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Abstract

This paper aims at analyzing the effects of changing from survey to administrative data on inequality and its structure. Taking advantage of the Spanish Survey on Income and Living Conditions (ECV) that continued asking households for their income despite assigning them the income data provided by the Tax Agency and the Social Security administration, different analyses are carried out. By using copula functions we pay special attention to the effect on the dependences between income sources. We find a significant growth in the disposable income of households when using administrative data. The incomes of both tails of the distribution increase considerably more than middle incomes, and administrative data produce significantly lower levels of inequality. Using administrative instead of survey data also gives rise to changes in the structure of inequality by income sources, rising the contribution of capital income. Both methods of data collection also produce significant differences in the observed dependences between income sources.

Keywords: inequality, surveys, administrative data, copula functions

JEL: C46, D31, D63

1. INTRODUCTION[1]

Studies on inequality in the distribution of income have gained considerable momentum in the last decade. The increase in inequality in the OECD countries, as evidenced by various reports (OECD, 2008, 2011 and 2015), has generated a growing interest both in identifying the possible causes of the increase in income differences between households and in discerning what should be the optimal design of the policies to reduce their extension. The development of both lines of research has led to fundamental contributions, some of them crossing the frontiers of economic analysis and moving to the forefront of social debate (Piketty, 2013; Atkinson, 2015). The economic crisis – with a regressive impact in many countries – and some of the subsequent adjustment policies added more pressure to the tendency of increasing inequality already present in many countries.

A second reason for the renewed growth of inequality studies has been the increasing availability in many countries of datasets that cover extensive periods of analysis. In several OECD countries, household surveys carried out with homogeneous methodologies over long and continuous periods allow reconstructing changes in the distribution of income in the very long term. Household surveys, however, are not exempt from major problems, which can impose important limits to have accurate diagnoses of the trends and determinants of inequality and to design policies based on them: non-response, measurement error, sampling errors or income underreporting, and, in general, a limited representation of the richest households due to undercoverage, top coding and underreporting of top incomes. Some of these problems have been growing over time (Meyer et al., 2015). Furthermore, attempts to reducing some of them – like non-response – may also amplify measurement error, which some authors find to be a much larger source of bias than all other error components (Meyer and Mittag, 2019a).

These limitations of the surveys affect the measurement of inequality. The under-coverage of the highest incomes, for example, implies a systematic underestimation of

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inequality since it is in this tail of the income distribution that some of the most important changes in inequality have occurred over the last two decades. The same happens with survey errors in social benefits, as they do not adequately reflect the income of those in the lower tail of the distribution.

As an alternative, the use of administrative records has been expanded to analyze changes in income distribution. It has been generalized, for example, the use of tax records to measure inequality, especially when focusing on the richest percentiles (Atkinson and Piketty, 2010). A great advantage of tax data is the availability of very long periods of analysis and a better coverage of higher incomes. These data are also affected, however, by some limits that condition its use as the main reference in the study of the distribution of income. Among other problems, tax avoidance and tax evasion, income shifting, theoretical problems to form households from tax units and, especially, limited coverage of households with incomes below the income tax threshold stand out. Tax records may include only taxable sources of income and miss informal sources that may be captured in the surveys (Meyer and Mittag, 2019b). As stressed by Alvaredo et al. (2015), since tax data are collected as part of an administrative process, the definition of income, or income units, cause difficulties for comparisons across countries, but also for time-series analysis where there have been substantial changes in the tax system.

In addition, the theoretical advantage that tax data best capture higher incomes is limited by the fact that several fiscal manipulation strategies are sensitive to changes in marginal tax rates and income reporting rules. As a result, the income recorded in tax data may not remain steady over time, and high-income earners are most able to adjust the way that they receive and report income (Slemrod, 1995; Burkhauser *et al.*, 2012; Auten and Splinter, 2019). Changes in reporting rules may thereby alter the way income is reported at the top of the distribution. Whereas some authors defend that this type of fiscal manipulation may affect the measurement of top income only for short-term trends (Piketty and Saez, 2003), these trends can be especially relevant to understanding changes in inequality in the face of certain shocks, such as increased unemployment or a drastic change in the tax-benefit system.

The problems of surveys to properly collect benefits has also increased the use of administrative records of social benefits to reduce reporting errors in survey measures of program participation. As found by Lynn et al. (2012), survey measures of benefit receipt are subject to measurement error. Some survey respondents may under-report benefit receipt due to simple forgetting, misplacement in time or misclassification, or due to conscious suppression. Given that some programs in survey data are sharply under-reported, the distributional and poverty-reducing effects of transfer programs may not be accurate. However, some recent works show that while administrative data are usually considered the “gold standard” for this type of variables they can still be missing, incorrectly entered, or outdated (Courtemanche et al., 2019).

In practice, opting for one type or another of data – survey or administrative – may imply obtaining results of inequality and other processes related to the income distribution that are not always similar. Dahl et al. (2011) found that the trends in individual earnings and household income volatility with administrative earnings records were in contrast to what is usually found in survey data. A similar result was obtained by Carr and Wiemer (2018) using consistent samples drawn from survey-linked administrative earnings data. Burkhauser et al. (2012) found significant differences in the percentiles with higher income in the United States in survey (Current Population Survey) and tax data, questioning some of the results commonly accepted until then with respect to the shares of the higher percentiles.

Some authors have tried to combine fiscal data and survey data by harmonizing the definitions of variables to improve the representativeness of higher incomes (Burkhauser et al., 2016), but there are still very few works that have advanced in this line. By linking a subset of individuals from household survey to the same individuals’ tax returns, Higgins et al. (2018) found that individuals in the upper half of the income distribution tend to report less labor income in household surveys than those same individuals earn according to tax returns, and underreporting is increasing in income. In the case of social benefits, Lynn et al. (2012) used administrative data on benefit receipt matched at the individual level to the survey microdata to find that under-reporting is far more prevalent than over-reporting of benefit receipt in survey data. Meyer and Wu (2018) link administrative data from Social Security and survey data finding that the latter yield effects of some social benefits on near poverty that are two-thirds what the administrative data generate.

The possible implications on inequality measurement of opting for one type of data may therefore be important. Given the problems mentioned for the two types of data, the best procedure for a more accurate measurement of inequality is linking survey and administrative data. This strategy combines the accuracy of the administrative information with the rich demographic detail and population representativeness of the surveys.

In Spain, the main dataset for measuring inequality – the Spanish Survey on Income and Living Conditions (ECV) – went from collecting the income data of the participating households from questionnaires and interviews to extracting them directly from administrative records. How does this change affect the evolution of inequality? How does its structure change? What sources of income modify their contribution to total inequality when measured with administrative data instead of the traditional method? The Spanish data provide an unique opportunity to answer these questions by comparing the two different data sources for the same individuals. Since the National Institute of Statistics (INE) continued to ask households for their income with the traditional methodology despite assigning them the income data provided by the Tax Agency and the Social Security administration, it is possible to evaluate the impact of moving from one data source to another.

This paper aims at analyzing the effects of the change in the income data source on income inequality and its structure. Different types of analysis are carried out trying to identify the change in each income source and its impact on inequality with the new criterion. We pay special attention to the possible effect on the dependences between sources of income – that is an issue so far very little studied in this strand of the literature – using copula functions. We believe that our paper makes a contribution in identifying which individual and household characteristics are most associated with income underreporting, how administrative data produces lower inequality results, and, most innovative, how administrative data gives rise to a different structure of dependences between income sources.

Among our main findings are a significant growth in the disposable income of households when using administrative data, that is especially relevant in the case of capital income. The incomes of both tails of the distribution increase considerably more – more intensely in the lower tail of the distribution – than those of the middle strata, producing levels of inequality that are significantly lower with administrative data. We also find that both methods of data collection also produce significant differences in the observed dependences between income sources.

The remainder of the paper is organized as follows. Section two describes the change in the way to collect income in the survey, paying special attention to the variations in each source of income. In section three we analyze the socioeconomic profiles in which the methodological change has caused a greater variation in disposable income. In section four we estimate the impact of using administrative data on inequality. In section five we identify the effect of administrative data on the corresponding distributions for each income source and on the dependences between income sources. Section six concludes.

2. THE CHANGE IN THE INCOME COLLECTION METHOD: EFFECTS ON INCOME LEVELS

Since 2004, the countries of the European Union have the same data source – with common methodology and questionnaires – to collect information on living conditions and household income (EU-SILC, in Spain ECV). The objective pursued by the European Community institutions when creating this new dataset was to advance in the comparability of results in the main indicators of inequality, poverty and social inclusion in the member countries of the European Union. To this end, the questionnaires, the codification of the different variables, and the weighting systems were harmonized. The ECV provides information on individual and household income, the material and demographic characteristics of households, and a broad set of sociodemographic information. There is also a very detailed information on material well-being, necessary to estimate the incidence of multidimensional deprivation. Each year this information is complemented with that coming from specific modules.

The sample size is about 16,000 households, distributed in 2,000 census sections. Another relevant aspect is the rotating panel character of the survey, thanks to the accomplishment of four consecutive interviews to the same households renewing 25% of the sample each year. There is availability of longitudinal files with information for every three years since

2004-2006. Until relatively recent times, there was a problem of lack of representativeness of certain population groups, such as immigrants, with a certain bias in the survey of foreigners with a higher level of income than the group's average. The National Institute of Statistics (INE) corrected this problem taking as reference from 2012 the Population Census of 2011 instead of 2001.[2] Equally or more important, the variable of nationality was incorporated for the calibration of each survey.

In terms of the measurement of inequality, the main methodological change occurred in 2013. Until that year, household income collected in the survey had as its sole source that declared by households at the time of the interview. From that date, the information provided by the Tax Agency and Social Security was included as the income of households and individuals. Using this new way to collect income, the INE recalculated that of previous waves bringing the new series to 2009. Although the official data are those that appear with the new methodology, until 2014 the INE continued to collect income through the interview method. The preliminary analyses carried out by the INE showed that the transition from one system to another did not seem to have an impact on the size of inequality measures although the effect on the average levels of the different income sources was going to be very significant (Méndez and Vega, 2011).

The motivation for the change of methodology was, fundamentally, the improvement of the quality of the information and a better knowledge of the households' income sources. As mentioned above, one of the traditional problems of household income surveys is non-response in certain components of income. Another limitation is the difficulty of knowing through interview data both the gross income of each member of the household and the social contributions and taxes paid, which often means that the statistical production centers themselves must simulate them. Some EU countries, in fact, had already used administrative files for the generation of income in EU-SILC. This is the case of the Nordic countries, especially, and the Netherlands, France, Austria or Slovenia in some components of income.

The procedure to transfer the income data from the administrative files consists of collecting through the national identity number of the individuals included in the sample

[2] In order to facilitate the comparison with the previous waves, the original data of these surveys were re-weighted using the new Census.

the data recorded in the tax sources and the Social Security files. That number is available in more than 98% of adults.[3] For the allocation of social benefits, the INE uses the Registry of Public Social Benefits. In the preliminary studies of the INE some divergences were found between the type of benefits declared by some households and those actually received (INE, 2010). This is the case, for example, of some non-contributory old-age pensions classified as such by the interviewees themselves but which appeared in the Social Security files as contributory. Another difficulty is that some benefits that appear in the Registry, such as retirement due to disability, are not classified as such in the survey. The previous evaluation carried out by the INE (2010) revealed that the average value of the data coming from the administrative files was somewhat higher than that declared in the survey (4.6%).

Data from the Tax Agency are used for the other income sources, extracted mainly from the Personal Income Tax (IRPF) files. The two main problems for the use of tax records are the high number of people without the obligation to declare income, and the joint declarations which can considerably limit the necessary individualization of income. To solve the first of these problems the INE uses tax withholding files, which include income earners without the obligation to declare. One of the main advantages of the use of tax data is that there are many households that when interviewed do not declare to have capital income but do have them in their tax data. According to the estimations made by the INE (2010), before the generalization of the new procedure the average capital income with tax data was double that with the traditional criterion. The opposite happens in self-employment income although the difference was not so great (6%).

Since the change in methodology, the information on household income provided by the INE for the year 2009 onwards is based on administrative data. However, until 2014 the INE continued carrying out the survey with the previous methodology. The access to these files – available on demand – allow to check directly with the microdata the effect that has considering one type or another of income collecting on the different income sources. We focus on the survey corresponding to 2014 since this is the last one with data for the two methods of collecting income.

[3] The singularity of the financing system of the regional communities prevents the same procedure from being used in the case of some regions, like the Basque Country and Navarre, where income information is still collected by the interview method.

A necessary first step is the identification of the main income sources in each survey. The criterion of aggregation that has been followed is to group the different incomes into five major sources: labor income, self-employed income, capital income, benefits and taxes.[4] These incomes appear in the different files of the survey, being necessary – in some cases – the aggregation of the different income sources of each member of the household. While most of the social benefits are included in the individuals file, there are some that correspond to the households file – family, social exclusion, housing benefits and taxes.

[FIGURE 1]

Figure 1 shows the change that occurs in the average levels of disposable income and its different components when going from a criterion for measuring income through the traditional method to administrative records.[5] All the variations are significant and, except in the case of self-employment income, there is an increase when going from interview to administrative data. In line with what was anticipated by the INE, the first relevant result is the increase in disposable income (higher than 14%).[6]

This growth is mainly explained by higher levels of labor income – given their weight in total income – which grows more than 17%, and capital incomes, which are more than 2.5 times higher in administrative than in survey data. The latter is undoubtedly the source where there is greater discrepancy between the two types of income data. The best coverage of capital income with administrative data is an important advance in an income source for which underreporting has traditionally been very large. The opposite occurs with self-employment income which decreases more than 10% in administrative as compared to survey data.

Especially relevant is the difference that may exist in the components of income related to thepublic sector intervention, given the universal nature of administrative records. The conversion of gross to net income is in fact a common problem in income surveys. Many

[4] In the sake of simplicity we have grouped taxes and social contributions into a single category.
[5] We adjust incomes using the OECD modified equivalence scale.
[6] This result is very similar to that of Goerlich (2019), who finds that administrative data raised income by around 16%.

surveys do not contain raw data and it is necessary to use algorithms for the conversion of the net data to gross, being difficult to collect all the complexity of the tax-benefit systems for the different individuals that make up a household (Immervoll and O'Donoghue, 2003). The INE points out that although in the fieldwork the gross and net level are requested for each source of income, the ignorance that in many cases the informants have on gross income makes it necessary to construct a model that allows the conversion of gross to net in each type of income (Méndez, 2007). As stressed by some authors, these algorithms can affect the distributional outcomes (Goerlich, 2016). The change from survey to administrative data increases the average level of income for cash benefits by 15.4%. The change in average taxes and social contributions is much more marked (around 50%). Again, this difference can decisively affect the measurement of the redistributive effects of taxes.

3. DETERMINANTS OF INCOME UNDERREPORTING IN SURVEY DATA

The change from survey to administrative data can have important effects on the measurement of the economic well-being of households. Opting for one procedure or another may produce changes in the relative situation of each type of household in the distribution of income. It may be relevant, therefore, to identify in which categories of the population the change in income is more important when moving to administrative records. However, the INE does not collect the survey and administrative data in the same file. It provides different files for each type of data with different household identification numbers in each file. In order to identify the characteristics of households and individuals that determine a greater difference between the two types of data, it was necessary to merge the two surveys. The objective was to obtain a single file from the resulting matching with the different income variables with the two methodologies for the same households. We used matching methods drawing information from the different files provided by the INE.[7]

Once the matching was completed – and it was verified that the same differences in the average levels of income sources estimated in the previous section were maintained – it was possible to analyze in which socioeconomic categories the change of criterion has

[7] Less than 5% of the observations remained unmatched and the randomization tests did not detect any pattern in which they had been left out.

greater incidence. To identify the specific effect of each characteristic we estimate a Probit model, in which the dependent variable is having an income difference higher than the average for the whole population when moving from survey to administrative data. We have defined this binary variable in three ways:

$$p_i = 1 \text{ if } (y^A{}_i - y^S{}_i) > \mu(y^A - y^S) \text{ and } p_i = 0 \text{ otherwise}$$
$$p_i = 1 \text{ if } (y^A{}_i - y^S{}_i) > 1.5\ \mu(y^A - y^S) \text{ and } p_i = 0 \text{ otherwise}$$
$$p_i = 1 \text{ if } (y^A{}_i - y^S{}_i) > 2\ \mu(y^A - y^S) \text{ and } p_i = 0 \text{ otherwise}$$

where y^A is disposable income with administrative data, y^S is disposable income with survey data, and $\mu(y^A-y^S)$ is the average difference in disposable income with administrative and survey data. Differences are calculated as percentages.

[TABLE 1]

Table 1 shows the results of the estimated model. Some characteristics seem not too much relevant to explain changes in income levels, such as gender, marital status, housing tenure, and educational attainment. In the latter case, only the coefficient corresponding to the individuals with the highest level is significant once the rest of the characteristics are controlled. This result may be related, as it will be seen, with a larger income difference in households in the upper percentiles among which there is a much higher presence of graduates than in the lower deciles.

The results also show that when age increases – especially in individuals over 65 years of age – the income growth when moving to administrative data is lower. This result is related to the fact that the income of this group is largely dependent on social benefits. As noted in the previous section, the difference in the values of benefits is small in relation to other income sources. The different types of household generally have significant coefficients, being lower in households with dependent children than in single persons. Single parenthood does not appear as a characteristic associated with greater underreporting, with insignificant effects in almost all models.

One of the categories where we do find a higher likelihood of income changes when moving to administrative data is that of immigrants from outside the European Union. The stricter the criterion for defining that probability – a difference in income well above the average – the more important the effect. Among the individuals who are working, the impact of the change in the income collection method is much lower than in the rest of the population. This result is related to the lower variation observed in labor income with both methods. The same happens with retired people for the reasons already mentioned. The opposite case is that of the unemployed, which seems to indicate a marked underreporting of income from unemployment benefits when they are collected through interviews.

4. EFFECTS ON INEQUALITY

One of the most important consequences of the change in the method to collect income is the possible effect it can have on inequality. To the extent that the change to administrative data produces a better reporting of some incomes – especially some of the most unequal such as capital income – the change in method could affect the measurement of inequality.

A first approach to this possible effect on inequality is the comparison of the density functions of disposable income with the two types of data. Figure 2 shows the two distributions for the year 2014, the last one for which comparison is possible. The data reveal that changing to administrative data produces a shift to the right of the distribution, a reduction in the number of households with incomes close to the modal value, and a considerable stretch of the distribution in its upper tail. While in the survey data about 5% of households have an equivalent income around 30,000 euros, that percentage rises to almost 8% with administrative data. There is also a greater presence of low-income households in the distribution resulting from survey data, with 18% of households with less than 6,000 euros, a percentage significantly higher than the one resulting from administrative data (13%).

[FIGURE 2]

The way in which the change in methodology affects different parts of the distribution of disposable income is best appreciated when differences by percentiles are estimated. Figure 3 shows the growth in the average income of each percentile in percentage terms. A first result is that administrative data increase the level of income in the whole distribution (higher than 10% in all percentiles). A second result is that this growth is not uniform throughout the distribution. It is especially marked in the first percentiles where income grows more than 20%. Moreover, between the poorest 5% and the richest 5% there is a clear decreasing profile to regrow in the higher income stratum, with income increases higher than 15% in the richest percentiles.

[FIGURE 3]

Given this effect in the different sections of the distribution, the result should therefore be a reduction in inequality when moving to administrative data. The reason is the higher increase in income in the lower percentiles – more likely to underreport their real income in the survey – although possibly smoothed by the growth also recorded by the richest percentiles. In the latter case, it is easy to interpret that this growth occurs thanks to a better coverage of capital income.

Table 2 shows a wide variety of inequality measures estimated with the two income distributions that result from the double criterion in the collection of income. In general, the differences for most indicators are small but significant. This is the case of the Gini index, which modestly decreases when moving to administrative data. This result is not repeated in all measures, which in some cases increase when moving to administrative data.

[TABLE 2]

This variety of results is related to the different interpretations of inequality that each index summarizes and to the difference in the incidence of the change in both tails of the distribution. In the case of the Theil index,

$$\text{Theil}(c)=(1/c(c-1))\left\{[(1/n)\Sigma_i^n(y_i/\mu)^c]-1\right\} \quad c\neq 0\ ,\ c\neq 1$$

$$\text{Theil}(1)=(1/n)\,\Sigma_i^n(y_i/\mu)\log(y_i/\mu), \qquad c=1$$

$$\text{Theil}(0)=(1/n)\,\Sigma\log(\mu/y_i), \qquad c=0$$

the differences between the result with c=0 (mean logarithmic deviation) and c=2 (half the coefficient of variation squared) are clearly related to the changes shown in Figure 3. When c=0, the index weighs more the differences between incomes in the lower tail of the distribution, and a very marked growth was observed in the lower income percentiles. When c=2, changes in the upper tail of the distribution receive more weighting. As shown in Figure 3, the change in methodology also produces a growth in the higher income percentiles although lower than that of the other tail of the distribution. When the changes are weighted equally throughout the distribution (c = 1), the change in inequality is very modest and insignificant.

Something similar happens when estimating the family of Atkinson indices giving different values to the parameter e:

$$\text{Atk}(e)=1-[(1/n)\,\Sigma_i^n(y_i/\mu)^{1-e}]^{1/(1-e)}, \qquad e\geq 0\ ,\ e\neq 1$$

$$\text{Atk}(e)=1-\exp[(1/n)\,\Sigma_i^n\text{Ln}(y_i/\mu)^{e}], \qquad e=1$$

As this parameter grows, more weight is given to income transfers at the lower tail of the distribution and less to those at the upper tail. This greater sensitivity to what happens in the upper part of the distribution means that when taking high values of the parameter (e=2) the result is a very large increase in inequality with administrative data. By contrast, when low values are taken (e = 0.5) inequality decreases.

The availability of different ECV waves with administrative data and with the traditional interview method allows us to assess not only how inequality changes in a given year, but also what differences there are in the trend of inequality. The two types of distributions can be analyzed between 2009 – the first year with administrative microdata – and 2014 – the last date in which the INE continued to collect income through the interview method.

[FIGURE 4]

The period for which data exist corresponds to part of the most critical phase of the last economic crisis. Between 2009 and 2014, the per capita net national disposable income fell in real terms by more than 11%. In the same period, the unemployment rate raised from 18% to 24% (Labour Force Survey). Figure 4 shows that, regardless of the indicator chosen to measure inequality and the income data source, inequality increased during the period considered. This growth is particularly noteworthy in the Atkinson index with the highest parameter of aversion to inequality (e = 2) and can be also appreciated in the Gini index.

A second relevant result – common in the set of estimated indicators – is that the growth of inequality during this period is considerably greater when using interview than administrative information. Thus, while the rate of growth of the Gini index during the years considered is 6% with administrative data, it is almost double (11.3%) with survey data. Something similar happens with the Theil (c=1) or the Atkinson (e=0.5). The widest differences arise with the Atkinson index (e=2) and the Theil (c=2), that is, with the indicators most sensitive to aversion to inequality and to changes in the upper tail of the distribution. It follows therefore that one of the most important consequences of the change in the income collection method is a smaller increase in inequality with administrative with respect to survey data.

5. EFFECTS ON INEQUALITY BY INCOME SOURCES

The replacement of income data collected by interviews with administrative data can affect the estimated levels of inequality through different channels. One of the most direct is through the different impact that the change in each income source may have had on income percentiles. Although in some of the main income sources the changes seem relatively modest on average, it is possible that the dispersion in their corresponding distributions changes when moving to administrative data. In the case of capital income or taxes and social contributions, the magnitude of the difference observed with the two criteria of income collection makes it easy to predict also a very different magnitude of inequality in each source.

The better coverage of capital income could be determinant of an inequality level in disposable income different from that which results from the traditional method of collecting income. Some recent studies have emphasized the role that the increase in the percentage of capital income can have over inequality in the distribution of disposable income (Milanovic, 2017; Bengtsson and Waldenström, 2018). A better coverage of these incomes should also imply a different level of inequality in their distribution and the same could happen with other sources of household income.

[FIGURE 5]

Figure 5a shows the density functions of labor income in each household with the two criteria for collecting income. Although the difference in average labor income when changing criteria was relatively small (17.4%) compared to other sources of income, some significant changes come up in the two resulting distributions. One of the most prominent is some displacement to the left of the labor income distribution with administrative records, indicative of a greater number of low-wage earners with this criterion. Second, the bimodal profile of the distribution with administrative data stands out, with the first of these values probably reflecting earnings corresponding to part-time employment. The highest modal value in the case of labor income with survey data evidences the greatest weight in the distribution of average wages. Finally, as in the case of the net disposable income, administrative data have greater coverage of high-wage workers.

The differences are much less marked in the densities of the self-employment income (Figure 5b). The profile of the two distributions is very similar, with the only nuance of the slightly more inward shape of these incomes with survey data in the decreasing section from the modal value. Noticeably, these incomes are usually underreported in the household surveys, but, at the same time, they receive in Spain a specific treatment in the personal income tax, which means that, in many cases, the taxable income differs markedly from the income actually received. This is the only case in which the average income is lower with administrative than survey data. This difference between the two types of variables occurs, above all, in the section between 18,000 and 30,000 euros, always in terms of equivalent income. This gap is also observed in higher incomes until the upper tail of the distribution begins to stretch, given the better coverage of the highest self-employment incomes in administrative data.

Regarding capital income, we have already noticed that this is the income source with the highest change in mean from survey to administrative data. Moreover, as Figure 5c shows, there is a much higher proportion of households with very low capital income in the distribution with survey than with administrative data. The average and maximum values of this source are very different in each case, almost doubling that of the data obtained through interviews.

The distributions of the taxes variable do not differ substantially with the two methodologies (Figure 5d). The large increase in the average value of taxes when these are collected with data from the Tax Agency is mainly concentrated in the largest number of households that now happens to be in the income bracket between 5,000 and 12,000 euros. The distribution moves to the right when moving from survey to administrative data, and there is also a greater concentration of taxes paid around the modal value of survey data.

Finally, cash benefits present a somewhat different profile to the previous ones (Figure 5e). In both distributions there is a greater concentration of this type of income around low values. However, although the difference is small, there are two characteristics that make the corresponding densities somewhat different. First, although the modal value with interview and administrative data is similar, the number of households accumulated around this value is clearly lower with administrative data. Second, from this value there is a greater number of households for each income level in the case of administrative data except in the far right of the distribution, collecting the survey data unusually high benefits.

The different shapes observed in the distributions of each income source allow us to anticipate that the indicators that summarize inequality in each case will differ as measured by the traditional method of interview or using administrative data. Table 3 shows these indicators and the difference between the two methods, also indicating the statistical significance of the latter. A first result is the different sign and significance of the Gini index by income sources, as compared to other inequality indexes. In particular, according to Gini index, in most income sources the methodological change gives rise to a more equal distribution, although the differences – except in capital income and cash benefits – are not significant. The only exception is taxes, whose internal inequality must be interpreted inversely to the other sources. The different results for the Gini index could be explained – as it was deduced from the analysis of the density functions of each source – by the fact that an important part of the changes that occur in the different incomes with administrative data are much larger in the tails of each distribution than in middle incomes.

[TABLE 3]

This result is also found with the Atkinson index with the parameter that represents a lower aversion to inequality, but not with the Theil index when all incomes receive a similar weighting. It is precisely in this indicator that the effect of the methodological change on inequality in all income sources is larger.

Among the different income sources analyzed, the most important changes are those affecting capital and self-employment income, being smaller – although depending on each indicator – the changes in the inequality of labor income. Given the greater weight of the latter on total household income, it is normal that the effect on inequality of disposable income is small in most of the indicators. On the other hand, the impact of the greater coverage of capital income produces in general a reduction in inequality in this source. The opposite occurs with self-employment income with almost all indicators showing higher inequality levels.

If the results corresponding to the effect of the methodological change on inequality in the different sources are compared with the previous results on the change in their average levels, there seems to be a certain relationship. In general terms, the income sources in which levels change the most when modifying the method of income collection –capital income and taxes – are also those in which moving to administrative data has the greatest impact on inequality.

6. EFFECTS ON THE STRUCTURE OF INEQUALITY AND DEPENDENCES BETWEEN INCOME SOURCES

A very important dimension of inequality that may be affected when moving from survey to administrative data is the structure of inequality by income sources. The inequality of the distribution of disposable income is the result of the inequality in the different sources of income, the weight in the total income of each source and the correlations between them. As mentioned above, some studies have examined how changing from survey to administrative data can affect the first two components. Far less research has examined how the different methods of collecting income can yield different results in terms of the dependences between the income sources.

In recent years, increasingly robust procedures have been developed for the analysis of inequality by income sources, taking into account both changes in the structure of the population and those related to its various components. The decomposition of inequality by income sources has as its main reference the pioneering contributions of Shorrocks (1982, a, b). His works were based on inequality at a fixed moment in time. Jenkins (1995) generalized this analysis to decompose trends.

Recent studies have expanded the decomposition method through two extensions. One has been to consider a wider variety of inequality indicators, and another one is the combination in a single method of analysis of changes in individual characteristics and changes in income sources and their dependences. The pioneering contribution was Dinardo et al. (1996), which was further developed in the field of inequality of disposable income by Daly and Valleta (2006). It is a structural method, in which the contribution of each component is identified through a counterfactual. They compare the distribution with the observable characteristics in the present moment and the one that would exist if those characteristics had not changed over time. The major criticism that this approach has received is that the results can be very sensitive to the specification of the model (Cowell and Fiorio, 2011), being also a very limited approximation to identify the interrelations between income sources.

In our specific case, the analysis is markedly simplified because – being the same individuals and households –, there is no change in the characteristics and we can focus on the other two types of effects. In our approach to the change produced by the administrative data in the structure of inequality, we will combine two type of analysis that try to overcome the limits of the cited approaches. First, as proposed by Larrimore (2004), we create a counterfactual that maintains the order of the initial distribution of income – survey data – to determine how the changes in the marginal distributions of each income source, when moving to administrative data, affect the differences in the distribution of disposable income. The main limitation of this approach is that it does not explicitly quantify the interrelations between the different income sources. For this reason, in a second analysis we evaluate the change in dependences between income sources through copula functions.

Let $X^{(i)}$ denote the total income of individual i in the initial distribution with survey data and let us assume that it can be represented as the sum of the incomes obtained from each source, f_{ki}, with k=1,…,d, i.e.

$$X^{(i)} = f_{1i} + f_{2i} + \ldots + f_{di}$$

To estimate the impact of the change in the distribution of the first income source on the inequality in disposable income, the income of that source with survey data (f_{1i}) can be replaced for each individual by the income of that same source with administrative data (f'_{1i}), that is:

$$X^{(i)'} = f'_{1i} + f_{2i} + \ldots + f_{di}$$

The difference between the inequality with the initial distribution and this simulated distribution can be interpreted as the contribution of each source to inequality. However, the sum of these contributions is not 100%, since we should add the effect of the dependences between income sources.

[FIGURE 6]

Figure 6 shows the change in the contribution to inequality in disposable income when replacing survey by administrative data in the different sources. The contribution of each source varies according to the indicator taken as a reference. Except in the case of the Atkinson Index with e=2, in all other indices the greatest change in the contribution to inequality is that of labor income. With that index, taxes are the source with the largest change in its contribution to inequality. In any case, this latter effect is largely dependent on inequality aversion. The impact of replacing taxes with administrative data has a negative effect on inequality with parameters of aversion less than 1, and the impact is very small when the parameter equals one.

The effects of capital income are similar in terms of the sign – although with different size – to those of labor income. In almost all indices, the shift from survey to administrative data noticeably increases the contribution of labor income to inequality, except in the case again of the Atkinson Index with the highest aversion to inequality. The effect of the changes in benefits and self-employment income are not very relevant in quantitative terms.

A last and very important dimension of inequality that could be affected by the change of criteria in the method for collecting income data is the structure of dependences between income sources. As mentioned above, inequality in disposable income is the result of the inequality in the different income sources, the relative weight of each source in total income, and the interactions between them. Therefore, a key issue is identifying, as accurately as possible, the effect on the dependences between income sources. However, this issue is often forgotten. In this paper, we address the problem of both measuring the dependence between the different income sources and analyzing whether using administrative or survey data could affect such dependence. As this is a multidimensional problem with more than two variables involved and those variables are non-normally distributed, we need measures of dependence that capture other types of relationships beyond linear correlation.

In this setting, copulas become an essential tool, as they enable building scaled-free measures of multivariate dependence that generalize some well-known coefficients of association like the Spearman's rho. Since there are few applications of this approach in welfare economics (see Decancq (2014) and Pérez and Prieto (2015, 2016a)), we first review some preliminary results concerning copulas and dependence.

A d-dimensional copula is a multivariate distribution function $C{:}I^d \rightarrow I$, whose one-dimensional margins are uniform on I, where I = [0,1]. The Sklar's theorem ensures that given d continuous random variables, $X=(X_1,\ldots,X_d)$, with joint cumulative distribution function F and marginals $F_1,\ldots,F_d$, respectively, there exist a unique copula C such that

$$F(x_1,\ldots,x_d) = C(\, F_1(x_1) \,, \,\ldots\, , F_d(x_d)\,) \;\text{ for all } (x_1,\ldots,x_d) \in R^d \qquad [1]$$

Hence, for a given real vector $\boldsymbol{u} = (u_1,\ldots,u_d) \in \mathrm{I}^d$, the value $C(\boldsymbol{u})$ represents the proportion of individuals in the population with positions outranked by $\boldsymbol{u}$ – i.e., with a lower or equal position than $\boldsymbol{u}$ in all dimensions. For instance, $C(0.1,\ldots,0.1)$ will represent the probability that a randomly selected individual is simultaneously in the first decile ("low ranked") in all dimensions. By contrast, the survival function $\bar{C}$ associated with the copula C, is defined as

$$\bar{C}(\boldsymbol{u}) = p(U_1 > u_1,\ldots,U_d > u_d),$$

where $U_i = F_i(X_i)$, i=1,…,d, are uniform $U(0,1)$ random variables with joint distribution C. Hence, the function $\bar{C}$ represents the proportion of individuals in the population with positions higher than $\boldsymbol{u}$ in all dimensions. That is, $\bar{C}(0.9,\ldots,0.9)$ will represent the probability that a randomly selected individual is simultaneously in the 9th decile ("top ranked") in all dimensions. In general, $\bar{C}$ is not a copula. If the variables $X_1,..,X_d$ are independent, their copula will be the independent copula Π, defined as $\Pi(\boldsymbol{u}) = u_1 \times \ldots \times u_d$.

The essential feature of the copula approach is that it allows us to decompose the joint distribution of X into their one-dimensional marginal distribution functions and the dependence structure between them, which is captured by the copula, as stated in [1]. In terms of the discussion on the possible effects of the different methods of data collection, the key question is whether this dependence differs with the two types of data. Given that we deal with five income sources, measures of multivariate dependence are needed to test whether the two types of data yield similar results in terms of the relationships between the different sources.

There are several copula-based measures of multivariate dependence proposed in the literature (see Schmid *et al.* (2010)). In this paper, we focus on three multivariate extensions of the bivariate Spearman's rho based on orthant dependence concepts. Roughly speaking, measuring lower (upper) orthant dependence amounts to compare how likely it is that the variables $X_1,\ldots,X_d$ take simultaneously small (large) values as compared to how likely this would be were the variables independent.[8]

[8] For a detailed description of these concepts see Nelsen (1996, 2006).

The first copula-based multivariate extension of Spearman's rho we consider is due to Wolff (1980) and Nelsen (1996) and it is defined as follows:

$$\rho_{\mathrm{d}}^{-} = \frac{(d+1)}{2^{d}-(d+1)} \int_{\boldsymbol{I}^{d}} [C(\boldsymbol{u}) - \Pi(\boldsymbol{u})]\mathrm{d}\boldsymbol{u}\ . \qquad [2]$$

Hence, ρ_{d}^{-} can be regarded as a measure of average lower orthant dependence, as it measures, to some extent, the rescaled "average distance" between our multivariate data (represented by its copula *C*) and independence (copula *Π*) in the lower orthant.

In a similar fashion, Nelsen (1996) defined a measure ρ_{d}^{+} of average upper orthant dependence as follows:

$$\rho_{\mathrm{d}}^{+} = \frac{(d+1)}{2^{d}-(d+1)} \int_{\boldsymbol{I}^{d}} [\bar{C}(\boldsymbol{u}) - \bar{\Pi}(\boldsymbol{u})]\mathrm{d}\boldsymbol{u} \qquad [3]$$

This measure can be regarded as a rescaled "average distance" between $\bar{\mathrm{C}}$ – representing the behaviour of our data in the upper orthant – and $\bar{\Pi}$ – representing independence in such orthant.

The third multivariate version of Spearman's rho, due to Nelsen (2002), is the average of the two generalizations described above, namely:

$$\rho_{d} = \frac{1}{2}(\rho_{d}^{-} + \rho_{d}^{+}) \qquad [4]$$

Positive values of the three coefficients in [2]-[4] indicate positive lower orthant, upper orthant and orthant dependence, respectively. Furthermore, when the components of *X* are independent (C=Π), the three coefficients become zero, whereas in the case of maximal dependence, i.e. the outcomes in all the variables $X_1,\ldots,X_d$ are ordered in the same way, they all reach their maximum value, 1. A lower bound for the three of them is $[2^{d} – (d + 1)!]/\{d![2^{d} – (d + 1)]\}$; see Nelsen (1996). For our purposes, the coefficients ρ_{d}^{-} and ρ_{d}^{+} are preferable, as they can reveal some forms of dependences that ρ_{d} fails to detect; see Example 2 in Nelsen (1996). Noticeably, in the bivariate case (d=2), the three coefficients above become the well-known bivariate Spearman's rho. In practice, the copula C is unknown and the coefficients in [2]-[4] must be estimated from the data by using the empirical copula. Pérez and Prieto-Alaiz (2016b) propose feasible nonparametric estimators of ρ_d^- and ρ_d^+ that are easy to compute and share good asymptotic properties. The average of these estimators could be used to estimate ρ_d.

The discussion so far is based on the assumption that the univariate margins are continuous. Without this assumption, the underlying copula *C* in (1) is no longer unique, although it is uniquely determined on $RanF_1 \times \ldots \times RanF_d$. Accordingly, the coefficients in equations [2]-[4] should be modified when dealing with possibly non-continuous random variables; see, for instance, the proposals in Quessy (2009) and Mesfioui and Quessy (2010) and their corresponding estimators in Genest *et al.* (2013).

Next, we apply the measures discussed above to the analysis of the dependence between the different income sources in order to check whether the degree of dependence change depending on the type of data used. To ease the computation and interpretation of the results, the income sources have been aggregated into three components (d=3): labor income (labor income plus self-employment income), capital income and the net results of taxes and transfers (taxes minus cash transfers). Since our variables are not strictly continuous, to compute the empirical versions of the coefficients [2]-[4], we use the estimators proposed by Genest *et al.* (2013) for d=3. In order to compute the standard errors of these estimators, we approximate their bootstrap distribution by resampling with replacement repeatedly from the original data (1,000 subsamples). Then, on the basis of the bootstrap distributions obtained, we test whether the difference between survey and administrative data is significant. Table 4 depicts the results.

[TABLE 4]

Several conclusions emerge from this table. First, regardless of the coefficient used, there is a positive and significant multivariate dependence between the income sources, both in survey and administrative data. Second, regardless the data source, the largest coefficient of multivariate dependence is ρ_d^+. This means that high values of the three income components tend to occur together – i.e., people with high labor income are more likely to have simultaneously high capital income and few net public transfers. Moreover, this simultaneous occurrence of "good" rankings in the three components is more likely with administrative than with survey data. By contrast, the coefficient ρ_d^- is significantly greater with survey than with administrative data. This means that small levels of the three income components (labor, capital, tax-public transfers) tend to occur together more likely with survey than with administrative data. Noticeable, there is no significant difference between the coefficient ρ with the two types of data. This results underlines the caveats of only using this coefficient since, as commented before, it could mask some type of dependences that are only captured by ρ_d^- and ρ_d^+.

In general terms, it can be said that both methods of data collection also produce significant differences in the observed dependences between income sources. Therefore, moving from one method to another affects not only the level of inequality and its changes over time, but also the very structure of inequality.

7. CONCLUSIONS

The past decade has witnessed an intense debate over the trends and consequences of inequality. The importance of its analysis requires having robust datasets to understand its changes, determinants and implications. Almost all countries have datasets that allow for a sufficiently comprehensive picture of the evolution of inequality in the long term. In most cases, these are household surveys that provide detailed data on the different income sources that each individual receives. However, survey income data are affected by different types of problems – non-response, measurement error, limited representation of top incomes – that may limit their ability to provide accurate diagnoses for decision making.

Due to these limitations, some countries are replacing in the surveys the income data collected through interviews by administrative data. Such a process can have important effects on the measurement of inequality and, therefore, on the optimal design of redistributive policies. It is necessary to evaluate not only how it affects the general indicators but also the inequality by income sources and the structure of dependences between these sources.

The change in the method of income collection in the main household survey in Spain (ECV) – moving from survey to administrative data – has made it possible to evaluate the possible impact that this type of changes has on income inequality and its structure. A great advantage compared to previous studies is that both types of data are available simultaneously for the same individuals and households. In this paper we have reviewed in depth some of the effects that this methodological change has had on inequality and its structure by income sources.

The general result is that moving to administrative data has effects on the levels of the different income variables included in the survey, the magnitude of inequality in the distribution of income, and its structure by income sources. Our analysis confirms, first, a significant growth of household disposable income with administrative data. This increase is especially important in capital income, with a notable improvement in a source where levels of under-reporting in survey data are usually very high. The opposite occurs in self-employment income, reflecting the comparison between survey and tax data the special treatment these incomes receive in the personal income tax.

A second contribution has been to identify the population categories that show greater differences depending on the method of income collecting. While there are some little differentiating characteristics – gender, marital status or educational level – there are others associated with a higher probability of income under-reporting in surveys. This is the case, among others, of age, the type of household, nationality, and unemployment status, for which the administrative data substantially correct the lack of coverage of the surveys.

One of the fundamental questions that the paper addresses is whether the change in the method of income collection affects the measurement of inequality. It can be stated that the difference in income according to one or another criterion is not independent of the level of household income. The incomes of the tails of the distribution increase considerably more – especially in the lower part of the distribution – than those of the middle strata. On the other hand, inequality indicators are significantly lower with administrative data. This result is reversed only in those indicators assigning much more weight to the upper tail of the distribution.

A fourth contribution is the identification of those income sources that are most sensitive to the use of administrative data in terms of their corresponding inequality levels. Turning to administrative data generally leads to more equal distributions in each income source. One of the most relevant effects of using administrative data is the modification of the structure of inequality, rising above all the contribution of capital income, cash benefits and taxes.

Lastly, we have shown that there are also significant differences in the structure of dependence between income sources depending on which income data source we use. In particular, moving from survey to administrative data conveys both a significant increase in the upper orthant dependence and a significant decrease in the lower orthant dependence. This is a key issue in the design of optimal redistributive policies, as it affects the type of relationships that determine the effectiveness of public intervention.

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Figure 1. Change (%) in mean incomes when moving from survey to administrative data

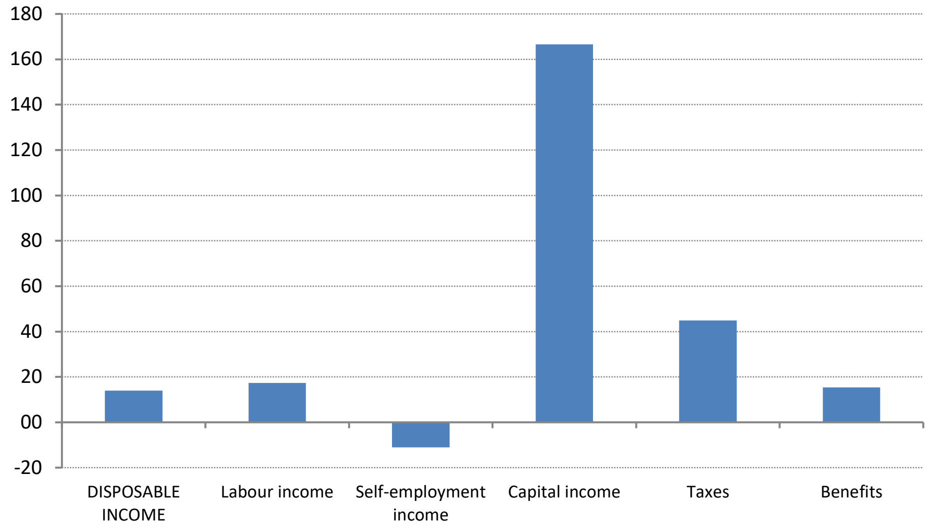


Figure 2. Distribution of disposable income, 2014

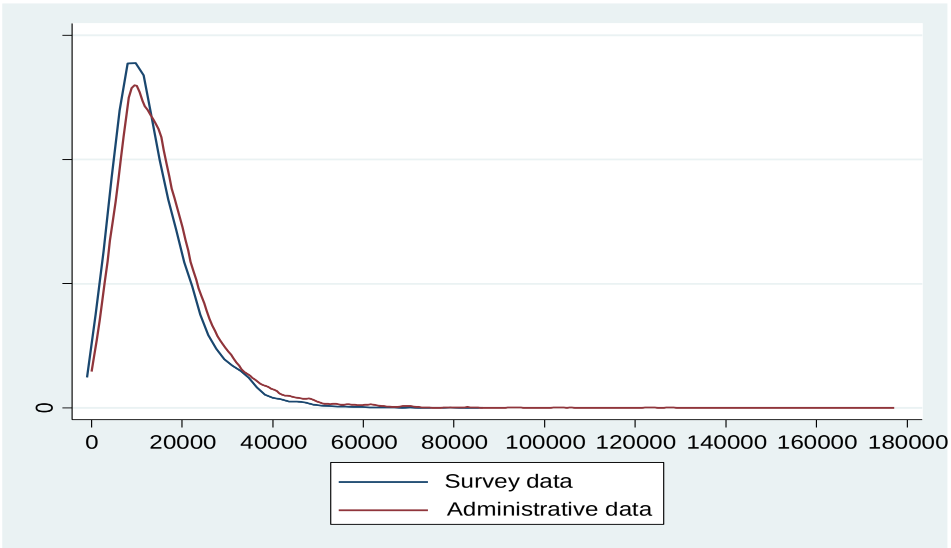


Figure 3. Growth (%) in the average levels of disposable income by percentiles when moving to administrative data, ECV 2014

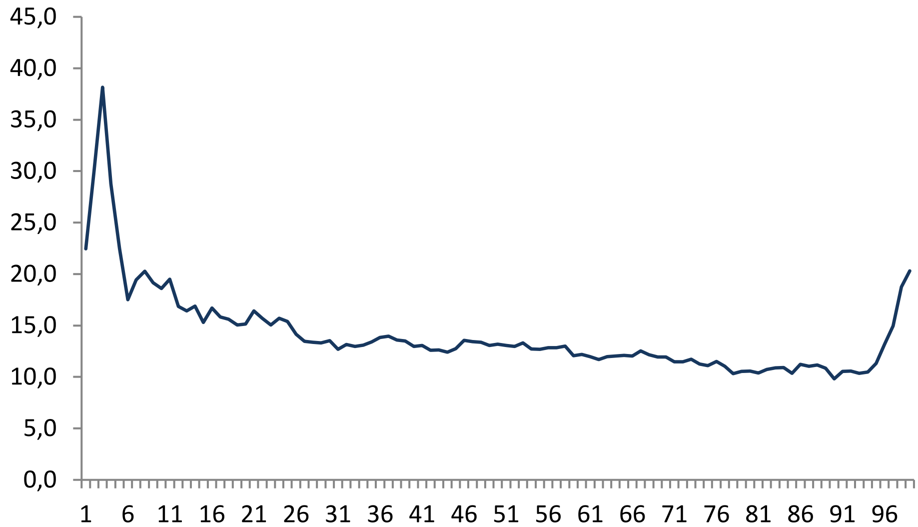


Figure 4. Inequality change (%), 2009-2014

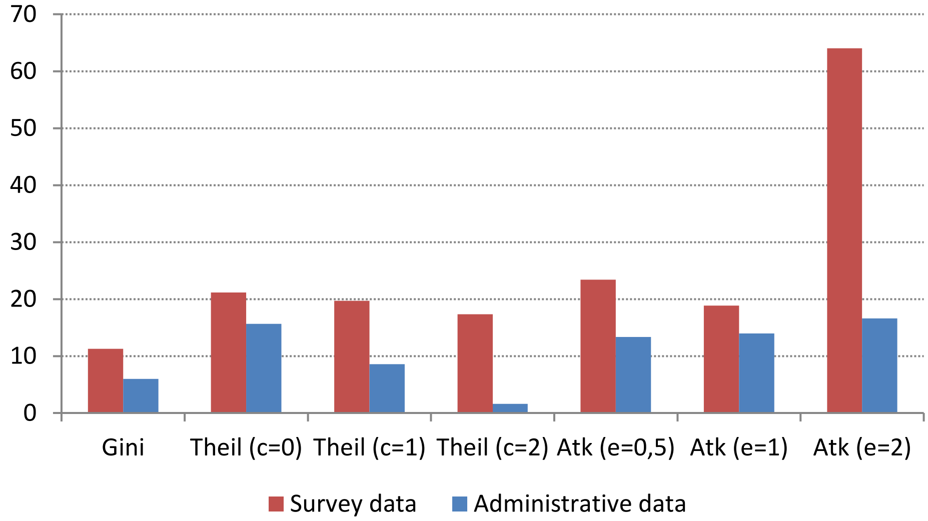
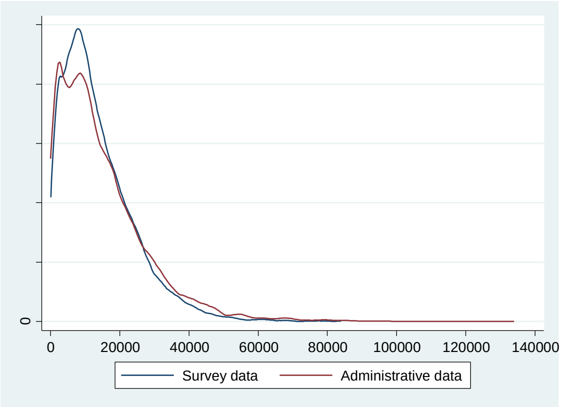
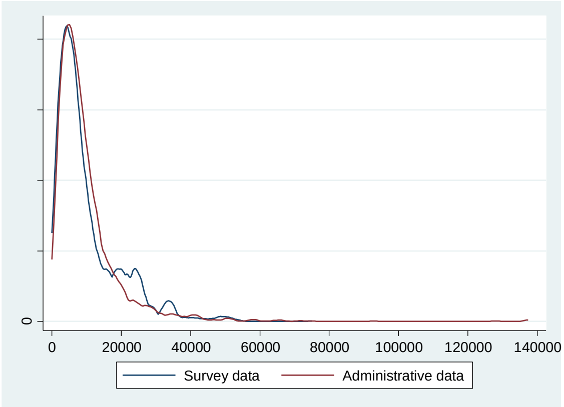


Figure 5. Distribution of income sources, 2014

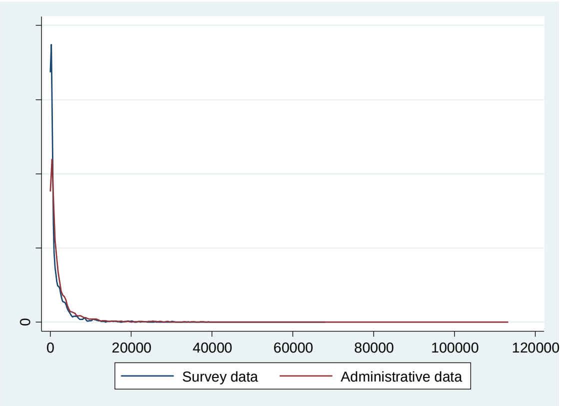
5a. LABOR INCOME



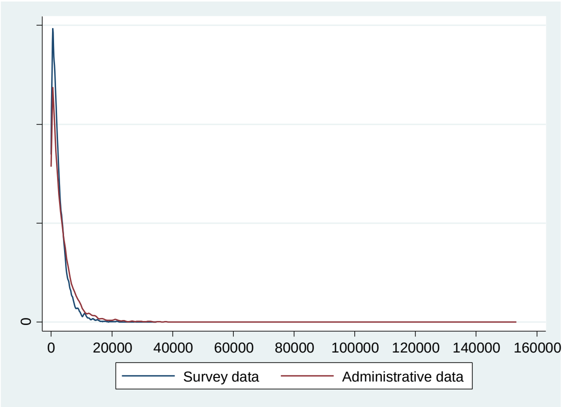
5b. SELF-EMPLOYMENT INCOME



5c. CAPITAL INCOME



5d. TAXES



5e. CASH BENEFITS

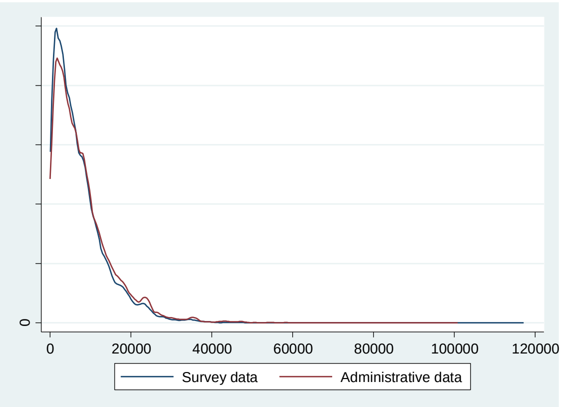


Figure 6. Change (%) in the contribution to inequality of income sources when moving to administrative data

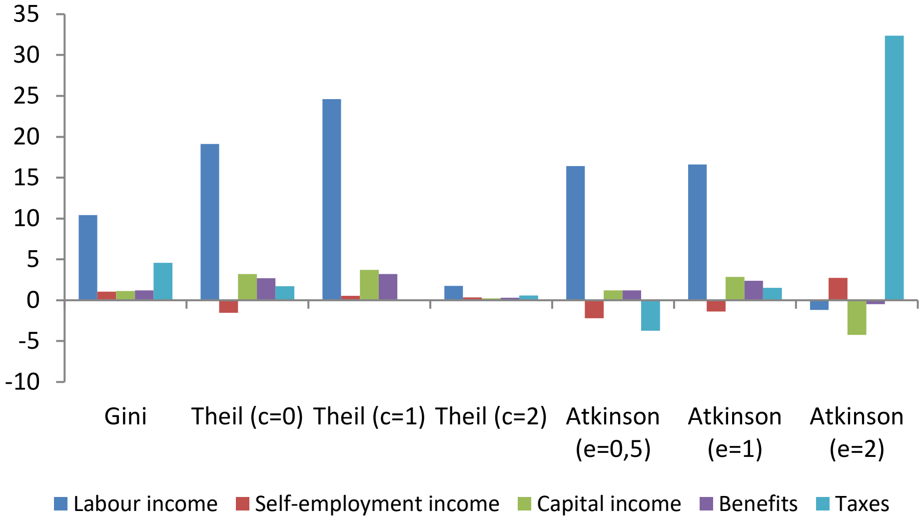


Table 1. Probability of reporting lower income in survey data

	Higher than the average		1.5 times higher than the average		Twice as high as the average	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Gender						
Female	-0.025	0.024	-0.002	0.028	0.022	0,035
Age						
25-35	-0.185***	0.051	-0.318***	0.059	-0.355**	0,073
35-45	-0.077	0.056	-0.171**	0.064	-0.208**	0,077
45-55	-0.068	0.058	-0.131**	0.065	-0.151*	0,079
55-65	0.002	0.064	-0.107	0.072	-0.067	0,088
65-75	-0.135*	0.080	-0.194**	0.094	-0.294**	0,126
75-85	-0.190**	0.087	-0.255**	0.104	-0.274**	0,140
>85	-0.158	0.105	-0.210*	0.126	-0.154	0,170
Marital status						
Married	0.066*	0.038	0.099**	0.043	0.063	0,054
Separated	0.195**	0.079	0.191**	0.088	0.218**	0,102
Widowed	-0.076	0.061	-0.084	0.074	-0.235**	0,102
Divorced	0.110	0.062	0.098	0.070	0.107	0,082
Household type						
Single person, male 30-64	-0.578**	0.224	-0.592**	0.231	-0.788***	0.235
Single person, male > 65	-0.780***	0.243	-1.066***	0.271	-1.583***	0.402
Single person, female < 30	-0.155	0.344	-0.224	0.358	-0.223	0.360
Single person, female 30-64	-0.488**	0.226	-0.487**	0.233	-0.659**	0.238
Single person, female > 65	-0.472**	0.227	-0.655**	0.238	-0.860***	0.255
Couple no children, at least one > 65	-0.704****	0.218	-0.859***	0.226	-1.286***	0.234
Couple no children, both < 65	-0.701***	0.216	-0.767***	0.222	-1.050***	0.224

Other households without children	-0.795***	0.215	-1.033***	0.221	-1.348***	0.224
One adult, at least 1 child	-0.283	0.223	-0.342	0.229	-0.579**	0.233
Couple, 1 child	-0.739***	0.216	-0.876***	0.222	-1.075***	0.225
Couple, 2 children	-0.688***	0.216	-0.831***	0.222	-1.054***	0.225
Couple, ≥ 3 children	-0.597**	0.222	-0.949***	0.232	-1.289***	0.242
Other households with children	-0.853***	0.216	-0.989***	0.222	-1.177***	0.224
Country of birth						
Rest of EU-27	-0.183*	0.099	-0.037	0.104	-0.040	0.125
Other countries	0.101	0.063	0.154**	0.069	0.164**	0.080
Educational attainment						
Primary education	0,038	0,044	-0,041	0,053	-0,034	0,071
Lower secondary education	0,045	0,045	-0,003	0,053	-0,034	0,071
Upper secondary education	0,008	0,052	-0,026	0,060	-0,069	0,079
Occupationally programmes	0,081	0,064	0,069	0,073	-0,032	0,094
Post-secondary non-tertiary education	0,089	0,328	0,277	0,330	0,304	0,386
Tertiary education	0,120**	0,047	0,081	0,055	0,004	0,074
Labor status						
Unemployed	0,269***	0,032	0,215***	0,036	0,208***	0,044
Retired	0,055	0,047	-0,047	0,056	-0,217**	0,078
Other inactive person	0,145***	0,035	0,054	0,041	0,034	0,050
Healt status						
Good	-0.055*	0.031	-0.074**	0.035	-0.056	0.044
Fair	-0.006	0.039	-0.022	0.045	0.005	0.056
Bad	-0.065	0.054	-0.085	0.063	-0.017	0.081
Very bad	-0.104	0.085	-0.196*	0.107	-0.203	0.151

Housing tenure						
Owner paying mortgage	-0.127***	0.029	-0.094**	0,033	-0,127**	0,042
Rented at market rate	-0.154***	0.046	-0.088*	0,051	0,076	0,059
Rented at a reduced rate	-0.077	0.071	-0.026	0,081	0,066	0,097
Free of charge accomodation	0.032	0.046	0.028	0,053	0,139**	0,062
Constant	-0.587**	0.221	-0.559**	0,229	-0,572**	0,236
Number of obs		26095		26095		26095
Log likelihood		-8304		-5942		-3489

Reference: male, <25 years old, single, single person < 30, Spanish nationality, lower than primary education, employed, very god health status, outright owner

***Significant at 1%, ** significant at 5%, * significant at 10%.

Table 2. Inequality indicators

	Survey data	Administrative data	Change (%)
Gini	0.346	0.339	-2.0**
Theil (c=0)	0.234	0.219	-6.4**
Theil (c=1)	0.191	0.190	-0.3
Theil (c=2)	0.210	0.220	4.9*
Atkinson (e=0,5)	0.106	0.099	-6.9**
Atkinson (e=1)	0.208	0.196	-5.7**
Atkinson (e=2)	0.766	0.878	14.6*

***Significant at 1%, **significant at 5%, *significant at 10%.

Table 3. Inequality indicators by income sources

	Survey data	Administrative data	Change (%)
Gini			
Labor income	0,588	0,585	-0,5
Self-employment income	0,959	0,953	-0,6
Capital income	0,948	0,872	-8,0***
Taxes	0,688	0,693	0,7
Cash benefits	0,675	0,658	-2,4***
Theil (c=0)			
Labor income	0,361	0,496	37,4***
Self-employment income	0,452	0,991	119,0***
Capital income	1,765	1,735	-1,7
Taxes	0,582	0,931	60,1***
Cash benefits	0,483	0,623	29,0***
Theil (c=1)			
Labor income	0,271	0,341	25,9***
Self-employment income	0,365	0,606	66,2***
Capital income	1,167	1,273	9,0***
Taxes	0,445	0,634	42,3***
Cash benefits	0,365	0,438	19,9***
Theil(c=2)			
Labor income	0,640	0,669	4,6*
Self-employment income	6,827	7,028	2,9
Capital income	13,76	6,175	-55,1***
Taxes	1,058	1,373	29,7***
Cash benefits	1,000	0,989	-1,1
Atkinson (e=0,5)			
Labor income	0,407	0,381	-6,2***
Self-employment income	0,893	0,865	-3,1***
Capital income	0,896	0,734	-18,1***
Taxes	0,335	0,348	3,9**
Cash benefits	0,504	0,463	-8,2***
Atkinson (e=1)			
Labor income	0,303	0,391	29,0***
Self-employment income	0,364	0,629	72,8***
Capital income	0,829	0,824	-0,6
Taxes	0,441	0,606	37,4***
Cash benefits	0,383	0,464	21,1***
Atkinson (e=2)			
Labor income	0,693	0,959	38,4***
Self-employment income	0,852	0,982	15,3***
Capital income	0,984	0,976	-0,8
Taxes	1,126	1,049	-6,8***
Cash benefits	0,757	0,953	26,0***

***Significant at 1%, ** significant at 5%, * significant at 10%.

Table 4. Copula-based measures of orthant dependence between income sources

	Survey data	Administrative data	Change (%)
ρ_d^+	0,311***	0,328***	5,3%***
ρ_d^-	0,274***	0,258***	-5,8%***
ρ_d	0,293***	0,293***	0,1%

***Significant at 1%, ** significant at 5%, * significant at 10%.