and capabilities to lead lives that they value and have reason to value, it is about expending choices.

Salient finding from this research work shows the human development Human development measurement affects public perceptions of the developed and developing world and can create public pressure for action and accountability, particularly when progress in reducing deprivation is not made. More precise definitions and fine-tuned measurement of human development remains a challenge to the "development community". For this reason, we work with measurement techniques that, combined with other recent contributions presented in the literature, might greatly contribute to make human development indices at different aggregation levels an operational tool of analysis that can be regularly used.

Among these contributions, it is important to highlight the recent efforts to define subgroup consistent, inequality or association-sensitive and nationally representative human development indices (e.g., Alkire & Foster, 2010; Foster et al., 2005; Seth, 2009). While this has not been the approach followed in this dissertation, it would be straightforward to use the information collected at municipal level (i.e., the distribution of the two components {Ei, -Wi} without health that we don't dispose a data) to construct that kind of nationally-representative index. Rather than summarizing detailed information into an aggregate measure, here we have emphasized the importance of exploring the distribution of human development at very low aggregation levels.

The empirical results shown in this suggest a medium human development in Algerian municipalities during the 2008 period. However, during these years the rural areas of the country continue to be disadvantaged vis-a`-vis their urban counterparts, so they might potentially be the target of policies aiming to further reduce inequality in human development.

The indicator we have presented in this dissertation is extremely useful to measure and monitor the levels of some basic human capabilities that are needed to lead a minimally decent life. Rather than taking into account a large and comprehensive set of indicators we have preferred to focus on a simple list of indicators that are meaningfully comparable in most regions of the world it might also be possible to find diverging trends across and within countries). Furthermore, the decomposition of human development levels by subcomponents reveals that the wealth index seems to be more reluctant to reduce inequality in its distribution.

While the methodology presented here allows a spatial model for the three key dimensions (expected years of schooling, mean years of schooling, and wealth) in order to surround the appropriate spatial model for the spread of our dimensions in municipalities of Algeria, with unprecedented geographical coverage and detail that were not feasible short ago, it still misses intra-municipal variability. This is the price that has been paid for using a straightforward methodology that does not rely on imputations and which is based on census data alone. As suggested by Tarozzi (2011), one possible way of bounding such intra-municipal human development variability is to explore the variability of education and standard of living indicators, which are defined at individual and household levels, respectively. Another possibility that might be attempted in future research is to use some combination of the imputation techniques recently proposed in the literature to generate household-level human development indicators defined for all households in the census—and not just those included in a survey.

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APPENDIX

APPENDIX N°1: Narayan et al: well-being according to the Voices of the Poor

Material Well-being: having enough

Food

Assets

Work

Bodily well-being: being and appearing well

Health

Appearances

Physical environment

Social well-being

Being able to care for, bring up, marry and settle children

Self-respect and dignity

Peace, harmony, good relations in the family/ community

Security

Civil peace

A physically safe and secure environment

Personal physical security

Lawfulness and access to justice

Security in old age

Confidence in the future

Freedom of choice and action

Psychological well-being

Peace of mind,

Happiness, Harmony (including a spiritual life and religious observance)

Source. Narayan et al. (2000, pp. 25–30, 37–38).

APPENDIX N°2: the dimensions of human development

Grisez et al. (1987)	Nussbaum (2000)	Max-Neef (1993)	Narayan et al. (2000)	Schwartz (1994)	Cummins (1996)	Ramsay (1992)	Doyal and Gough (1993)
Basic human values	Central human capabilities	Axiological categories	Dimensions of well-being	Human values	Domains of life	satisfaction Human needs	Intermediate needs
-Life Knowledge and appreciation of beauty -Some degree of excellence in work and play -Friendship -Self integration -Coherent self-determination,	-Life -Bodily health -Bodily integrity -Senses, thought, imagination -Emotions -Practical reason	-Subsistence -Protection -Affection Understanding -Participation -Leisure -Creation -Identity -Freedom	-Material well-being -Bodily well-being -Social well-being -Security -Freedom of choice and	Power Achievement Hedonism Stimulation Self-direction Universalism Benevolence Tradition Conformity	-Material well-being -Health -Productivity -Intimacy/ friendship -Safety -Community -Emotional	-Physical survival -Sexual needs -Security -Love and relatedness -Esteem and identity -Self-realization	Nutritional food/water Protective housing Work Physical environment Health care Security in

or practical reason -Religion, or harmony with some greater than- human source of meaning and value	-Affiliation -Other species -Play -Control over one's environment	action -Psychological well-being	Security	well-being		childhood Significant primary relationships Physical security Economic security Safe birth control/ child bearing Basic education

Rawls (1993)	Galtung (1994)	Allardt (1993)	Andrews and Withey (1976)	Lasswell (1992)	Qizilbash (1996a,b)	Diener and Biwas (2000)
Political liberalism	HR in another key	Comparative Scandanavian welfare study	Concern clusters	Human values	Prudential values For development	12 life domains

The basiclibe rties	1. Survival needs: to avoid	Having	Media	Skill	Health/nutrition/	Morality
		Econ resources	Societal	Affection	sanitation/rest/	Food
Freedom of	violence	Housing	standards	Respect	shelter/security	Family
movement,	Individual and collective	Employment	Weather	Rectitude	Literacy/basic	Friendship
freedom of	2. Well-being needs: to	Working	Government	Power	intellectual	Material
association	avoid misery	conditions	Safety	Enlightenment	and physical	Resources
and freedom	Nutrition, water, air,	Health	Community	Wealth	capacities	Intelligence
of occupational	movement, excretion,	Education	House	Well-being	Self-respect	Romantic
choice against	sleep, sex, protection	Loving	Money		and Aspiration	relationship
	against climate,	Attachments/	Job		Positive freedom,	Physical
a background	against diseases,	contacts with	Services		autonomy or	appearance
of diverse	against heavy degrading	local	Recreation		selfdetermination	Self
opportunities		community,	facilities		Negative freedom	Income
Powers and	boring work, self-expression,	family and	Traditions		or liberty	Housing
prerogatives		kin, friends,	Marriage		enjoyment	Social life
of office and	dialogue, education	associations,	Children		Enjoyment	
positions of	3. Identity needs: to avoid	work-mates	Family relations		Understanding	
responsibility	alienation	Being	Treatment		or knowledge	
in political		Selfdeterminat			Significant	

and economic institutions Income and wealth The social bases of self-respect	Creativity, praxis, work, self-actuation, realising potentials, well-being, happiness, joy being active subject, not passive client/object, challenge and new experiences, affection, love, sex; friends, offspring, spouse, roots, belongingness, networks, support, esteem, understanding social forces, social transparency, partnership with nature, a sense of purpose, of meaning, closeness to the	ion Political activities Leisure-time activities Opportunities to enjoy nature Meaningful work	Imagination Acceptance Self-adjustment Virtues Accomplishment Friends Religion Health Own education Beneficience Independene Mobility Beauty		relations with others and some participation in social life Accomplishment (sort that gives life point/ weight)

	transcendental,
	transpersonal

APPENDIX N°3: Suggested values for ε_i and ranges for income intervals

ε_i	Range of y	Elasticity
0	$y \leqslant y^*$	1.0
0.1	$y^* < y \leqslant 1.5y^*$	0.9
0.2	$1.5y^* < y \leqslant 2.0y^*$	0.8
0.3	$2.0y^* < y \leqslant 2.5y^*$	0.7
0.4	$2.5y^* < y \leqslant 3.0y^*$	0.6
0.5	$3.0y^* < y \leqslant 3.5y^*$	0.5
0.6	$3.5y^* < y \leqslant 4.0y^*$	0.4
0.7	$4.0y^* < y \leqslant 4.5y^*$	0.3
0.8	$4.5y^* < y \leqslant 5.0y^*$	0.2

APPENDIX 4

code_commu	COMMUNE	CODE	WILAYA	NATURE	Reg_strat	densité	pop1987	pop1998	pop2008
109	TIMIMOUN	1	ADRAR	COMMUNE	8	3,38116	21 556	28 595	33 060
110	OULED SAID	1	ADRAR	COMMUNE	8	12,5023	5 876	7 538	8 219
111	ZAOUIET KOUNTA	1	ADRAR	COMMUNE	8	1,88764	10 707	14 531	17 116
112	AOULEF	1	ADRAR	COMMUNE	8	7,10231	10 259	15 229	21 723
113	TIMOKTEN	1	ADRAR	COMMUNE	8	1,01481	9 762	14 134	18 598
114	TAMENTIT	1	ADRAR	COMMUNE	8	1,35336	5 300	7 912	9 481
115	FENOUGHIL	1	ADRAR	COMMUNE	8	1,55742	6 792	9 962	11 793
116	TINERKOUK	1	ADRAR	COMMUNE	8	0,792697	9 401	13 393	15 980
117	DELDOUL	1	ADRAR	COMMUNE	8	7,16723	5 521	7 465	8 647
118	SALI	1	ADRAR	COMMUNE	8	0,749594	8 554	11 304	13 138
119	AKABLI	1	ADRAR	COMMUNE	8	6,08222	3 513	7 513	10 171
120	METARFA	1	ADRAR	COMMUNE	8	5,93015	5 164	7 061	8 438
121	OULED AHMED TIMI	1	ADRAR	COMMUNE	8	2,81633	7 802	11 976	13 547
122	BOUDA	1	ADRAR	COMMUNE	8	2,33175	6 087	8 668	9 938
123	AOUGROUT	1	ADRAR	COMMUNE	8	0,829101	7 043	9 878	11 784
124	TALMINE	1	ADRAR	COMMUNE	8	4,33078	6 728	9 469	12 768
125	BORDJ BADJI MOKHTAR	1	ADRAR	COMMUNE	8	0,134967	4 859	9 323	16 437
126	SEBAA	1	ADRAR	COMMUNE	8	0,464978	1 441	1 989	2 312
127	OULED AISSA	1	ADRAR	COMMUNE	8	1,68693	3 917	5 497	7 034
128	TIMIAOUINE	1	ADRAR	COMMUNE	8	0,355885	3 219	4 206	4 493
201	CHLEF	2	CHLEF	CHEF-LIEU-WILAYA	1	1 405,84	104 805	146 157	178 616
202	TENES	2	CHLEF	COMMUNE-COTIERE	1	387,626	26 491	34 332	35 459
203	BENAIRIA	2	CHLEF	COMMUNE	1	263,926	10 296	13 509	15 697
204	EL KARIMIA	2	CHLEF	COMMUNE	1	298,693	19 995	25 060	28 821
205	TADJENA	2	CHLEF	COMMUNE	1	210,019	19 280	22 155	24 413
206	TAOUGRITE	2	CHLEF	COMMUNE	1	148,879	19 736	24 267	27 574
207	BENI HAOUA	2	CHLEF	COMMUNE-COTIERE	1	184,873	12 724	17 602	20 853
208	SOBHA	2	CHLEF	COMMUNE	1	187,419	24 332	28 646	34 455
209	HARCHOUN	2	CHLEF	COMMUNE	1	223,052	11 273	14 869	17 873
210	OULED FARES	2	CHLEF	COMMUNE	1	142,714	23 353	30 068	34 891
211	SIDI AKKACHA	2	CHLEF	COMMUNE	1	204,581	18 118	23 374	26 595