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Abstract

Local income data are an important economic indicator, widely used in a broad range of studies related to regional convergence, urban economics, fiscal federalism, housing and spatial analysis. Despite its importance, there is a lack of official data on local incomes and, most importantly, on local income distributions. In this paper we use official data on personal income tax returns and a reweighting procedure to derive a representative income sample at the local level. Unlike previous attempts in the literature to acquire local income estimates, the results obtained allow us to derive not only an average value for income but also its local distribution, a valuable and informative tool for analysing distributional and income inequality. We apply this methodology to Spanish Personal Income Tax micro-data and illustrate its potential use in analysing income inequality by means of computed Gini, Atkinson indexes and top 0.01%, 0.5% and 0.01% income share measures for the most populated Spanish municipalities (those with over 160,000 inhabitants).

Keywords: local income distribution, sample reweighting, income inequality, top incomes

JEL classification codes: C42, C61, D31, D63, O15

1. Introduction

Which municipalities are richer than others? What are the causes of such differences? Is there a pattern to the spatial distribution of local income? How do redistributive policies (such as progressive taxation or transfer programmes) affect the income distribution across municipalities? What is the impact of top income earners on economic growth and inequality? Information on the local income distribution is essential in answering all these questions.

Local income data are therefore an important economic indicator, widely used in a broad range of studies related to urban economics, fiscal federalism, housing and spatial analysis, among others. In addition, aspects of income inequality and poverty at the local level are receiving increasing attention from researchers in these areas. However, despite its importance, local income data remain a key missing element within the official statistics of many developed countries. The explanation lies, on the one hand, in the complexity of designing surveys that are statistically reliable, and on the other hand, in the high cost of field work, since it is necessary to carry out a large number of interviews in all the municipalities. As a result, most of the household income and expenditure surveys have a limited territorial representation, mainly at a regional or provincial level.

To redress this lack of information, a wide range of statistical techniques have been developed over the last two decades aimed at providing reliable estimates of local income. The majority often use micro-data information from surveys, combined with aggregate information about relevant variables for the considered population subgroups. Haslett *et al*. (2010) distinguish three main statistical methods with underlying similarities: small area estimation[1], imputation techniques[2], and spatial micro-simulation modelling[3].

Household survey data have been used widely as the primary source for empirical analysis on inequality, whereas little attention has been paid to income tax data. There is however a growing body of empirical literature focusing on tax-based research (see for instance Pikkety and Saez, 2003; Atkinson and Piketty, 2007; and Atkinson, Piketty and Saez, 2011). The availability of personal income tax micro-data samples has also provided an attractive method for modelling local income distributions. Although these samples have high population

[1] Small area estimation refers to a set of techniques designed for improving sample survey estimates using auxiliary information relating to analysed population subgroups. Some basic references on the methodologies used for small area estimation are Rao (1999, 2003), and Elbers, Lanjouw and Leite (2008).

[2] Imputation techniques are used to incorporate observations and variables in the construction of databases whose original information is either incomplete or has problems of sampling or no-response. For further details on these techniques, see Kovar and Whitridge (1995).

[3] Spatial micro-simulation modeling derives small area micro-data sets using reweighting techniques usually based on optimisation procedures. For a further explanation on the extent and implementation of these models, see for instance Rahman *et al*. (2010) and Tanton and Edwards (2013).

reliability, they are often statistically representative only at the regional level, as is the case in Spain. In view of this limitation, it is necessary to develop a statistical treatment that allows us to perform reliable income estimates for geographic areas below the regional level, i.e. the municipalities. Hence in this paper we develop a model of sample reweighting designed to overcome these problems, particularly in the context of distributional and income inequality analysis[4].

Thus the objectives of the paper are twofold. On the one hand, we seek to provide a representative income sample at the local level based on official tax statistics. To that end, we adapt a methodology for sample reweighting proposed in Deville and Särndal (1992), Creedy (2003) and Creedy and Tuckwell (2004) to the case of Spanish micro-data of personal income tax returns. In addition, we use this representative local income sample to derive local income distributions. Unlike previous attempts to obtain local income estimates, in this paper we obtain not only an average value of income for each Spanish municipality but also its local distribution, allowing us to carry out income inequality analysis via certain inequality measures such as Gini and Atkinson indexes. In addition, the data obtained allow us to study the top incomes within each municipality, a topic of increasing interest within researchers using income tax data at the country level (see for instance Atkinson, Piketty and Saez, 2011).

The article is organised as follows. In the next section we present the problem of estimating personal income at the local level and we review the related literature and data sources. The tax microdata-based model and the calibration approach implemented in the paper to obtain the new sample weights used to derive local income distributions is presented in the third section. The data used, the main findings and the validation of estimates are presented in the fourth section. In the fifth section we report an illustration of income inequality analysis for the case of Spain. Finally, in the last section, we conclude.

2. The problem of measuring local income: limitations and alternatives

2.1. State of the art

Most developed countries do not publish official statistics on personal or family income at the local level nor the degree of inequality of their income distributions. This lack of information represents an important limitation for economic analysis as these are variables frequently used in applied economic research. There exists, however, a few exceptions in the United States, United Kingdom or Australia.

[4] Bramley and Smart (1996) conducted a pioneering study in this line, in which they obtained income distributions for local districts of England using micro-data from the national Family Expenditure Survey.

The U.S. case is probably the most remarkable one. The U.S. Bureau of Economic Analysis provides data on personal income for the 366 metropolitan areas and their 3,113 counties, covering the period 1969-2011[5]. Personal income is measured before the deduction of personal income taxes and other personal taxes and is reported in current dollars, and it is defined as the income received by all persons from all sources (the sum of net earnings by place of residence, rental income, dividend and interest income, and current transfer receipts).

In the United Kingdom, estimations of the gross disposable household income (henceforth GDHI) for the 139 local areas defined as NUTS3 (metropolitan and non-metropolitan counties) are published by the Office for National Statistics (ONS) annually (period 1997-2011). The most appropriate local indicators available are used and drawn from a wide variety of survey and administrative sources. According to the National Accounts, GDHI is defined as the amount of money that all of the individuals in the household sector have available for spending or saving after current taxes on income and wealth, social contributions paid and social benefits obtained.

In Australia, since 2005 the Bureau of Statistics has provided small area estimates of the sources of personal income for each state and territory according to the various levels of the Australian Standard Geographical Classification, including Local Government Areas. These estimates, available for the years 1995-96 to 2010-11, are compiled using a combination of individual income tax data from the Australian Taxation Office (wage and salary income, own unincorporated business income, investment income, superannuation and annuity income and other taxable income) and Government cash benefit income from the Commonwealth Department of Family and Community Services.

Unlike the previous examples, in Spain, the National Statistical Office (henceforth INE) does not provide data on family or personal income at the local level. Over the last decade, several Regional Statistical Institutes (IDESCAT in Catalonia, EUSTAT in the Basque Country or IAEST in Aragon, among others) have provided, though not always on a regular basis, statistics including the per capita GDHI of those municipalities included in their jurisdictions. In general, these are local estimates based on the Spanish Regional Accounts data provided by the INE. The territorial imputation is carried out using indirect estimation methods. These methods are based on econometric techniques that use the regional or provincial GDHI along with other socioeconomic indicators available at the local level (i.e. total population, number of unemployed residents, members of the population with a bachelor's degree or higher, number of vehicles registered, number of commercial and industrial establishments, average housing price,

[5] For further details, visit http://www.bea.gov/regional/index.htm.

etc)[6]. Due to the lack of official statistics, the Lawrence R. Klein Research Institute (Autonomous University of Madrid) has become the main source of local income data in Spain. Certainly, there are many other estimates from the academic field that have also estimated the municipal income, usually with a regional scope, using indirect methods to territorialise the GDHI[7].

The use of territorialised macroeconomic variables such as the gross value added (henceforth GVA) or the GDHI to derive local income measures has two main limitations for the analysis of personal income distributions. Firstly, these magnitudes do not adequately represent the personal or household ability to pay taxes, nor the portion of income they can use for consumption or savings, since they include capital income under the criteria of where production activity is located instead of where their owners reside. For instance, we can think of a residential municipality with a high standard of living where owners of businesses locate their activities in other municipalities, even in other regions or countries. Of course, there will also be municipalities whose residents do not have a high standard of living but where very profitable companies are located, due to, for example, their lower wages. Another important limitation of using macroeconomic aggregates to estimate local income is related to the impossibility of obtaining distributions of income for municipalities, and consequently measures of inequality. Whatever the statistical or econometric method used to estimate the per capita income of each municipality, the result is a unique value, which makes it impossible to obtain information about the dispersion of the magnitude.

The availability of micro data samples at the local level are essential in order to compute inequality measures related to the personal income distribution of a municipality. As far as we know, the U.S. Census Bureau is the only institution with experience in this regard. Its American Community Survey (ACS) Public Use Microdata Sample (PUMS) provides annual data on personal and family income[8,9].

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[6] Alternatively there are direct estimation methods based on the spatial localisation of the different components of the gross disposable income from a production point of view. Their use is very rare given the complexity of such imputation.

[7] Among others, we can mention Arcarons *et al*. (1994) and Oliver *et al*. (1995) in Catalonia, Esteban and Pedreño (1992) in Valencia Community, Fernández and Sierra (1992) in La Rioja, De las Heras (1992) and De las Heras and Murillo (1998) in Cantabria, Herrero (1998) in Castile and Leon, Remírez-Prados (1991) in Navarra, and Chasco y López (2004) in Murcia. Some of these introduce complex estimation methods, such as multivariate factor and cluster analysis or econometric multiequational models. Likewise, using spatial econometric techniques Alañón (2002) offers estimates of gross value added for the Spanish municipalities, and Chasco (2003) and Buendía *et al*. (2012) obtain GDHI per capita estimates for the Autonomy Community of Madrid and the Region of Murcia, respectively.

[8] For this survey, total personal income is defined in terms of pre-tax income and includes the sum of the amounts reported separately for wage or salary income, net self-employment income, interest, dividends, net rental and royalty income, income from estates and trusts, social security or railway retirement

Household surveys that include information on the income of their members are the natural statistical source for providing micro-data on personal income. For the EU Member States these surveys are The European Community Household Panel (ECHP), from 1994 to 2001 (eight waves), and The European Union Statistics on Income and Living Conditions (EU-SILC) since 2003. Unlike their high quality level, guaranteed by the coordination and supervision of Eurostat, their sampling design makes them invalid for estimates in smaller territorial areas. A large number of survey interviews are required to meet an acceptable degree of statistical representativeness at the municipal level. Thus the number of survey interviews required would be greater than that needed at the regional or national level. This is why the lack of available micro data for small areas is mainly a cost problem. In addition, misreporting and income underreporting in expenditure and revenue surveys are substantive concerns that are hard to mitigate[10]. Moreover, as noted in Deaton (2003), personal income survey data show an important underestimation when compared with equivalent magnitudes included in the National Accounts, making them inappropriate for small area estimation[11].

2.2. Personal Income Tax returns as an alternative income data source

Tax returns on the Personal Income Tax (henceforth PIT) collected by national tax administrations are an interesting alternative for overcoming the aforementioned territorial representativeness limitations shown by household surveys for analysing personal income distribution. As pointed out by Atkinson and Piketty (2007), the use of tax data for studying the distribution of personal income goes far back in time[12]. Nonetheless, in most OECD countries, micro-level tax returns data sets are available only for the post-1970 or post-1980 period, except for the United States, where the Internal Revenue Service (IRS) began releasing annual micro-level data sets for income tax returns in 1960 (Atkinson and Piketty, 2007).

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income, supplemental Security Income, public assistance or welfare payments, retirement, survivor, or disability pensions, and all other income.

[9] Currently, the ACS publishes single year data for all areas with populations of 65,000 or more. Among the roughly 7,000 areas that meet this threshold are all states, all congressional districts, more than 700 counties, and more than 500 places. Areas with populations less than 65,000 will require the use of multi-year estimates to reach an appropriate sample size for data publication. In 2008, the Census Bureau began releasing 3-year estimates for areas with populations greater than 20,000. They also release the first 5-year estimates for all census tracts and block groups from 2010.

[10] Meyer and Sullivan (2011) evaluate the implications of these drawbacks for income inequality analysis. Furthermore, Lohmann (2011) addresses the question of data collection in EU-SILC, finding a greater reliability advantage in those countries that supplement the information from survey interviews using administrative or register data for a wide range of variables, such as occurs in the Nordic countries.

[11] Using a cross-country data set for developing and transitional economies, Ravallion (2003) analyses how the national accounts deviates on average from mean household income or expenditure based on national sample surveys. A detailed statistical study of these discrepancies is offered in Canberra Expert Group's Report (2001).

[12] Early estimates date back to Bowley (1914) and Stamp (1916) for the United Kingdom, even though the estimates made by Kuznets (1953, 1955) for United States can be considered as the pioneering income distributions obtained using tax data.

The representativeness of these tax microdata is appropriate for small territorial estimates, as in the case of municipalities. Generally, these annual PIT returns display information about the different categories of taxable income: wage or salary income, retirement, survivor, or disability pensions, some public assistance payments (including in some cases unemployment benefits), net self-employment income and individual business income, interest, dividends, royalty income, net rental, income from other estates and capital gains. In some countries, imputed rent for homeowners and some exempt income are also included. The sum of these variables can provide an adequate measurement of pre-tax income, in line with the one presented in the ACS-PUMS (US Census Bureau).

Over the past decade, an increasing number of papers have focused their attention on the concentration of income and wealth in top income earners (see Atkinson *et al*., 2011), fostering the use of tax income data as a tool for personal income distribution analysis. In this regard, it is important to notice that this tax definition of income is consistent with the notion of ability to pay commonly used in microeconomic models (Piketty and Saez, 2003), besides constituting a reasonable measurement of individual wellbeing (Leigh, 2007). In relation to the reliability of tax data to measure personal income, as noted in Feldman and Slemrod (2007) and Slemrod and Weber (2012), survey data are often not very credible due to the problem of untruthful responses to delicate questions. Therefore income tax data are generally more reliable, especially when personal income is measured from wages and salaries, pensions, subsidies, interests and dividends, all of them withheld at the source of payment.

However, the estimation of personal income distributions using tax data also has some conditioning factors. The unit of analysis is probably the most controversial issue (the individual versus the family). However, as noted in Atkinson (2007), the individual approach is useful when analysing personal income distributions and, as such, it has been commonly used in the related literature on income inequality and redistribution. Of course, there are differences when choosing the individual as the unit of analysis instead of the household, but these have to be resolved by interpreting the results, without thereby having to give up the statistical potentialities of the individual approach. Secondly, these data might be biased because of tax evasion and avoidance. Nevertheless, Atkinson *et al*. (2011) point out that when tax data are compared to other sources of information such as surveys, the influence of tax evasion and avoidance on the distributive results is not large enough to mean that they should be rejected out of hand. In this sense, Hurst *et al*. (2010) and Paulus (2013) also found a non-negligible income underreporting by self-employed on income surveys compared to tax data.

Thirdly, as noted above, the taxable income usually includes all incomes obtained by residents in a territory regardless of its source. Ideally, one would like to measure the gross income before any deductions or exemptions, even though this is not always possible. This is due to the fact that available information comes from the tax forms according to the rules of taxation. and as such, the income reported includes all essential components of personal income in an economic sense, with the exception of certain exemptions of income that are not taxed. Accordingly, the main limitation arises from the criteria for measuring certain kinds of incomes taxed, as is the case of income from business activities (largely estimated by means of objective methods), real estate imputed rents for homeowners, and capital gains. Despite this, when we look at the measurement of aggregated household disposable income at the national level we observe that it often offers lower income levels than the tax data[13]. To sum up, we can say that the aggregation of the different income components corresponds reasonably to gross income before personal allowances and deductions are applied.

3. Tax microdata-based model

3.1. The model

Let $F(Y)$ be the personal income distribution (measured by the variable taxable income) for a given year t corresponding to the reference population N. In turn, $F(y)$ is the distribution function of the same variable for the sample obtained from population administrative census of tax returns.

For each of n tax units, micro-data sample contains information on this income variable and other variables of territorial identification, such as provincial or municipal codes. Insofar the sample has been obtained using a particular sampling technique, a sample weight w_i^h was assigned to each observation i extracted.

Let y_i be the taxable income corresponding to sample tax unit i. The estimated total population in terms of taxable income $\left(\hat{Y}\right)$ can be obtained using the original weights provided in the sample, such that:

$$\hat{Y} = \sum_{i=1}^{n} y_i w_i \qquad [1]$$

In so far as the spatial stratification variable was fixed at the provincial level, both the population estimates for the provinces and for the whole national population keep the stated confidence level in the sample design. However, to obtain estimates at the municipal level it is

[13] For instance, see Picos (2006) for the analysis of the Spanish case or Hurst *et al*. (2010) for the United States.

necessary to calculate new population weights, to the extent that our estimates would now face smaller spatial areas used as a strata sample extraction.

We define this "new weight" as $z_{i,j}$, such that the total population income estimated for the municipality j can be obtained as follows:

$$\hat{Y}_{j|z} = \sum_{i=1}^{n_j} y_{i,j} z_{i,j} \qquad [2]$$

Following Creedy and Tuckwell (2004), we use the distance criterion to assess the closeness between $z_{i,j}$ and $w_{i,j}$ in each of j spatial areas. In general terms, let denote this distance through the function, $\phi(w_{i,j}, z_{i,j})$, what must verified in aggregate terms that:

$$D = \phi(w_{i,j}, z_{i,j}) \,, \; D \in \mathbb{R}_+ \qquad [3]$$

Therefore the method for obtaining the new weights that allow estimates of income at the municipal level using a micro-data sample consists of solving the following optimisation program: to minimise distance function [3] subject to municipality restriction [2]. To carry out this reweighting we need information on true population totals for the taxable income variable for each j municipality, so that the estimated value $\hat{Y}_{j|z}$ can be replaced in [2]. This information is taken from the administrative census of personal income tax[14].

3.2. Computational settlement: the calibration approach

In this section we provide an overview of the method that we use to adjust the original micro-data sample weights provided by the Spanish Tax Administration (henceforth AEAT) in order to make them representative with respect to both the average income and the aggregate number of taxpayers in each Spanish municipality. The methodology closely follows Creedy (2003), Creedy and Tuckwell (2004) and Deville and Särndal (1992) and it was coded in Stata 12.

Following Creedy (2003), let us consider a sample of *n* taxpayers and *K* individual-level variables, both monetary (as taxable income or tax liability) and non-monetary (as age, sex, province and municipality of residence). We collect these variables for the generic taxpayer *i* in the following vector: $x_i = [x_{i1}, x_{i2}, \dots, x_{ik}]'$. If we define the original sample weight with the vector $w = [w_1, w_2, \dots, w_i, \dots, w_n]$, the estimated population values of each *K* individual-level variable is given by:

$$\hat{X}_{k|w} = \sum_{i=1}^{n} w_i x_{ik} \qquad [4]$$

[14] These population data have been provided by Spanish Tax Administration Agency.

The AEAT provided us with the true population totals for some of these *K* variables (X_k). Specifically, we managed to obtain the aggregate income and the total number of taxpayers in each *j* Spanish municipality from the AEAT. With this information in hand it is possible to compute a new vector of sample weights for each municipality, $z_j = \left[z_{1j}, \dots, z_{n_j j}\right]$, where $\sum_{j=1}^{J} n_j = n$, that is as close as possible to the original sample weights, while satisfying the set of *K* calibration equations:

$$X_k^j = \sum_{i=1}^{n_j} z_j x_{ik} \quad [5]$$

where X_k^j is the true population value of each *K* individual-level variable in each *j* municipality. Indeed, if we denote the distance between the original and the new sample weights with the function $\phi(w_{i,j}, z_{i,j})$, the new sample weights can be obtained by minimising the following Lagrangian function with respect to ***z***:

$$L = \sum_{i=1}^{n} \phi(w_{i,j}, z_{i,j}) + \sum_{k=1}^{K} \lambda_k \left[X_k^j - \sum_{i=1}^{n_j} z_j x_{ik}\right] \quad [6]$$

where $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_K]'$ are the Lagrange multipliers.

Clearly, the solution of the minimisation problem strongly depends on the property of the distance function $\phi(w_{i,j}, z_{i,j})$, and in what follows we require the function $\phi(w_{i,j}, z_{i,j})$ to respect two fundamental properties:

- The first derivative of $\phi(w_{i,j}, z_{i,j})$ with respect to $z_{i,j}$ must be expressed as a function of the ratio between the new and the original weights:

$$\frac{\partial \phi(w_{i,j}, z_{i,j})}{\partial z_{i,j}} = \phi'\left(\frac{z_{i,j}}{w_{i,j}}\right) \quad [7]$$

- The inverse of the first derivative of $\phi(w_{i,j}, z_{i,j})$ must be explicitly invertible.

If these properties hold, then the *n* first order conditions for the problem in [6] are:

$$\phi'\left(\frac{z_{i,j}}{w_{i,j}}\right) - x_i'\lambda = 0 \quad i = 1,2, \dots, n \quad [8]$$

Then, we can obtain the new weights so that:

$$z_{i,j} = w_{i,j} \phi'^{-1}(x_i'\lambda) \quad i = 1,2, \dots, n \quad [9]$$

and given a solution for the Lagrange multipliers, which can be obtained through an iterative procedure (Newton's method) after some algebraic manipulations of equations [9], [5]and [4].

Specifically, if we substitute equation [9] into equation [5] and then subtract from both sides equation [1], after certain rearrangements we obtain:

$$\left(X_k - \hat{X}_{k|w}\right) - \sum_{i=1}^{n} w_i\left[\phi'^{-1}(x_i'\lambda) - 1\right]x_i = 0 \qquad [10]$$

The root of this function can be computed by means of the following iterative recursion:

$$\lambda^{(I+1)} = \lambda^{(I)} - \left[\frac{\partial f(\lambda)}{\partial \lambda}\right]^{-1} f(\lambda) \qquad [11]$$

where $f(\lambda)$ is given by the left hand side of equation [10] and, at each iteration $I+1$th, is evaluated using the value of the Lagrange multipliers in the previous Ith iteration, $\lambda^{[I]}$. Hence, given a set of initial values for λ, equation [11] can be repeatedly evaluated until convergence is reached, where possible.

The four distance functions used in this paper are presented in Table 1. The first function, the Chi-squared distance function, is probably one of the most popular choices in the applied literature because the constrained minimisation problem in equation [6] has an explicit solution and the new weights can be obtained immediately. However, this function places no constraints on the size of the adjustment to each weight, and therefore some of the new weights could take negative values.

Table 1. Different distance functions

	$D(w,z)$
1. Chi-squared	$\frac{(z-w)^2}{2w}$
2. Minimum Entropy	$-w\, ln\left(\frac{z}{w}\right) + z - w$
3. Modified Minimum Entropy	$z\, ln\left(\frac{z}{w}\right) - z + w$
4. Deville and Särndal (1992)	$\left(u - \frac{z}{w}\right) ln\left(\frac{u - \frac{z}{w}}{u-1}\right) + \left(\frac{z}{w} - l\right) ln\left(\frac{\frac{z}{w} - l}{1-l}\right) + \frac{u-l}{\alpha} w$

Note: u and l are known constants in the interval $l < 1 < u$; $\alpha = \frac{u-l}{(1-l)(u-1)}$.

To avoid this problem, the other three distance functions in Table 1 incorporate a non-negative constraint on the size of the adjustment. Nevertheless, for these functions a closed-form solution to the constrained minimisation problem is no longer available and the iterative procedure explained above has to be used. This implies that problems of non-convergence may arise, which could depend on the combination of a specific distance function with the original weights or on the starting values that enter the first iteration of the recursion.

Functions 2 and 3 force the new weight to be positive but they do not place an upper bound to the adjustment. Hence implausible large weights with respect to the original ones could result after the calibration process. This issue is considered by the fourth distance function proposed by Deville and Särndal (1992), because it constrains the new weights within a user-defined range. In particular, the ratio of the new to the original weight is bounded as follows:

$$l < \frac{z}{w} < u \qquad [12]$$

where both l and u are known parameters that enter the distance function before the calibration process[15].

4. Empirical results

4.1. Description of the Spanish municipal map

Spain is a decentralised country composed of three different levels of government: the Central Government, 17 regional governments known as Autonomous Communities (created by mandate of the Spanish Constitution in 1978) and some 8,110 Local Governments. As is shown in Table 2, the latter are characterised by their high degree of fragmentation. About 60% of existing municipalities have fewer than 1,000 inhabitants and represent just 3.37% of the total population, which implies a structure of many independent units of government with very small populations.

Table 2. Spanish municipalities according to population size, 2007.

Population threshold	Number of municipalities	% of Total Population
< 1,000 inhab.	4,877	3.37%
1,000 – 5,000 inhab.	1,968	10.06%
5,000 – 20,000 inhab.	895	19.37%
20,000 – 50,000 inhab.	235	15.50%
50,000 – 100,000 inhab.	77	12.05%
> 100,000 inhab.	59	39.66%

Source: Own production using population counts from the Spanish National Statistics Institute.

The aforementioned levels of governments coexist with a historically administrative division of the Spanish territory, the Province. The present division of the country into 50 provinces has remained essentially unchanged since its design in 1833. Each province consists

[15] The initial values for these parameters are 0.2 and 3, respectively. If convergence is not achieved after 100 iterations with different starting values, the new bounds for these two parameters are drawn from two uniform distributions with supports: 0.1-1 and 1-6.

of a group of municipalities, and one or more provinces yield to an Autonomous Community. Central and Local Governments are formed according to direct election by universal suffrage and subject to a proportional representation criterion, whereas governmental institutions at the province level respond to the representation of political parties in each province's municipalities. That is to say, members of the Provincial Government are elected by the municipal councillors among themselves.

4.2. The data

Micro-data (PIT, 2007). To carry out the estimate of local income distributions we use micro-data contained in the annual Spanish PIT sample. In particular in this paper we use the sample for the year 2007, which includes 1,351,802 records extracted from a population providing 18,702,875 personal income tax returns (Picos *et al.*, 2011). This database has been developed by the Spanish Institute of Fiscal Studies (Instituto de Estudios Fiscales, IEF henceforth), in collaboration with the Spanish National Tax Administration (Agencia Estatal de Administración Tributaria - henceforth AEAT), the entity in charge of extracting annual samples from its administrative registers of Spanish personal income tax[16].

For the construction of this annual sample the minimum variance stratification under Neyman's allocation method has been used. Thereby population income may be estimated in a highly precise manner with a reasonable sample size. Three stratification variables have been used in the sampling process: a) the province, as territorial stratum (48 provinces with common fiscal regime, plus the Autonomous Cities of Ceuta and Melilla[17]); b) the income level of the tax filers (to that end, income sample places in 12 level)[18]; c) the type of tax return (separate or joint filing). Hence, the "original weight" is calculated for each observation as the ratio between the size of the population of its belonging stratum h and its corresponding sample size, $w^h = N^h/n^h$. To select the sample, the tax returns were classified in each one of the 1,152 strata (48x12x2). Previously, the size of the total sample n was calculated for a specific relative sampling error ($e < 0.011$) with a confidence level of 3 per 1,000. Next, the population for each stratum (N_h) was determined using the population quasi-variance of the sample income for each one of them (S^2_h). Finally, using the values N_h and S^2_h, the number of observations that had to be extracted randomly for each stratum (n_h) was determined, so that $\sum_h n_h = n$. Table 3 shows the final sample sizes and their distribution by province.

[16] To date, micro-data samples are available to researchers and analysts, free of charge, on application to the IEF (http://www.ief.es) for the years 2002-2009.
[17] This territorial stratum also includes an additional group of Spanish non-resident taxpayers that paid taxes under Article 10 of Law 35/2006.
[18] The sample income was calculated as the sum of net incomes, imputed income and capital gains and losses.

Table 3. Final micro-data sample sizes and their distribution by province

Province	Province Code	Number of sample observations (used in estimates)
Álava	1	-
Albacete	2	19,784
Alicante	3	44,072
Almería	4	24,353
Ávila	5	12,534
Badajoz	6	28,710
Balears (Illes)	7	32,885
Barcelona	8	86,880
Burgos	9	18,131
Cáceres	10	22,842
Cádiz	11	34,890
Castellón	12	25,682
Ciudad Real	13	21,542
Córdoba	14	33,076
Coruña (A)	15	37,749
Cuenca	16	14,172
Girona	17	24,974
Granada	18	33,254
Guadalajara	19	12,594
Guipúzcoa	20	-
Huelva	21	21,255
Huesca	22	14,167
Jaén	23	30,891
León	24	23,201
Lleida	25	20,342
Rioja (La)	26	16,820
Lugo	27	21,261
Madrid	28	110,208
Málaga	29	40,883
Murcia	30	38,140
Navarra	31	-
Ourense	32	19,439
Asturias	33	36,084
Palencia	34	12,065
Palmas (Las)	35	31,743
Pontevedra	36	33,238
Salamanca	37	18,651
Santa Cruz de Tenerife	38	30,891
Cantabria	39	23,579
Segovia	40	11,297
Sevilla	41	44,700
Soria	42	8,624
Tarragona	43	27,661
Teruel	44	11,822
Toledo	45	24,773
Valencia	46	53,361
Valladolid	47	22,904
Vizcaya	48	-
Zamora	49	14,452
Zaragoza	50	36,454
Ceuta	51	5,244
Melilla	52	5,068
Non residents	99	615
Total of observations		**1,337,957**

Source: own production using data drawn from the Spanish Personal Income Tax 2007 annual sample.

The original records provided by the AEAT are incorporated in a bi-dimensional file that contains the PIT returns extracted using a sampling process (one per row). For each observation the file offers a series of variables for which the source of information is, directly or indirectly, the return form for the corresponding year[19].

Regarding territorial representation, the annual sample of micro-data includes tax returns for 5,346 of the 7,024 Spanish municipalities, all of them belonging to the 15 Autonomous Communities with a common tax system (the database does not include observations for the Basque Country and Navarra, which have their own tax systems (so-called "foral tax systems").

Using variables contained in the annual Spanish PIT sample for 2007, we establish the definition of total personal income as the sum of the following items forming part of the gross taxable income[20]: salary and wage income, retirement pensions, general unemployment subsidies, some non-exempt welfare payments and some disability pensions, net self-employment income, interest, dividends, royalty income, survivor annuities, net rental and income from other estates including imputed rent for second dwellings homeowners, and realised capital gains (except those from reinvesting in the customary dwelling). Therefore, our total personal income is defined in terms of pre-tax gross income, namely before applying personal and family allowances, employment income deductions, exemptions from contributions to private pension plans, and other specific deductions[21].

The unit of analysis in the annual Spanish PIT sample is the tax return. Since the financial year 1988, the Spanish PIT has been individually based by constitutional mandate. Although married couples can voluntarily file a joint return, this option is never advantageous when both spouses receive an income. As a consequence, in the same way that Alvaredo and Saez (2009) do, we identify the unit of analysis as being the individual taxpayer.

Population data (PIT 2007). Statistics with population data for the Spanish PIT are collected by the AEAT. To carry out this study, the Department of Information Technology of the AEAT has provided us with a database containing information on the municipal income tax for the year 2007. This PIT database includes the following aggregate information for each of the 7,024 municipalities included in the common tax regime: the number of income tax returns filed in the municipality, the average taxable income and the average tax liability. For

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[19] According to the nature of the variables included in the file, these can be split into two groups: non-monetary variables, which contain the main qualitative and personal characteristics of each return; and monetary variables, which contain information from the boxes of the annual PIT return form.

[20] For a complete description of the components of income taxed by the PIT in 2007 see Picos *et al*. (2011).

[21] This definition is the same as the one used in Alvaredo and Saez (2009).

identification purposes, the database includes a specific municipal code established by the AEAT, and the name of the municipality[22].

4.3. Main findings and validation of estimates

As aforementioned, the AEAT provided us with a micro-data sample of 5,346 out of 7,024 Spanish municipalities, i.e. those with common fiscal regime. We discarded 18 municipalities that only had one observation in the sample, since for them it was not possible to apply any of the reweighting methods presented in Section 3[23]. Additionally, the AEAT provided us with two total population magnitudes, i.e. the number of taxpayers and the aggregate gross taxable income of each municipality. Hence the set of calibration equations in our exercise is defined from these data.

Table 4 shows the percentage of the 5,328 municipalities for which convergence has been achieved when the recursive algorithm was used. The table also reports the percentage of municipalities for which non-negative weights were observed after the calibration with the Chi-squared distance function.

Table 4. Percentage of municipalities for which a new non-negative vector of weights was obtained

Distance function	Percentage
Chi-squared	82.2%
Minimum Entropy	91.6%
Modified Minimum Entropy	94.8%
Deville and Särndal (1992)	73.3%

Source: Own production

For 250 municipalities (1,953 personal income tax returns) none of the functions listed above produced a new vector of weights, either because of non-convergence issues or because the Chi-squared distance function produced negative weights[24]. However, from the Kernel density of the population size of these municipalities, it can be seen that they are quite small, with less than 1,000 inhabitants (see Figure 1). Accordingly, the total number of PIT taxpayers in these municipalities is also small (below 500 tax returns). As a result, from the Kernel density

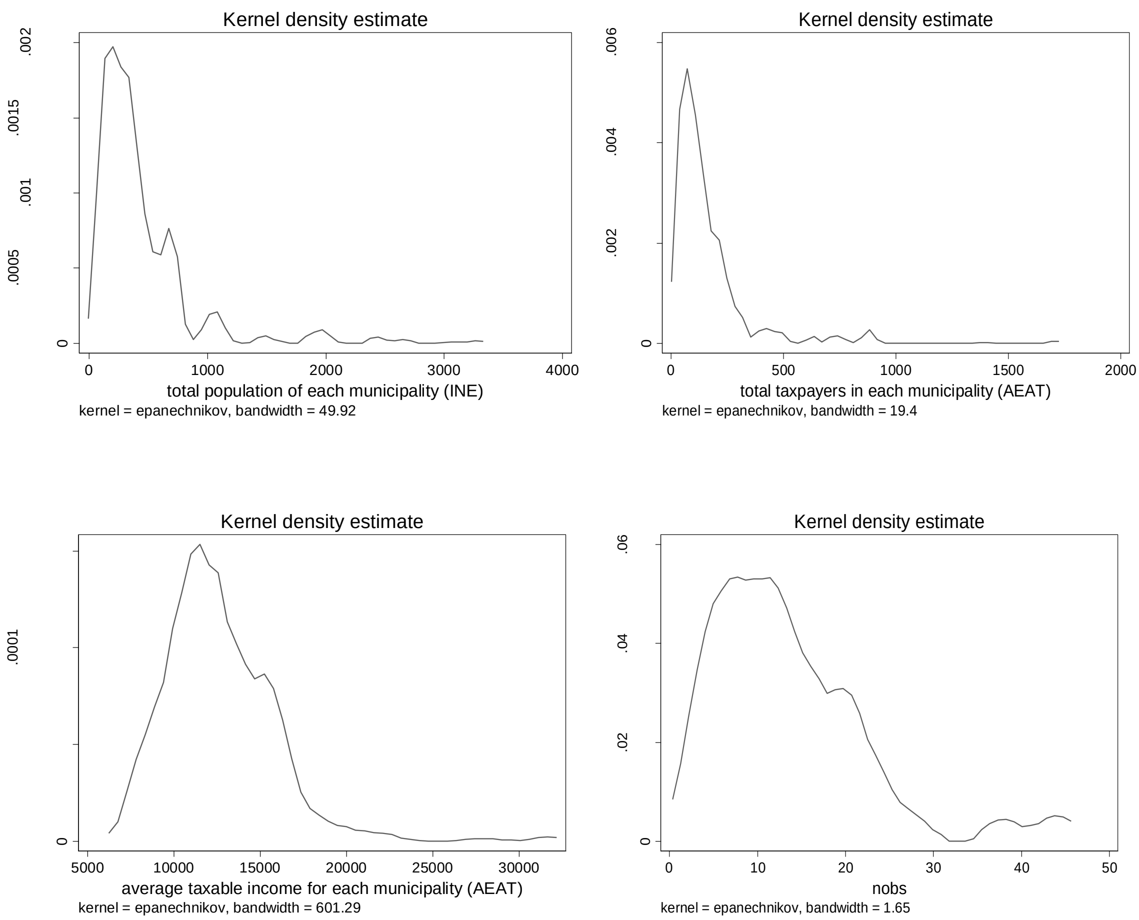
[22] There is an important previous task of linking tax codes (population data) to postal codes (sample data) and then to the 5-digit codes given by the Spanish National Statistics Institute to identify each municipality.

[23] Estimating the new weights requires at least two observations for each municipality.

[24] Note that whenever a new weight is not produced for a given observation of a given municipality, all observations of that municipality are dropped from the analysis.

of the number of observations included in the AEAT sample it can be seen that the number is considerably smaller (below 30 tax returns included in the sample).

Figure 1. Kernel density of municipalities without a new vector of weights.



Source: Own production

Table 5 shows the number of municipalities for which each distance function was chosen for estimating the new optimal vector of weights. For selecting among different vectors of weights we follow Särndal (2007) and require the chosen vector for municipality j:

(i) not to take negative values:

$$z_{i,j} \geq 0 \quad \forall i \tag{13}$$

(ii) not to have values that are too large compared to the original vector. In this regard, the goodness-of-fit criterion (minimising the sum of the squared residuals) is used

$$\min \sum_{i=1}^{n} (w_{i,j} - z_{i,j})^2 \tag{14}$$

(iii) and to originate from a calibration exercise that converged as smoothly as possible.

Table 5. Chosen distance function for each municipality

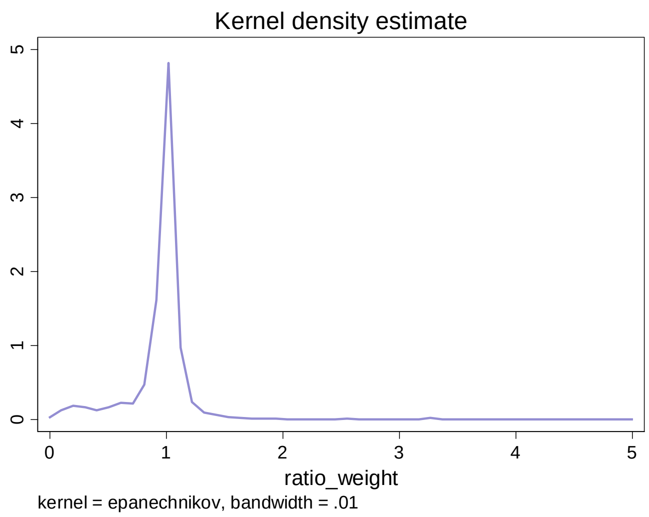
Distance function	Number of municipalities	%
Chi-squared	1,607	31.65%
Minimum Entropy	2,496	49.15%
Modified Minimum Entropy	473	9.31%
Deville and Särndal (1972)	502	9.89%
Total:	*5,078*	*100*

Source: Own production

As can be seen, the Minimum Entropy distance is the function adopted in most cases, according to the selection criteria explained above. The Chi-squared and the DS distance function then follow. However, as Deville and Särndal (1992) prove, all the above-listed functions generate asymptotically-equivalent calibration estimators. Hence changes of the distance function will often have only minor effects on the variance of the calibration estimator, even if the sample size is rather small.

Figure 2 shows the distribution of the ratio of calibrated new sample weights with respect to the original sample weights. As can be seen, the majority of these values are around one, meaning that the new weights are fairly close to the original sample weights. For the sake of clarity, the distribution of this ratio by percentiles is reported in Table 6. The results indicate that the values of the ratio between the new and the original sample weight range from 0.06 to 1.80. In addition, both the mean and the median are close to one, with a standard deviation of 0.98.

Figure 2. Ratio of new sample weights to original sample weights



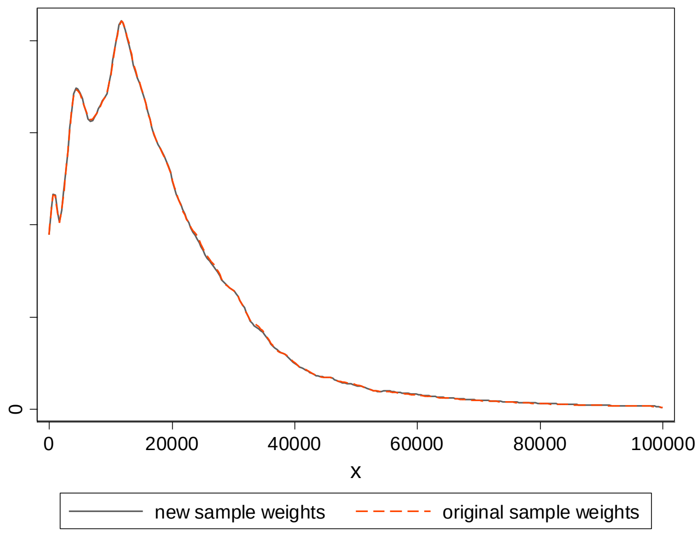
Source: Own production

Table 6. Distribution of the ratio of new to original sample weights.

Percentiles	Ratio z/w
1%	0.06013
5%	0.31796
10%	0.62805
25%	0.91277
50%	0.99691
75%	1.04968
90%	1.14317
95%	1.24089
99%	1.80791
Mean	0.97445
St. Dev.	0.98183

Source: Own production

Figure 3. Overall income distribution

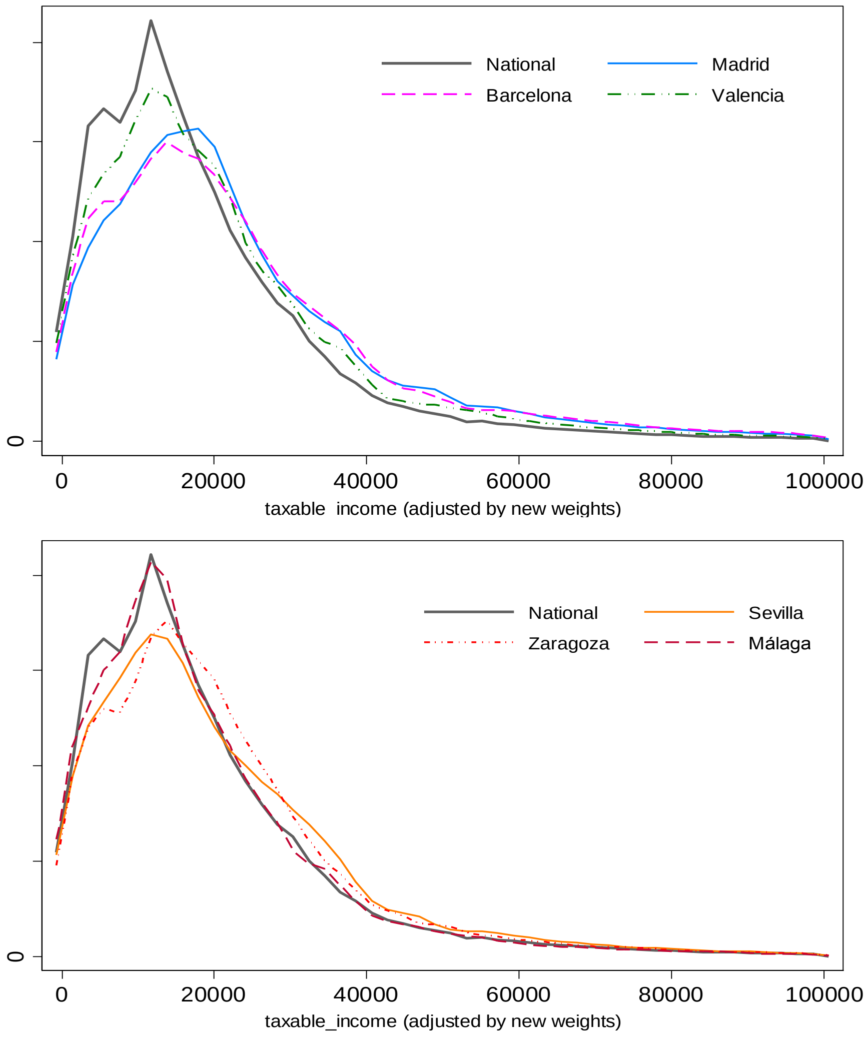


Own production. For present purposes, the distribution is truncated at 100,000 euros.

Once the new sample weights are obtained, we can derive representative personal income distributions for all the Spanish municipalities included in the sample of micro-data provided by the AEAT. Figure 3 shows the income distribution for the entire sample (all municipalities included), before and after reweighting. As expected, the overall income distribution derived from the new sample weights replicates the overall income distribution when using the original sample weights. In general terms, differences are expected in local income distributions, as original weights were only representative at the provincial level while the new sample weights are now representative at the municipal level. In any case, the sample is always representative of the entire population, i.e. the weights are used for grossing up from the sample in order to obtain estimates of population values. As can be seen in Figure 3, estimates of the income density function for the national total with new and old weights are virtually identical.

In Figure 4 we present some of the results obtained for the Spanish municipalities included in the sample. In particular, we display the local income distributions of the six biggest municipalities in terms of population counts. In every graph, the local income distribution for the entire sample is illustrated by the black solid line. Plotted income density functions show the existence of heterogeneous distribution patterns, especially among the three most populated cities (i.e. Madrid, Barcelona and Valencia). Their local income is more uniformly distributed than the income distribution as a whole. These cities present a more skewed right income distribution and a lower mode, as a consequence of a lower concentration of income in the lower tail distribution and greater densities in the upper tail.

Figure 4. Local income distributions of selected Spanish municipalities*



Source: own elaboration

5. Personal income inequality in Spanish municipalities

The estimated local income distributions obtained in the previous section are a valuable and informative tool for distributional and income inequality analysis. As an illustration, in this section we perform an analysis of local inequality for a sample of Spanish municipalities based on the computation of two of the most common measurements of inequality, the Gini and the Atkinson indexes. In line with the abovementioned literature on top incomes, we also include measurements of the top 1%, 0.5% and 0.1% income shares.

The Gini coefficient (Gini, 1912) is probably the standard in the income inequality literature. This index is defined as the area between the 45° (which indicates perfect equality) and the Lorenz curve,

$$G(y) = 1 - 2\int_0^1 L(p;y)dp \qquad [15]$$

where the Lorenz curve of income $L(p;y)$ at such p-values of ranked relative cumulated-population (so that, $p \in (0,1)$) can be defined mathematically by the expression,

$$p = F(q) \Longrightarrow L(p;y) = \int_0^q yf(y)dy/\mu_y \qquad [16]$$

Accordingly, the Gini coefficient takes values between zero (perfect equality) and one (complete inequality).

The second income inequality measurement used in our analysis is the Atkinson index (Atkinson, 1970). This index differs from the Gini index in its explicitly ethical foundation. In fact, the Atkinson index is based upon a social welfare function, including a weighting parameter ε which measures aversion to inequality, so that the index becomes more sensitive to changes at the lower end of the income distribution as approaches to 1, while if the level of inequality aversion falls (i.e. as it approaches 0) the index becomes more sensitive to changes at the upper end of the income distribution. For $\varepsilon = 0$ the equally distributed equivalent income is simply the average level of income, while for $\varepsilon \to \infty$ the Rawlsian criterion is used (i.e. social welfare function is close to the maximum concavity).

From a continuous approach to the income distribution, the Atkinson index is defined as,

$$A_\varepsilon(y) = 1 - \left(\int_0^\infty \left(\frac{y}{\mu_y}\right)^{1-\varepsilon} f(y)dy\right)^{\frac{1}{1-\varepsilon}} \qquad [17]$$

And it values on the interval ranging from 0 (if the income is distributed equally) to 1 (if the inequality is the highest). In our analysis, we have chosen the ε parameter values 0.5 and 1.

As is known, the value 1 provides similar findings to Gini index, while the value 0.5 provides information for a reduced aversion to inequality.

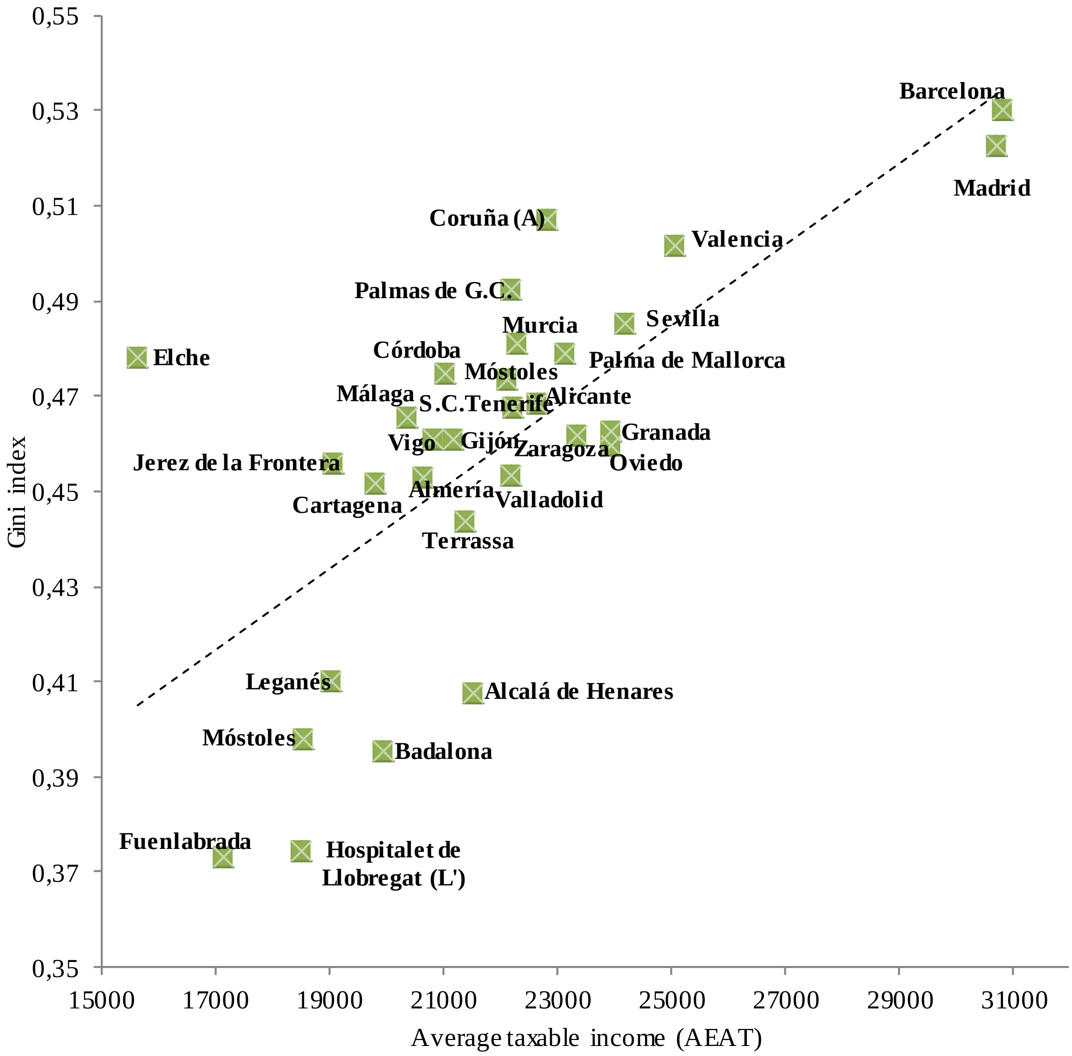
Using the AEAT micro-data and the new sample weights, we calculate these two different income inequality measures at the municipality level[25],[26]. The results for both income inequality indexes are reported in Figures 5 and 6, respectively. Detailed results on these indexes are presented in the Appendix.

For the purpose of this empirical exercise we have selected a small sample of Spanish municipalities. In particular, only the results for the 35 most populated municipalities are reported. Three main finding arise from the results. On the one hand, the Gini coefficient has a wide range of variation, as it takes values from 0.37 to 0.53. On the other hand, there exists a clearly positive correlation between the Gini coefficient and the average gross taxable income of the municipality, with a correlation coefficient of 0.65. This result suggests that richer cities have more income inequality (more unequal income distributions) than the poorer ones. This result also holds for the Atkinson coefficients, whose results exhibit a similar pattern of variation than those presented for the Gini coefficient, even though we find some differences between cities due to the specific degree of inequality aversion that is behind every measure calculated. As can be seen in the comparison of Figures 5 and 6, the different degrees of inequality aversion for the three inequality indices considered provide some changes in the relative order of cities with an average income below 25,000 euros.

[25] There are several plausible alternatives for calculating these expressions when using micro-data. In particular, we use the Stata's *ineqdeco* ado file provided by Jenkins and adapted for our stratified sample of micro-data. The inequality aversion parameter of the Atkinson index (ε) takes the values 0.5, 1 and 2.

[26] Confidence intervals via bootstrap re-sampling methods (Mills and Zandvakili, 1997) have been calculated for both inequality measures. In particular, two types of bootstrap confidence intervals are obtained, using respectively the alpha-percentile method and the normal-distribution method. Given the large size of the micro-data sample used in our analysis, the number of bootstrap replicates has been set at 100. Likewise, we have calculated the standard errors for both inequality indexes. The results show very low bootstrapped standard errors, an expected result given the very large size of our sample. Nonetheless, they are available on request from the authors or in Hortas-Rico *et al.* (2013).

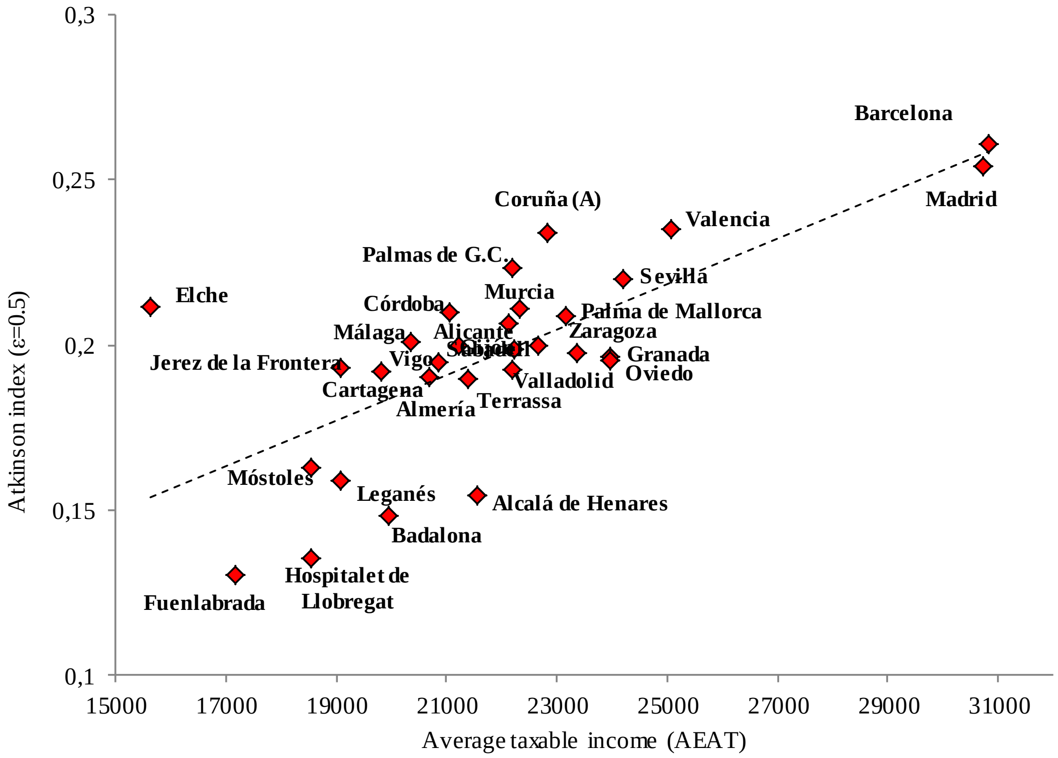
Figure 5. Gini index of selected Spanish municipalities according to the new weights, 2007.

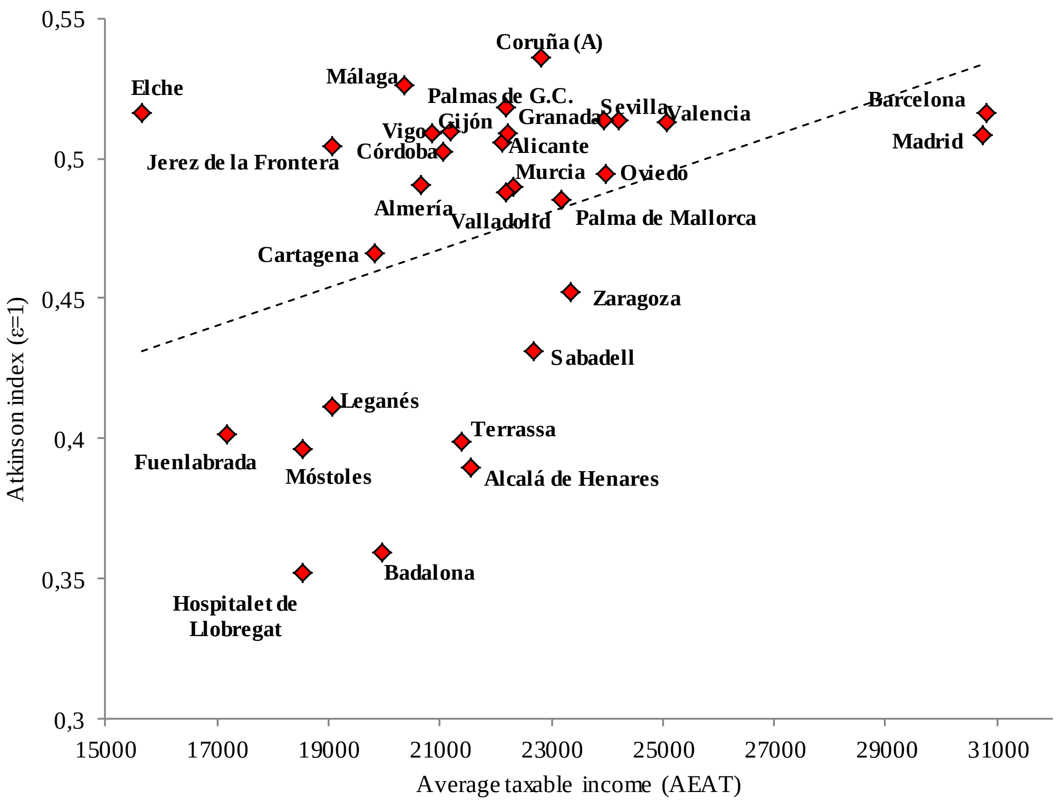


Source: Own elaboration.

Finally, the results of the concentration of income among the top income earners show, on the one hand, that the wealthiest Spanish group – the top one percent - accumulates 12.52 percent of the total gross taxable income. When this top percentile is broken down into the top 0.5 percent and the top 0.1 percent, we observe that their income shares are 0.0932 and 0.0474, respectively. Overall, these results for the top shares in Spain are similar to those found in other countries like the United States (Atkinson, Piketty and Saez, 2011). On the other hand, the calculated measurements show that in the four most populated cities (i.e. Madrid, Barcelona, Valencia and Seville) the concentration of income in the top quantile selected is higher than the result for the whole population, as it is also the case in some other small cities such as Las Palmas de Gran Canaria, A Coruña, Terrassa and Albacete.

Figure 6. Atkinson index of selected Spanish municipalities according to the new weights, 2007.





Source: Own elaboration.

6. Concluding remarks

Local income data are a key economic indicator, widely used in applied economic research. Despite its importance, there is a lack of official data on personal incomes for territorial areas smaller than the provinces or regions. This paper makes use of official data on personal income tax returns and a reweighting procedure to derive a representative income sample at the local level. The methodology implemented here relies on the calibration approach proposed in Deville and Särndal (1992), Creedy (2003) and Creedy and Tuckwell (2004) for survey reweighting. In doing so, we adjust the original micro-data sample weights in order to make them representative at the local level, given that our estimates would now face smaller spatial areas used as a strata sample extraction.

Unlike previous attempts in the literature to acquire local income estimates, the results obtained allow us to derive not only an average value of income but its local distribution, a valuable and informative tool for income inequality analysis. We apply this methodology to Spanish micro-data and illustrate its potential use in income inequality analysis. The results suggest remarkable relationships between some variables of interest, such as the level of income in the municipalities, their inequality, the concentration of top incomes and their population size, among others. Nonetheless, a further analysis of those relationships lies beyond the scope of this paper and, as such, should be addressed in future research.

Overall, the methodology presented here represents a starting point for income inequality analysis at the local level. A wide range of potential implementations arise from these results. The illustration presented here could be extended to the whole set of municipalities, in order to get a picture of income inequality within municipalities in Spain. In addition, the recent availability of PIT annual samples for several years would allow us to perform both cross-section and longitudinal income inequality analyses for Spanish municipalities. Also note that the present paper has focused on pre-tax income, but its extension to after-tax income would allow us to undertake redistributive analysis in order to evaluate the impact of personal income tax in municipalities. Likewise, the data provided here would allow us to deeply investigate the behaviour of top incomes by municipality, complementing existing research literature on this topic. Lastly, we would like to clarify that the only purpose of these findings is to provide an illustration of the possibilities for applied economic analysis offered by the implemented methodology. We think the availability of representative information on the income level of Spanish municipalities and its distribution opens up a fruitful area of research in many topics of urban economics and local public finance.

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Appendix. Inequality and concentration indexes for selected Spanish municipalities*

Municipality	Gini Index	Atkinson index**		Top income shares		
		0.5	1	top 1%	top 0.5%	top 0.1%
Madrid	0.52257	0.25433	0.50861	0.16920	0.13093	0.06898
Barcelona	0.53002	0.26068	0.51648	0.16628	0.12997	0.07409
Valencia	0.50176	0.23535	0.51314	0.14381	0.11073	0.06064
Sevilla	0.48521	0.22003	0.51346	0.12687	0.09629	0.05144
Zaragoza	0.46188	0.19791	0.45234	0.11083	0.07994	0.03697
Málaga	0.46565	0.20113	0.52640	0.10190	0.07325	0.03452
Murcia	0.48116	0.21130	0.49000	0.11951	0.08916	0.04254
Palma de Mallorca	0.47876	0.20897	0.48497	0.12156	0.08707	0.03800
Palmas G.C.	0.49246	0.22351	0.51806	0.13209	0.09922	0.04850
Córdoba	0.47483	0.20989	0.50218	0.11351	0.08570	0.04327
Alicante	0.47337	0.20666	0.50588	0.10937	0.07957	0.03789
Valladolid	0.45337	0.19275	0.48763	0.10069	0.07409	0.03640
Vigo	0.46074	0.19503	0.50910	0.09679	0.06739	0.02760
Gijón	0.46088	0.19978	0.50967	0.10498	0.07562	0.03375
Hospitalet Llobregat	0.37441	0.13554	0.35222	0.06934	0.04841	0.02451
Coruña (A)	0.50698	0.23379	0.53598	0.12584	0.09370	0.04715
Granada	0.46257	0.19664	0.51347	0.08613	0.05936	0.02450
Elche	0.47830	0.21167	0.51644	0.11048	0.07924	0.03523
Santa Cruz de Tenerife	0.46752	0.19853	0.50907	0.09098	0.06282	0.02562
Oviedo	0.45946	0.19538	0.49440	0.09881	0.06911	0.02837
Badalona	0.39552	0.14828	0.35900	0.07997	0.05599	0.02853
Cartagena	0.45181	0.19198	0.46609	0.11060	0.08077	0.03942
Móstoles	0.39790	0.16316	0.39620	0.10647	0.08537	0.05953
Jerez de la Frontera	0.45574	0.19317	0.50464	0.09670	0.06835	0.03141
Terrassa	0.44346	0.18991	0.39856	0.13269	0.09943	0.02964
Sabadell	0.46838	0.19984	0.43086	0.11535	0.08218	0.03813
Alcalá de Henares	0.40751	0.15428	0.38978	0.08036	0.05624	0.02583
Fuenlabrada	0.37292	0.13051	0.40139	0.05050	0.03085	0.01003
Almería	0.45299	0.19054	0.49024	0.09791	0.07201	0.03408
Leganés	0.40992	0.15910	0.41152	0.07911	0.05712	0.03279
Santander	0.47659	0.20738	0.50444	0.10884	0.07598	0.02925
Burgos	0.42545	0.16743	0.40575	0.08623	0.05943	0.02573
Castellón de la Plana	0.47092	0.20238	0.45382	0.11633	0.08221	0.03346
Alcorcón	0.41525	0.16207	0.40295	0.08700	0.06209	0.03048
Albacete	0.46965	0.21249	0.49021	0.13361	0.10659	0.06143
All municipalities in the sample	**0.48773**	**0.21952**	**0.50257**	**0.12521**	**0.09321**	**0.04745**

Own production

* Spanish municipalities with a population size above 160,000 inhabitants (arranged in order from most to least populated)

** The results for the Atkinson index with an inequality aversion parameter of 2 are not reported, since it took a value of 1 for all the municipalities considered.