Title: Using census data to explore the spatial distribution of human development

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Abstract:

The human development index (HDI) has been criticized for not incorporating distributional issues. We propose using census data to construct a municipal-based HDI that allows exploring the distribution of human development with unprecedented geographical coverage and detail. Moreover, we present a new methodology that allows decomposing overall human development inequality according to the contribution of its subcomponents. We illustrate our methodology for Mexico's last three census rounds. Municipal-based human development has increased over time and inequality between municipalities has decreased. The wealth component has increasingly accounted for most of the existing inequality in human development during the last twenty years.

Keywords: Human Development Index, Measurement, Spatial Distribution, Inequality, Census, Mexico.

1. INTRODUCTION

Since it was first introduced in the 1990 Human Development Report, the Human Development Index (HDI) has attracted a great deal of interest in policy-making and academic circles alike. As stated in Klugman et al (2011): "Its popularity can be attributed to the simplicity of its characterization of development − an average of achievements in health, education and income − and to its underlying message that development is much more than economic growth". Despite its acknowledged shortcomings (see Kelley 1991, McGillivray 1991, Srinivasan 1994), the HDI has been very helpful to widen the perspective with which academics and policy-makers alike approached the problem of measuring countries development levels (see Herrero et al 2010). Among other things, the HDI has been criticized for the arbitrariness of its weighting scheme (see Cherchye, Ooghe and Puyenbroeck 2008, Foster, McGillivray and Seth 2009, Permanyer 2011a,b), the limited well-being dimensions incorporated in the analysis (see, for instance, Anand and Sen 1992, Neumayer 2001 or Ranis, Stewart and Samman 2007) and for the neglect of distributional issues in its conceptualization (see Sagar and Najam 1998, Grimm, Harttgen, Misselhorn and Klasen 2008). More specifically, the HDI has been rightly criticized for only giving an average value at the country level that might hide large inequalities. It is in this context that this paper aims to make a contribution: using widely available census data and a simple methodology we suggest estimating human development indicators at municipal level to uncover their distribution with unprecedented geographical coverage and detail.

There have been different attempts to incorporate inequality in the assessment of human development levels, particularly in the last few years. Hicks (1997) proposed an

inequality-sensitive Human Development Index whose values are penalized for unequal distributions within a given country. The intuitions put forward in that paper where analyzed axiomatically by Foster et al (2005) [[[Endnote#1]]] and further refined by Seth (2009) [[[Endnote#2]]]. These ideas have crystallized in the recent presentation in UNDP's 2010 Human Development Report of the Inequality-adjusted Human Development Index (IHDI): an index that discounts average achievements in a dimension by the existing inequality in that dimension (see Alkire and Foster 2010 for further details). It is important to highlight that these contributions are focused on the construction of nationally representative distribution-sensitive human development indices rather than on the estimation of human development levels for certain population subgroups. In order to fill this important gap, alternative but methodologically analogous versions of the HDI have been recently defined for specific population subgroups. Grimm et al (2008, 2010) present an HDI for the different income quintiles and Harttgen and Klasen (2011a) calculate the HDI separately for internal migrants and for nonmigrants. More recently, Harttgen and Klasen (2011b) propose a similar methodology to construct a household-based Human Development Index. As stated by the authors, these approaches are particularly attractive as they open up the possibility of performing many kinds of comparative analysis that were not previously available (e.g.: comparisons between and within population subgroups based on a wide range of socio-demographic and economic characteristics).

Notwithstanding the undisputable advantages that the choice of those subgroup-specific HDI methodologies entails, there are important shortcomings that are worth pointing out. First, the different approaches attempt to forcibly replicate the original HDI variables which were originally defined at the country level [[[Endnote#3]]] and estimate them for the new units of analysis. However, this can be conceptually

problematic when the units that are being compared represent extremely small population subgroups (e.g.: in the case of households without children it becomes particularly problematic to define something like a household-based life expectancy, a gross enrolment ratio or the expected years of schooling). As a result, the authors need to rely on many imputations and complex technical assumptions that are hard to verify – to say the least.

Second, it is not possible to know which of the three HDI components (i.e.: standard of living, education or health) accounts for most of the existing inequality levels in human development. Using the household-based approach presented in Harttgen and Klasen (2011b) it is possible to determine the different component-specific inequality levels. However, these approaches do *not* allow knowing the specific contribution of the three components to *overall* inequality in the human development distribution. Even if such decomposition analysis could be very useful to guide policy makers in any attempt to reduce disparities in human development within a country, we are not aware of any methodology providing that information.

Third, as these HDI indicators are constructed on the basis of household surveys alone, it is generally not possible to estimate their distribution in such a way that they are statistically representative for sub-national geographical units (e.g.: state, province, municipality and so on) because of large sampling variation. Yet, this more detailed spatial information is crucial for a variety of purposes. On the academic side, the lack of reliable data at sub-national levels is a major hurdle that critically undermines the possibility of empirically testing alternative theoretical efforts proposed in different disciplines of the social sciences that aim to establish formal links and interactions between micro and macro aggregation levels. From the policy-making perspective, there is a huge need – especially in the developing world – for more accurate information that

can be used for the design and evaluation of public policy and to reduce the risk of falling into the ecological fallacy. The design of fine-tuned policy instruments can be particularly useful to deal with clusters of poverty or underdeveloped regions that are otherwise concealed under national averages [[[Endnote#4]]].

To sum up, the existing approaches to define subgroup-specific HDIs: (i) are based on involved imputation and estimation methodologies whose underlying assumptions are difficult to verify; (ii) they are not informative regarding a) the geographical distribution of human development, and b) the contribution of the different HDI components to overall human development inequality. In order to overcome these limitations we propose to use census data and a straightforward methodology to construct a municipal-based HDI. Our approach allows exploring the distribution of human development with unparalleled geographical coverage and detail, so it has the potential of being extremely useful for academics and policy-makers alike. Among other things, it opens up the possibility of monitoring the evolution of key welfare indicators at very low aggregation levels and complementing that wealth of information with a vast array of Geographic Information System (GIS) tools commonly used by regional planners (see, for instance, Anselin, Sridharan and Gholston 2007). In addition, we present a simple method that allows decomposing human development inequality according to the corresponding contribution of each of its three subcomponents. This kind of decomposition can be particularly useful to identify the components that deserve priority attention in the attempts to reduce inequality in human development distributions.

The municipal-based HDI proposed in this paper is an attempt to unfold the spatial dimension in the human development distribution. In this context, it should be seen as a complement to the aforementioned subgroup-specific HDIs recently proposed in the literature. At this point, it must be emphasized that the attempt to estimate human

development at municipal level is certainly not new. For instance, the Mexican Consejo Nacional de Población (CONAPO) used the poverty mapping methodology [[[Endnote#5]]] to generate a municipality-based Human Development Index (see CONAPO 2001). Analogously, UNDP Brazil used similar methodologies to generate a Human Development Atlas that estimates a municipal HDI for the year 2000 (see http://www.pnud.org.br/atlas/). Other UNDP national offices have generated their own HDI estimates at sub-national levels (e.g.: Bolivia, El Salvador). However, these exercises typically use country-specific methodologies that render international comparisons particularly difficult – if feasible at all. The main aim of this paper is to propose a simple methodology that can be easily reproduced in a wide variety of settings to generate human development estimates at very low aggregation levels on the basis of census data alone. The simplicity of the methods presented here allows replicating our results for any country with census data satisfying some minimal requirements, so they can potentially be the catalyst for future research on within- and between-country inequality in human development. This is particularly the case in a moment in which census data are becoming more readily available and comparable (see, for example, the IPUMS census data project coordinated by the Minnesota Population Center).

The rest of the paper is organized as follows. Section 2 presents the methodology we have followed to construct our municipal-based HDI. Section 3 applies that methodology to illustrate the evolution of human development in Mexico between 1990 and 2010. We conclude in Section 4.

2. METHODOLOGY

In this section we present the methodology used to estimate human development levels 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 national level – that approach would force us to rely on estimation and imputation methodologies – we find more appropriate to adapt the methodology by picking other variables that are more meaningful at municipal level. The choice of municipality as unit of analysis has been basically determined by data constraints. Ideally, one would like to have indicators at the lowest possible aggregation level – i.e.: the individual – 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 (see below). An adverse implication of working at municipal level is that intra-municipal variability in human development is lost [[[Endnote#6]]]. On the positive side, the exhaustiveness of census data allows estimating the spatial distribution of human development levels with unprecedented geographical coverage.

(a) *Health*

This is by far the most difficult component to estimate at individual or household level, since direct health information is typically unavailable for most census data. While there might be some country-specific exceptions, there are no health questions routinely collected in the census questionnaires that can serve the purpose of obtaining estimates in such detail. Similar difficulties have also been encountered by other attempts to construct household-based health indicators (see Harttgen and Klasen (2011b) in the

context of the HDI and Alkire and Santos (2010) for multidimensional poverty indices). At municipal level and for larger geographical units, there are well-known indirect estimation techniques based on two questions routinely collected in census questionnaires concerning child survivorship [[[Endnote#7]]] that can be used to generate health estimates. These methods, which were largely developed by William Brass, basically use information on child survivorship to estimate probabilities of dying at age x ($q(x)$) which can later be later transformed into life tables to estimate life expectancies (see Brass 1975) [[[Endnote#8]]]. This is basically the method used by UNDP Brazil and CONAPO (2001) to estimate life expectancies at municipal level in Brazil and Mexico respectively. Unfortunately, the accuracy of these methods is contingent upon a series of assumptions on mortality and fertility conditions that are difficult to verify − to say the least − particularly at municipal level. In order to avoid using methods that rely on strong and unverifiable hypothesis, in this paper we have opted for using a much simpler methodology. The health indicator for municipality 'i' will be the proportion of surviving children among women between ages 20-39, which will be denoted by P_i. This indicator is particularly suitable for small size populations and has been used among other things to describe the socio-demographic characteristics of indigenous populations in Latin America (see ECLAC 2010).

Before entering in the aggregate HDI, the health component has to be normalized between zero and one. For that purpose, we follow the HDI standard methodology and define the municipal level normalized health index as $H_i=(P_i - P_{min})/(P_{max} - P_{min})$, where P_{min}, P_{max} are the minimal and maximal benchmark values [[[Endnote#9]]].

(b) *Education*

The education component can be easily estimated at municipal level using the same variables as the ones used in the "new" country-level HDI (i.e.: the HDI presented in the 2010 Human Development Report). Using census data, for each municipality 'i' we can compute: (1) the average years of schooling of adults aged 25 or more (denoted as AYS_i), and (2) the expected years of education for children in schooling age (denoted as EYS_i) [[[Endnote#10]]]. Setting the maximum and minimum thresholds established by the new HDI methodology [[[Endnote#11]]], these indicators are normalized and then averaged to derive the corresponding municipal level education index E_i. Once the AYS and EYS indices are normalized, the education index for municipality 'i' is obtained as $E_i = \left(\sqrt{AYS_i \cdot EYS_i} \right) / 0.978$. By construction, the values of E_i are bounded between zero and one.

When measuring the education component, we agree with UNDP that the new variable AYS is better than the adult literacy rate (ALR) used in the pre-2010 HDI because literacy rates are already quite high in most parts of the world. The ALR world-wide distribution is clustered around its upper tail (highly skewed to the left) and does not greatly differentiate among countries (contrary to what happens with the average years of schooling distribution). While ALR is a crude measure that just focuses on the literate/illiterate status of individuals, AYS is a finely-grained measure that gives a more detailed account of the educational attainment of adult population. On the other hand, EYS is another way of expressing the former school enrollment component of the "old" HDI.

(c) *Standard of Living*

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The standard of living dimension is estimated using GDP per capita in the pre-2010 HDI formulation and with the GNI per capita in the new HDI version. However, when it comes to estimate any of those figures at municipal level many technical difficulties arise. Some censuses sparsely collect information on individuals' income, but that information is not typically available and its quality has been questioned by different authors (e.g.: see Lopez-Calva et al 2005 for the case of Mexico). In order to fill this gap, poverty mapping techniques have been applied for some countries (see World Bank 2007). Unfortunately, the use of this sophisticated methodology is contingent upon the availability of high-quality household surveys carried out the same year the census was taken and the quality of the corresponding results has been heavily qualified by Tarozzi and Deaton (2009). In our effort to keep our methodology plain and easy to replicate in as many settings as possible, in this paper we suggest to use asset indices to derive a welfare distribution. Our asset indices are constructed at the household level (h) using the following aggregation formula:

$$A_h = \frac{a_{h1} + \ldots + a_{hk}}{k} \qquad [1]$$

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'. By construction, A_h is normalized between zero and one: it equals one when household 'h' owns all assets in the list and zero when it owns none. Recall that all assets in the asset index A_h are given the same weight $1/k$. While some authors use Factor Analysis or Principal Components techniques to derive the corresponding weights (e.g.: Filmer and Pritchett 2001, Sahn and Stifel 2000, 2003, Harttgen and Klasen 2011b), we have preferred to keep the equal weighting scheme as already done by many others (e.g.: Montgomery et al 2000, Case et al. 2004, Hohmann and Garenne 2010) for the sake of simplicity and transparency.

This way the meaning of the index is well defined (it simply counts the proportion of owned assets) and its values are clearly comparable across time and space. Notwithstanding those conceptual differences, when comparing alternative weighting schemes for asset indices Filmer and Scott (2012:388) conclude that "*in most situations, the specific approach used is unlikely to matter much*". After computing the asset index A_h for each household in the census, a wealth index – denoted by W_i – is computed for each municipality '*i*' as a weighted arithmetic mean of the asset indices of the households belonging to '*i*' (each household weighted by its size). By construction, W_i is normalized between zero and one.

The use of asset indices as a measure for the standard of living component requires careful discussion and justification. Asset indices have been widely used in the literature (e.g.: Filmer and Pritchett 2001, Sahn and Stifel 2000, 2003, Grimm et al 2008, Harttgen and Klasen 2011b) and their advantages and disadvantages are well known (Filmer and Scott 2012 provide an excellent survey in this regard). On the negative side, we highlight the following points. First, since asset indices are discrete functions, there might be the risk that observations are clustered around certain values, therefore posing an important challenge to the task of estimating the underlying welfare distribution. In order to reduce the extent of this problem McKenzie (2005) suggests considering as many assets as possible. In the context of this paper, however, this problem is less severe because our basic unit of analysis is the municipality, not the household. Since the wealth index for each municipality (W_i) is obtained as the average of many household-level asset index observations (typically thousands of them), the corresponding distribution across municipalities is highly smooth (see Figure 10 in section 3 for the case of Mexico in years 1990, 2000 and 2010).

Second, the list of assets included in these indices typically refers to basic commodities that do not cover many of the goods and services that are generally available to high-income households. As a consequence (i) asset indices are better prepared to distinguish between poor households than among rich ones, an issue that could potentially be problematic in inequality analysis (McKenzie 2005), and (ii) the distribution of asset indices will tend to be more equal than the corresponding distribution of income it is meant to estimate. While acknowledging the empirical validity of the last point, it should be borne in mind that the normalization of the income component between zero and one using an affine log transformation [[[Endnote#12]]] before entering into the HDI does reduce inequality to levels that might well be similar to those of asset index distributions. To illustrate, Figure 1 shows the municipal-based per capita income distribution for the case of Mexico in year 2000 obtained from CONAPO (2001). Even if that distribution suppresses intra-municipal income variability, it has the expected extreme right (positive) skewness of income distributions. However, as shown in Figure 2, the distribution of the affine log transformation of those municipally averaged per capita incomes looks normally distributed and − importantly for our purposes − is relatively similar to the distribution of the corresponding municipal wealth indices W_i calculated for the same year (in fact, the municipal-based wealth index shows even more variability than the logged per capita income).

[[[Figure 1]]]

[[[Figure 2]]]

Third, asset indices have been criticized because they might not correctly capture differences between urban and rural areas. Asset indices might be biased due to differences in prices and the supply of the corresponding assets and because of

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alternative preferences in both areas. Since many assets are cheaper, more easily available and more desirable in urban areas, urban households might appear to be wealthier than their rural counterparts. Again, the fact of working at municipal rather than household level might reduce that problem to a certain extent because of the heterogeneity of households within municipalities (many of which are separated in urban and rural areas).

On the positive side, asset indices have different advantages that must be stressed. To start with, the reporting of household assets is less vulnerable to measurement errors than the reporting of income or expenditures (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 and fluctuations over time than income or expenditure, something that seems to be in line with the conceptual foundations of the HDI. In turn, asset indices would not be very appropriate if they were used to shed light on the impact of short term shocks (e.g.: health, weather of financial shocks; see Filmer and Scott 2012). Different studies have investigated the appropriateness of asset indices as a proxy for material welfare (that is: income or expenditures) and report quite encouraging results. For instance, Sahn and Stifel (2003) conclude that analysts may prefer to use asset indices – rather than expenditures – as an explanatory variable or as a means of mapping economic welfare to other living standards and capabilities such as health and nutrition. More recently, Filmer and Scott (2012) attempt to validate the use of various asset indices by comparing their performance with respect to per capita expenditures and report that the gradient of the outcomes of asset indices closely follow the results obtained with per capita expenditures. Moreover, McKenzie (2005) reports that asset indicators can be used to provide reasonable measures of inequality when no data on income or consumption is available. To sum up, even if their values should be

taken with caution, asset indices seem a viable – though imperfect – way of assessing material welfare.

(d) *The municipal-based HDI*

After computing the municipal-based health (H_i), education (E_i) and standard of living (W_i) 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 (i.e.: $(H_i + E_i + W_i)/3$) and from 2010 onwards, the HDI uses the geometric mean (i.e.: $\sqrt[3]{H_i \cdot E_i \cdot W_i}$). Henceforth, the additive and multiplicative versions of the municipal-based HDI will be referred to as $MHDI^a$ and $MHDI^m$ 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 (i.e.: similar) 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 reported in that paper might be an artifact of the way in which the HDI was constructed, so – as the authors acknowledge – they 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 (see section 3), the municipal averages of the different components are strictly positive, so the values of $MHDI^m$ 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, $MHDI^a$ 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 – importantly for the purposes of this paper – it allows knowing the contribution of the different components to overall inequality in human development, an issue to which we now turn.

(e) *Inequality decomposition by factor components*

Given the fact that the $MHDI^a$ is obtained after adding up the values of its three subcomponents, a question that naturally arises in this context is: for a given distribution of $MHDI^a$ values which of the three basic components accounts for most of the observed inequality levels across municipalities? Stated otherwise: for a given

distribution of municipal human development levels, what is the contribution of the three subcomponents to the observed inequality levels in MHDI? In order to answer conceptually related questions (e.g.: what is the contribution of different income sources' inequality to that of total income?), the economics literature has proposed several methods (e.g.: Shorrocks 1982, Lerman and Yitzhaki 1985). As warned by Lerman (1999), even with only two income sources, *A* and *B*, the inequality of total income, I_{A+B}, does *not* generally equal $I_A + I_B$ or the weighted sum of the two sources, $s_A I_A + (1- s_A) I_B$, where s_A is *A*'s share of income. For illustrative purposes in this paper we use the "decomposition by factor components" methodology suggested by Lerman and Yitzhaki (1985). Such methodology allows knowing the contribution of different income sources into overall income inequality as measured by the Gini index and can be straightforwardly adapted into the present context as follows.

For each municipality '*i*' let Y_i, H_i, E_i and W_i be the corresponding municipal human development, health, education and wealth indices. In case of additive human development indices we have that

$$Y_i = \frac{H_i}{3} + \frac{E_i}{3} + \frac{W_i}{3} \qquad [2]$$

The distribution of municipal human development, health, education and wealth indices will be denoted as *Y*, *H*, *E* and *W* respectively. Following Shorrocks (1982:195), if the human development distribution is ordered so that $Y_1 \leq Y_2 \leq \ldots \leq Y_n$, then the corresponding Gini index can be written as

$$G(Y) = \frac{2}{n^2 \mu_y} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) Y_i \qquad [3]$$

where n is the number of municipalities and μ_y is the mean of the human development distribution. Plugging equation [2] into equation [3] we obtain

$$G(Y) = \frac{2}{n^2 3\mu_y} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) (H_i + E_i + W_i) = \frac{\mu_h}{\mu_y} \overline{G}(H) + \frac{\mu_e}{\mu_y} \overline{G}(E) + \frac{\mu_w}{\mu_y} \overline{G}(W) \qquad [4]$$

where μ_h, μ_e and μ_w are the means of the health, education and wealth distributions and

$$\left. \begin{aligned} \overline{G}(H) &= \frac{2}{3n^2 \mu_h} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) H_i \\ \overline{G}(E) &= \frac{2}{3n^2 \mu_e} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) E_i \\ \overline{G}(W) &= \frac{2}{3n^2 \mu_w} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) W_i \end{aligned} \right\} \qquad [5]$$

which are known as the pseudo-Ginis for factors H, E and W respectively (see Shorrocks 1982:196 and Lerman and Yitzhaki 1985:152). These pseudo-Ginis are *not* the conventional Gini values $G(H)$, $G(E)$, $G(W)$, since the weights attached to the corresponding H_i, E_i and W_i in equation [5] correspond to the rank of municipality 'i' in the distribution Y, which in general is not the same as its rank in the distributions H, E and W. Equation [4] provides a natural additive decomposition rule for the Gini index where the contributions of the different sources are clearly established. This decomposition methodology has been used in many papers (see, for instance, Lerman and Yitzhaki 1985, Taylor 1992, Taylor and Wyatt 1996, Cancian 1998, 1999, Reardon et al. 2000) and will be used in this paper as well (see section 3) because it can be particularly useful to identify the component that should be the focus of priority attention when policy makers attempt to reduce inequality in human development.

3. AN EMPIRICAL ILLUSTRATION

In this section we illustrate the usefulness of our methodology by examining the evolution of Municipal HDI values in years 1990, 2000 and 2010 for the case of Mexico. Mexico 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 2010 were equal to 0.635, 0.698 and 0.75 respectively (using the new HDI methodology), a remarkable improvement. Those values are higher than the average HDI value for the region of Latin America. The methodology proposed in this paper aims to: (i) Spatially decompose the values of that country-level HDI and its three components across municipalities, (ii) Examine levels, trends and inequality levels of the human development distribution, and (iii) Show the contribution of the health, education and standard of living components in human development inequality across municipalities. In our years of study, the number of municipalities in Mexico was 2405, 2443 and 2456 respectively. This increase in the number of municipalities has also been observed – and even to a much larger extent – in all other countries in the region of Latin America. The congruity between municipalities over the different census rounds has been very high.

(a) *Data*

In order to estimate the municipal-based HDI we have used *complete* [[[Endnote#13]]] census data from Centro Latinoamericano y Caribeño de Demografía (CELADE in its Spanish acronym), the Population Division of United Nations' Economic Commission for Latin America and the Caribbean (ECLAC). Since the population in Mexico in our years of study was 81, 97 and 111 million individuals respectively, the computation of

our municipal-based HDIs required the manipulation of hundreds of millions of observations. For that purpose we have used REDATAM, a software developed in CELADE designed to manipulate complete census databases.

For the construction of the asset index A_h (see equation [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 radio. 8. Has TV. 9. Has refrigerator. 10. Has phone. 11. Has car. This is the list of assets available in the three censuses *at the same time*. While the 2000 and 2010 census questionnaires contain a longer list of assets (for instance: ownership of dishwasher, computer, mobile phone or internet connection), their inclusion would seriously compromise comparability over time, so we have preferred to keep the reduced list of assets shared by the three censuses. While this might probably give an overoptimistic impression of the "true" standard of living in Mexican municipalities for the years 2000 and 2010, 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 (this issue is discussed in more detail in section 4). Moreover, our results suggest that the average value of our wealth indicator across municipalities is not larger than the national-level GNI per capita index that is used in the nation-wide HDI (see below).

(b) *Results*

We start exploring the differences between the multiplicative and additive municipal-based human development indices $MHDI^m$ and $MHDI^a$. Figure 3 shows a scatterplot comparing their values in year 1990. By construction, the geometric mean takes smaller

values than the arithmetic mean, so all observations are below the 45° equality line. The farther away an observation is from the 45° equality line, the larger the $MHDI^m$ penalizes the corresponding municipality for an imbalanced distribution across the three dimensions. Large penalizations occur at the bottom of the human development distribution for a sizeable share of the Mexican municipalities (around 30% of the municipalities observe reductions in their human development levels above 10% when passing from the values of $MHDI^a$ to those of $MHDI^m$). In general, most observations are clustered and aligned just below the 45° equality line and the correlation coefficient is extremely high: r=0.982. Figure 3 also shows the scatterplot for the $MHDI^m$ and $MHDI^a$ values in year 2010 [[[Endnote#14]]]. In this case, however, the difference between both measures is negligible and the correlation coefficient is even higher: r=0.996. Since the values of $MHDI^m$ and $MHDI^a$ are relatively similar in year 1990 and extremely similar in years 2000 and 2010, in the rest of this section we will only report the values of the additive HDI (the results for $MHDI^m$ are available upon request).

[[[Figure 3]]]

Before exploring the distribution of our municipal-based human development indicator and its components over space and time, we have performed a validation check to assess the reliability of our results using an external source of data. Figure 4 shows a scatterplot comparing the values of our $MHDI^a$ index with the municipal-based human development index proposed by CONAPO for year 2000 (see CONAPO 2001). The relationship between both indicators is quite strong and the linear fit is pretty good, with a correlation coefficient equal to 0.87. Therefore, the municipal rankings in terms of alternative MHDI values are highly consistent when using the alternative

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methodologies. It turns out that the values of our $MHDI^a$ index tend to be lower than the corresponding values estimated by CONAPO, an issue that will be further discussed below. It is worth stressing that while CONAPO's methodology is partly based on sophisticated poverty mapping imputation techniques – see Endnote # 4 – and uses alternative sources of data, our methodology has the advantage of being much simpler and of being easily adapted to any country with census data satisfying some minimal requirements.

[[[Figure 4]]]

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 5 maps the values of $MHDI^a$ for the Mexican municipalities in year 1990. This map summarizes a wealth of information that is much more informative than the corresponding national-level average HDI. A glimpse at Figure 5 clearly shows that human development is not evenly distributed across the country and that seems to follow a spatial pattern where less developed municipalities tend to be surrounded by less developed municipalities as well and vice versa [[[Endnote#15]]]. It can be seen that large metropolitan areas like Mexico City, Aguascalientes, Guadalajara, Monterrey, Puebla or Tijuana have relatively high human development levels, as opposed to what is observed in more rural areas of the country. Mexico City, which is Mexico's largest metropolitan area, is surrounded by a ring of municipalities with substantially smaller human development levels. Figure 6 maps the values of $MHDI^a$ twenty years later. Interestingly, the values of that indicator are clearly much higher and seem to be more evenly distributed across the country.

Notwithstanding those clear improvements in human development levels, 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 Mexico City is surrounded by a ring of municipalities with relatively lower human development levels.

[[[Figure 5]]]

[[[Figure 6]]]

(i) *Distribution of human development and its components*

While the maps shown in Figures 5 and 6 are very useful to identify geographic patterns, they are not very informative on the *exact* distribution of $MHDI^a$ values across municipalities. Figure 7 shows the three density functions of the $MHDI^a$ values corresponding to the census rounds of 1990, 2000 and 2010 respectively. These density functions indicate at least three things: i) The average value of MHDI has clearly increased over time (however, the improvement from 1990 to 2000 has been greater than the improvement from 2000 to 2010). The mean values of those distributions across municipalities are μ_{1990}=0.44, μ_{2000}=0.57 and μ_{2010}=0.65; ii) The spread of the distributions (i.e.: inequality across municipalities) has apparently decreased over time; iii) The distributions become gradually skewed to the left. Overall, these are very encouraging results suggesting that the $MHDI^a$ distribution in Mexico has clearly improved over time and reduced inequality across municipalities during the last two decades – in line with the impressions obtained from Figures 5 and 6. The implications of these results, however, need to be qualified and discussed in more detail.

Concerning i) it is remarkable that the average values of our municipal-based HDI distributions are smaller than the corresponding "classical" (i.e.: Mexico-wide) HDIs

reported at the beginning of this section. To a large extent, these differences are attributable to the fact that our asset index is better prepared to distinguish between poor households than among rich ones, so that the nation-wide GNI index takes larger values than the average of our wealth index. Regarding ii) and iii), it must be stressed that decreasing inequality and increasing skewness to the left are attributable to a certain extent to the way in which the HDI is constructed. Since there are upper and lower bounds within each component – so that they can be normalized between zero and one to be comparable –, the human development distribution gradually concentrates in the upper tail of its distribution as municipalities improve their living conditions. Recall, however, that this problem is not specific to the municipal-based HDI proposed in this paper but applies to nation-wide HDIs as well: over the past twenty years the distribution of the HDI has become gradually concentrated towards its upper bound (see, for instance, http://hdr.undp.org/en/data/trends/).

[[[Figure 7]]]

Given the fact that the *MHDI*^{a} is a composite index, it is of great interest to explore the evolution of its three subcomponents over time. Figures 8, 9 and 10 show the density functions corresponding to the Health, Education and Standard of Living subcomponents of the index respectively for the census years 1990, 2000 and 2010. Interestingly, the evolution of the three components is notably different. Concerning the health distribution across municipalities we can observe that, contrary to what happened with the aggregate *MHDI*^{a} value, the improvement from 1990 to 2000 has been modest when compared to the large improvement observed from 2000 to 2010 (the respective mean values are 0.63, 0.70 and 0.85, see Figure 8). Moreover, the spread of the health distribution has notably decreased in the last census round, therefore suggesting that the factors positively influencing the health conditions in Mexican municipalities have

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become widespread all over the country. Regarding the education component, there has been a marginally decreasing and modest improvement across the 1990-2000-2010 period (see Figure 9). The slowing down of the improvement in the education component might perhaps indicate that the corresponding indicators are reaching an upper bound and could not reasonably take much higher values because of labor supply and demand constraints (i.e.: it is not reasonable to expect that all individuals in the population complete school education to the maximal possible level). Lastly, the evolution of the Standard of Living component shown in Figure 10 is quite different from the other two. In 1990, the values of the municipal wealth index were remarkably low with an average of 0.33 (i.e.: an average household only owned one third of the assets included in our list) and a distribution highly skewed to the right. Ten years later, the average value of the distribution notably increased to 0.56 and the spread of the distribution was substantially smaller. However, in 2010 the average of the distribution just increased to 0.62. This value is relatively small and has plenty of room for further improvement, especially when compared with the corresponding distribution of the health component for the same year.

[[[Figure 8]]]

[[[Figure 9]]]

[[[Figure 10]]]

In an interesting paper, McGillivray (1991) argued that the large correlation between the HDI components − most of them above 0.8 − lead to the construction of a *redundant* composite index. In this context, we aim to explore the extent to which the different components of our municipal-based HDI correlate with each other. Table 1 shows the values of the pair-wise correlation coefficients for the years 1990, 2000 and 2010. In the

three years, the correlation coefficient between wealth and education is moderately high (around 0.7) and decreases slightly at the end of the period. On the other hand, the correlation coefficients between wealth and health and between education and health take intermediate values (around 0.5) and clearly decrease over time. These results suggest that the pathways to human development at municipal level in Mexico are becoming increasingly diverse, with increases in one component not inevitably accompanied with increases in the other ones. Overall, the size of these coefficients is smaller than the values reported at the country level by McGillivray (1991). Therefore, our results indicate that the redundancy problem of our municipal-based HDI is not particularly acute.

[[[Table1]]]

(ii) *Inequality in human development*

The results shown in Figures 7 to 10 suggest that distribution spread has decreased over time in Mexico not only for the overall $MHDI^a$ distribution but also for its subcomponents. In this context, one might want to be more precise and quantify the extent of inequality in order to know the pace at which it has reduced over time and in order to make comparisons across dimensions. Table 2 shows the values of the standard Gini index (G) corresponding to the overall $MHDI^a$ distribution and its different subcomponents separately for the years 1990, 2000 and 2010. As expected, all distributions have reduced the values of the Gini index over time (see rows 2-5 in Table 2). Moreover, the wealth component exhibits the largest levels of inequality for the three moments in time. The large level of inequality exhibited by that component in 1990 (G=0.33) reduced by more than 50% in 2000 (G=0.149) but abruptly slowed down

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its downward trend by just reducing to $G=0.124$ in 2010. The opposite trend can be observed for the health component: it started with moderate levels of inequality across municipalities in 1990 and 2000 and then abruptly decreased in 2010, thus signaling to a widespread improvement and homogenization of child survival probabilities across the country. On the other hand, the education component has exhibited intermediate levels of inequality that have gradually decreased during the whole period, indicating the increasingly high homogeneity in education levels in Mexican municipalities. As can be seen in Table 2, the overall $MHDI^a$ distribution reduced its inequality across municipalities to a great extent from 1990 to 2000 but not that much from 2000 to 2010, a behavior that has been largely driven by the evolution of the wealth and education components.

For comparative purposes, the first row in Table 2 also shows the values of the Gini index applied to the Mexican income distribution taken from the World Bank's database. Its values – around 0.5 – are much larger than the ones observed for the distribution of human development and its components. However, as argued in section 2, inequality in human development is drastically reduced because of the normalization procedures that are applied to the different variables when computing the HDI. Analogously, when an income distribution is normalized via affine log transformations (see Endnote#12), the corresponding inequality levels are reduced to a large extent (see Figures 1 and 2).

Comparing our results with the inequality in human development results reported in Harttgen and Klasen (2011b: Table 2) we find substantial differences, their inequality values being typically larger than ours. We attribute these differences to two factors. First, Harttgen and Klasen (2011b) report problems with the distorting influence that the zero educational attainment of certain households has on their assessment of overall

inequality levels. This might eventually upwardly bias their results [[[Endnote#16]]]. Second, their results report inter-household variability, while the results presented here report inter-municipal variability. By construction, the later distribution should exhibit smaller inequality levels than the former.

Using the inequality decomposition by factor components techniques presented at the end of section 2, we are able to know the specific contribution that each of the three components has on the observed inequality levels in $MHDI^a$. Table 2 shows the contribution of the health, education and wealth components to overall $MHDI^a$ inequality (shown in bold in row 5) that is obtained using the aforementioned methodology for the years 1990, 2000 and 2010 (see rows 6-8). To illustrate: in 1990, overall $MHDI^a$ inequality as measured by the Gini index was equal to 0.17. The contributions of the health, education and wealth components to that value were equal to 33.5%, 20.8% and 45.7% respectively. As shown in Table 2, the contribution of the wealth component has always been the largest and it has become particularly important for the year 2010, when it accounts for as much as 60.2% of total inequality. This indicates that inequalities in human development are increasingly being accounted for by the distribution of wealth and – to a lesser extent – education, an important result with many policy implications. If policy makers were interested in reducing inequality in the distribution of human development, priority attention should be given to the wealth component.

4. DISCUSSION AND CONCLUDING REMARKS

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 propose new 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 by scholars, researchers, practitioners, national and international institutions and policy makers.

In this paper we have proposed a simple methodology to compute a municipality-based HDI on the basis of census data alone that, among many other things, can be used to uncover sub-national inequalities in basic well-being dimensions at very low aggregation levels. Moreover, we have proposed a simple but useful methodology to estimate the contribution of the different well-being dimensions to inequality in human development. On the one hand, the availability of such fine-grained data opens up new horizons and a virgin territory for further research in unforeseeable directions. Triangulating the analysis at the micro-, meso- and macro- level of aggregation, it will be possible to establish formal linkages between the corresponding geographical perspectives to unveil insightful relationships that have not been explored so far because of the lack of appropriately harmonized datasets. On the other hand, such exercise is extremely useful and can have many implications for policy-making purposes. Hopefully, the techniques presented here might contribute to develop a better picture of the extent of human development, eventually determine why underdevelopment prevails in certain areas and what perpetuates it, guide public policy, improve monitoring and evaluation and better understand its relationship with key socio-economic and demographic variables.

The empirical results shown in this paper suggest that human development is steadily increasing and reducing inequality across Mexican municipalities during the 1990-2010 period, an encouraging result for that country. Such results seem to be in line with different studies that find evidence of cross-country convergence on a number of welfare indicators, like education (Goesling and Baker 2008), fertility (Dorius 2008) the human development index itself (Crafts 2002) or other quality of life indicators (Kenny 2005). However, the decomposition of human development levels by subcomponents reveals that the wealth index seems to be more reluctant to reduce inequality in its distribution. Moreover, during the last two decades, this has been the component that has accounted for most of the observed inequality in human development. Hence, if policy makers aim to reduce inequality in human development across Mexican municipalities they should prioritize the standard of living dimension. These not so encouraging results might be more in line with the increases in world income inequality reported in Milanovic (2005).

An important caveat concerning the municipal HDI proposed in the paper is that it includes only very basic indicators which, some might argue, are just too crude and do not faithfully represent the well-being status of the corresponding inhabitants. While we acknowledge that many other quantitative and qualitative indicators are necessary to accurately portrait and monitor the well-being levels of a group of individuals, we are neither contending that this was the original nor the main purpose of the MHDI. The indicator we have presented in this paper – of which many plausible alternative versions could be easily proposed – 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 should be pointed out, however, that if our purpose were to give a faithful portrait of human well-being levels in all its dimensions, we might be forced to consider many local or region-specific indicators that would seriously compromise the validity of geographical and temporal comparisons. The trade-offs between the meaningfulness of indicators and their geographical and temporal comparability are unavoidable, forcing researchers to take decisions that can never resolve the existing tension between two irreconcilable poles.

While the methodology presented here allows international comparisons 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.

The approach we have taken in this paper of focusing on some basic indicators at very low aggregation levels using census data could as well be incorporated in the monitoring of United Nations' Millennium Development Goals (MDGs). To our knowledge, and despite their huge relevance for the lives of millions across the world, the evolution of the MDGs has only been tracked at the country level. However, these results might hide huge disparities at sub-national levels that are extremely important to identify, as has been suggested in this and other conceptually related papers. It is high

time that the great descriptive power of census data is fully exploited by researchers and policy-makers alike to guide them in their enterprise of fulfilling the promise of the Millennium Declaration for a better world. As stated in Alderman et al (2003:193):

> "[…] Finally, we believe that unit record census data is underutilized in many countries, especially in the developing world. Census data consist of basic, yet useful information that collects dust on the shelves waiting to be exploited. We encourage our readers to help make census data more accessible to researchers and policy-makers around the world".

This message is particularly relevant in a moment in which: (i) many of the censuses from the 2010 world census round are about to be (or have recently been) conducted, and (ii) census data are becoming readily available and comparable (consider, for instance, the IPUMS census data project at the University of Minnesota). Importantly enough, these censuses will be the last ones that will be conducted before the 2015 MDGs deadline is reached, so statistical exploitation techniques like the ones presented in this paper might be useful to ascertain the extent to which the goals have been attained or not.

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ENDNOTES

Endnote#1: Foster et al (2005) proposed an axiomatically sound class of distribution-sensitive human development indices which, unlike the index proposed by Hicks (1997), satisfied the axiom of subgroup consistency.

Endnote#2: Seth (2009) introduced the class of association-sensitive human development indices that are sensitive to the extent to which distributions overlap (i.e.: correlate) across dimensions.

Endnote#3: These variables are GDP per capita, life expectancy at birth, adult literacy rate and gross school enrolment ratios. In the new 2010 and 2011 HDI, the education variables have been substituted by mean years of schooling of adults aged 25 and older and expected years of schooling for children. Moreover, GDP per capita has been substituted by GNI per capita.

Endnote#4: In an attempt to have high-precision welfare estimates at very low aggregation levels, the World Bank has been using in the last few years the "poverty mapping" methodology introduced by Elbers, Lanjouw and Lanjouw (2003) for different developing countries (see World Bank 2007). This quite sophisticated methodology basically uses imputation techniques that combine the richness of household surveys information with the exhaustiveness of census data. Despite its popularity, Tarozzi and Deaton (2009) have severely criticized the poverty mapping methodology because the underlying assumptions upon which it is based are unlikely to be satisfied in practice.

Endnote#5: See Endnote #4.

Endnote#6: Since a municipal-based HDI suppresses variability within municipalities, the observed inter-municipal HDI variability is a lower bound of the variability that a hypothetical household-based or individual-based HDI would have.

Endnote#7: These questions are: 1. "How many children have you ever had?" 2. "How many of them are still alive?" They have been included in the recommendation list that the United Nations issue in order to improve census quality because of their usefulness for indirect estimation techniques.

Endnote#8: A good explanation of these and other indirect estimation methods can be found in United Nations (1983).

Endnote#9: In the empirical illustration shown in section 3 we have chosen P_{min}=75 and P_{max}=100. However, the substantive results of this paper remain unchanged for alternative specifications of those values.

Endnote#10: The expected years of education for children in schooling age measures something like the "school life expectancy" and is defined as the total number of years of schooling that a child of a given age can expect to achieve assuming that the current enrolment rates do not change over time. The expected years of education in municipality 'i' are calculated as the sum of age-specific enrolment rates over the schooling ages, that is: $EYS_i = \sum_{j=m}^{M} \left(E_{ij} / P_{ij} \right)$ where m (resp. M) is the smallest (resp. highest) schooling age, E_{ij} is the number of enrolled children of group age 'j' in municipality 'i' and P_{ij} is the number of children of group age 'j' in municipality 'i'.

Endnote#11: The maximum and minimum thresholds for these indicators used in this paper are the following: 13.1 and 0 for *AYS* and 18 and 0 for *EYS*. These are the thresholds used in the construction of the country-level HDI, which in turn are derived from the results of Barro and Lee (2010). Therefore, the normalization formulae are $(AYS - 0)/(13.1 - 0)$ and $(EYS - 0)/(18 - 0)$.

Endnote#12: Recall that in the construction of the HDI, the GDP per capita is normalized via the log transformation (log(GDP)-log(min))/(log(max)-log(min)), where min=$100, max=$40000 are the lower and upper thresholds established by UNDP.

Endnote#13: For statistical security and confidentiality reasons, census information is not publicly available. A special permit is needed to manipulate those databases – which

can be accessed on site only. We are grateful to Dirk Jaspers and his team in CELADE for permitting access to the census database.

Endnote#14: The comparison between $MHDI^m$ and $MHDI^a$ values in year 2000 is not shown to avoid burdening Figure 3 too much. However, the results are highly similar to those of year 2010 (the correlation coefficient also equals 0.99).

Endnote#15: The exploration of spatial patterns using spatial association measures like Moran's I (Moran 1950) or Getis and Ord's G_i and G_i^* indicators (Getis and Ord 1992) is a very interesting topic of research that is beyond the scope of this paper.

Endnote#16: In this context, the inequality levels in the health component distribution reported in both papers – which are not affected by the aforementioned boundary problems– are relatively similar.

FIGURES AND TABLES
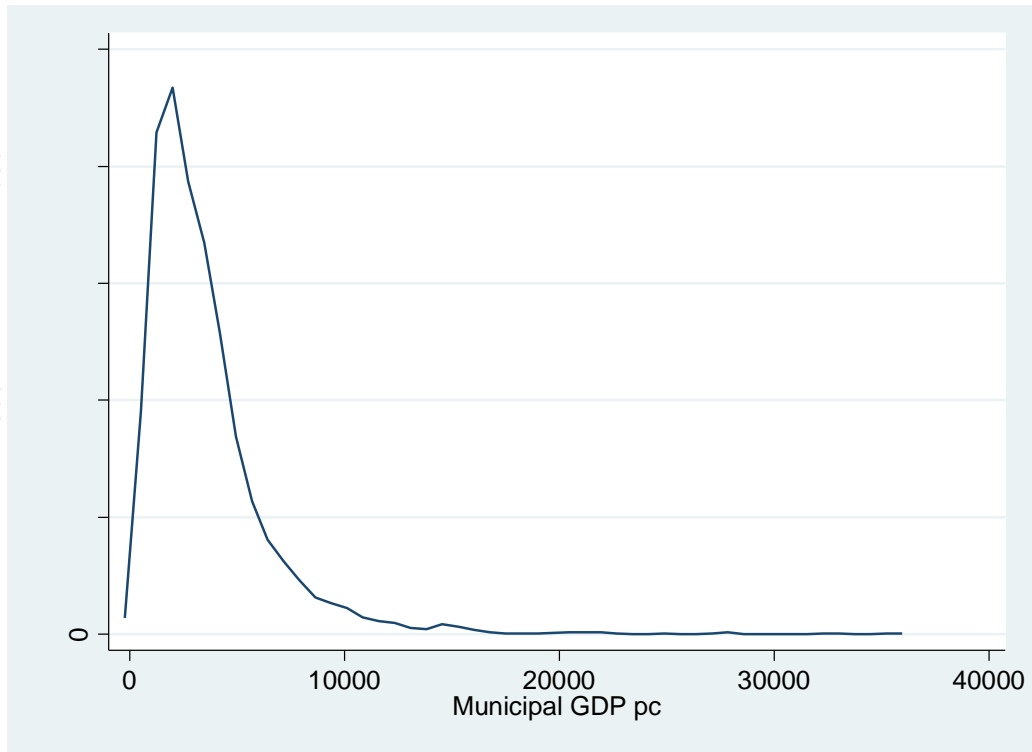
Figure 1. Kernel density of municipal GDP per capita for Mexican municipalities, year 2000. Author's calculations based on publicly available data from CONAPO (2001).
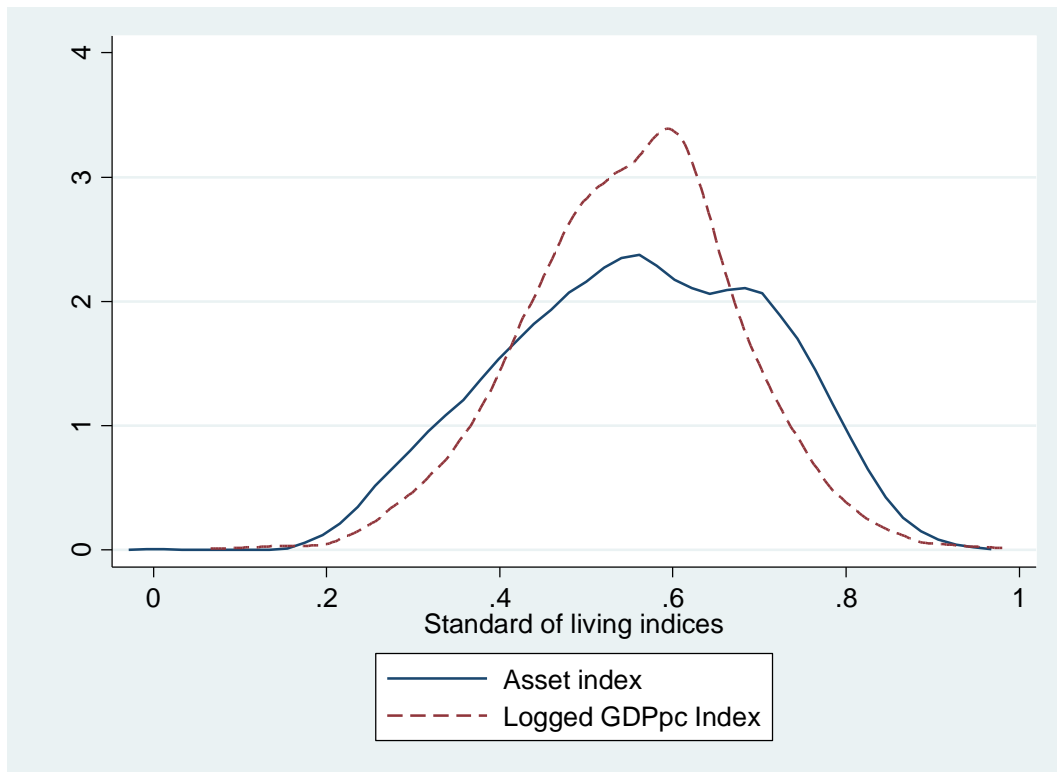

Figure 2. Kernel densities of Logged municipal GDP per capita and municipal asset index.

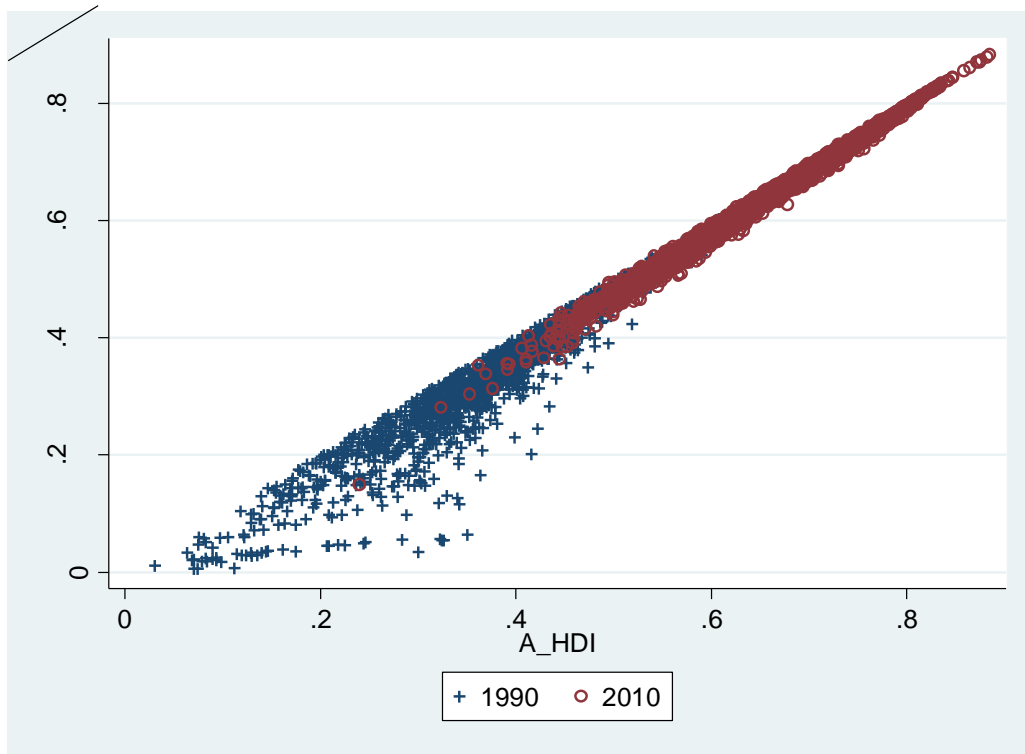Author's calculations based on data from CONAPO (2001) and 2000 Mexican census data.

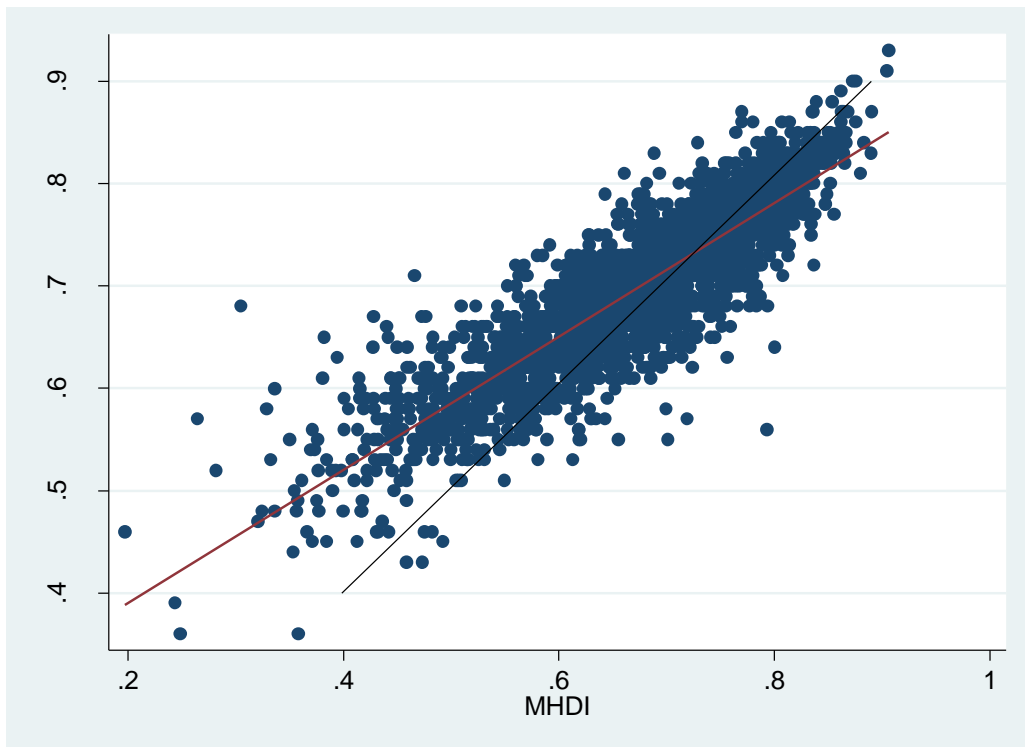Figure 3. Scatterplot of $MHDI^m$ vs $MHDI^a$ in years 1990 and 2010. We also show the 45º equality line.

Figure 4. Additive Municipal Human Development Index ($MHDI^a$) vs CONAPO's Municipal Human Development Index. Mexico 2000, 2443 municipalities. Equality and

best linear fit lines shown in black and red respectively for comparative purposes. Author's calculations using census data.

AHDI (#hits)

0 - 0.4 (884)
0.4 - 0.5 (703)
0.5 - 0.6 (524)
0.6 - 0.7 (263)
0.7 - 1 (65)

Figure 5. Municipal-based human development index *MHDI[a]*, Mexico 1990. Authors' calculations using Mexican census data from CELADE.
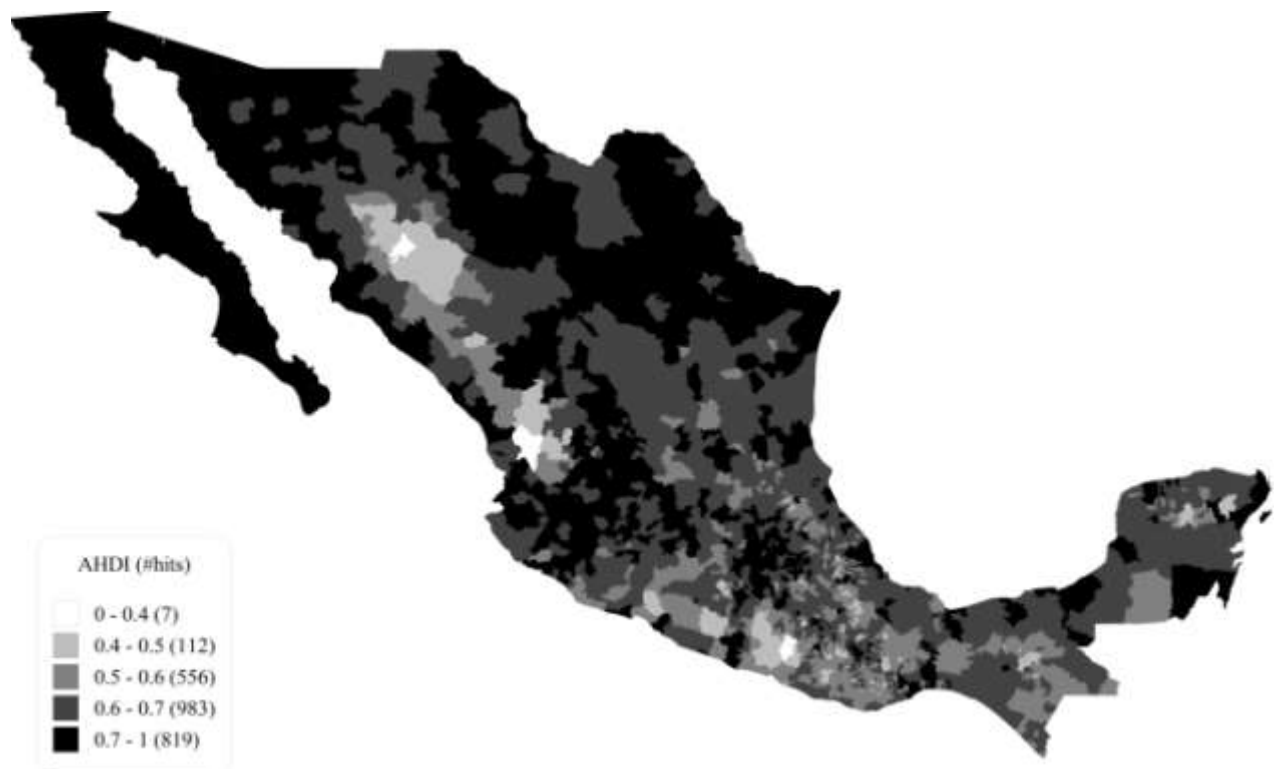

AHDI (#hits)

0 - 0.4 (7)
0.4 - 0.5 (112)
0.5 - 0.6 (556)
0.6 - 0.7 (983)
0.7 - 1 (819)

Figure 6. Municipal-based human development index *MHDI*[a], Mexico 2010. Authors'
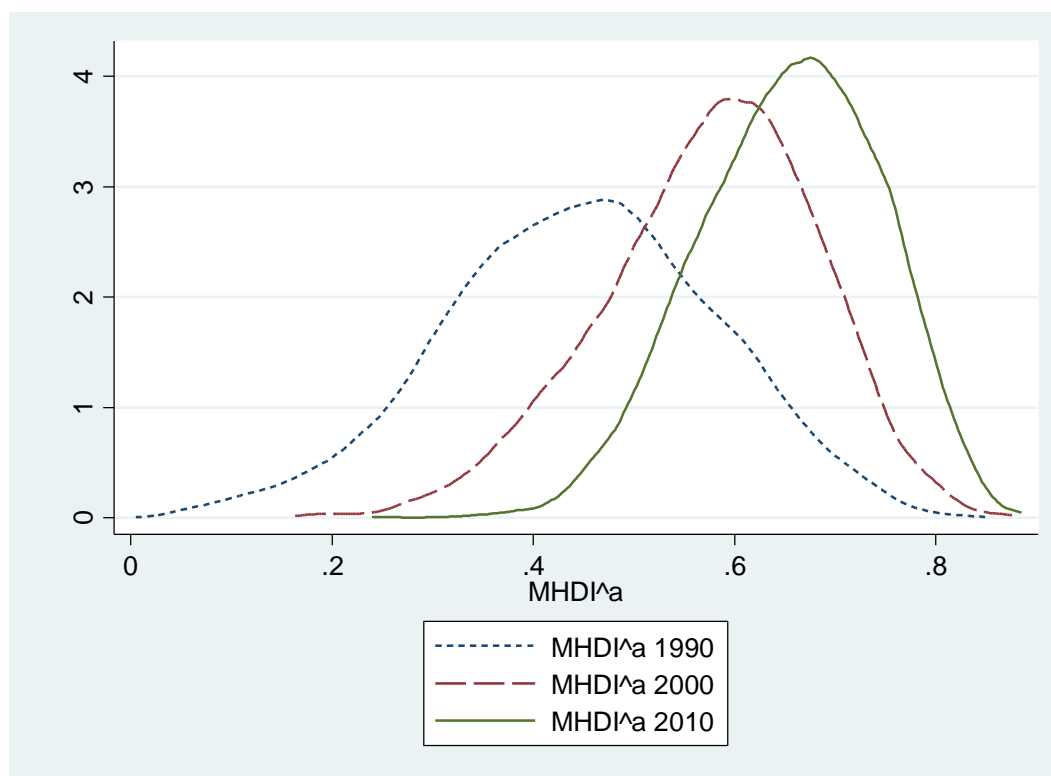calculations using Mexican census data from CELADE.

Figure 7. Density functions of the municipal human development index *MHDI*[a] for
years 1990, 2000, 2010 (Mexico). The mean values of the density functions are 0.44,
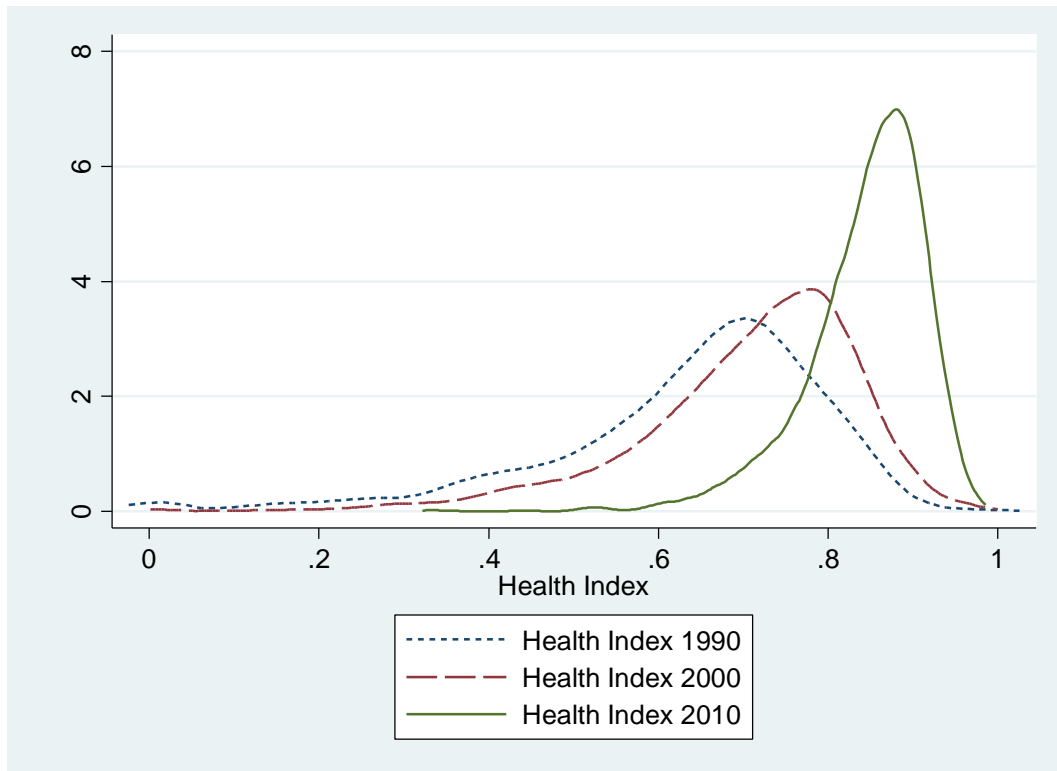0.57 and 0.65 respectively. Author's calculations using census data.

re 8. Density functions of the municipal health index for years 1990, 2000, 2010 (Mexico). The mean values of the density functions are 0.63, 0.71 and 0.84 respectively. Author's calculations using census data.
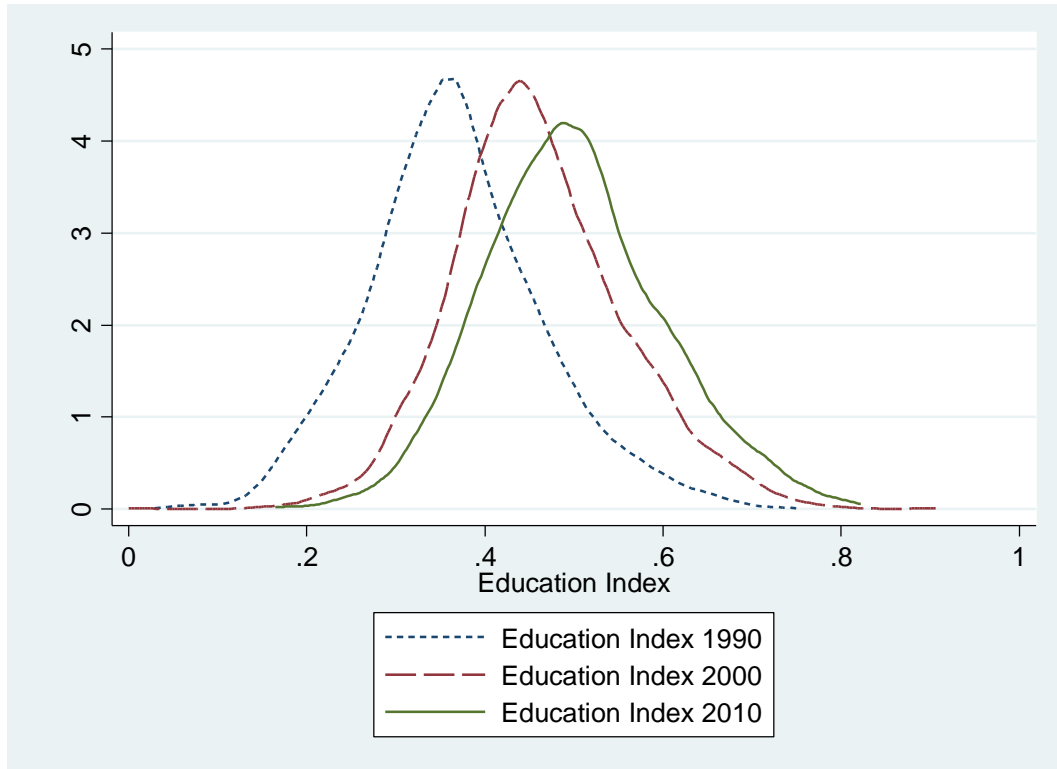
re 9. Density functions of the municipal education index for years 1990, 2000, 2010 (Mexico). The mean values of the density functions are 0.37, 0.46 and 0.50 respectively. Author's calculations using census data.

Figure 10. Density functions of the municipal wealth index W_i for years 1990, 2000, 2010 (Mexico). The mean values of the density functions are 0.34, 0.56 and 0.62 respectively. Author's calculations using census data.

Correlations	1990	2000	2010
W & E	0.75	0.68	0.71
W & H	0.59	0.53	0.49
E & H	0.59	0.50	0.44
N	2405	2443	2456

Table 1. Correlation coefficients between *MHDI*[a] components. *W, E* and *H* stand for Wealth, Education and Health components respectively. *N* is the number of municipalities in each census round. Author's calculations using census data.

| | **GINI** | | |
	1990	**2000**	**2010**
Income	0.551	0.531	0.517
Health	0.138	0.080	0.021
Education	0.149	0.113	0.104
Wealth	0.330	0.149	0.124
***MHDI*[a]**	**0.170**	**0.094**	**0.065**
Contributions to *MHDI*[a] inequality			
Health	33.5%	30.5%	10.5%

Education	20.8%	25.1%	29.3%
Wealth	45.7%	44.4%	60.2%

Table 2. Gini indices for the Income, Health, Education, Wealth and $MHDI^a$ distributions for the years 1990, 2000, 2010. Contributions of the Health, Education and Wealth components to the inequality in the $MHDI^a$ distribution. Author's calculations using census data (data on income inequality taken from World Bank's PovcalNet).