# Differently unequal: zooming-in on the distributional consequences of the crisis in euro area countries

Marco D'Errico

Department of Statistics and Quantitative Methods, University of Milan -- Bicocca

Corrado Macchiarelli London School of Economics and Political Science

> Roberta Serafini European Central Bank

First version: March, 2013. This version: December 2013

#### DRAFT AND PRELIMINARY - PLEASE DO NOT QUOTE

#### Abstract

Building on the recent empirical literature on inequality, this paper discusses how income distribution developed during the current crisis in euro area countries, as well as the marginal contribution of single income sources to aggregate inequality. Based on an extended definition of income - including additional components which do not appear in the standard Eurostat definitions - we complement the information provided by the Gini index and quantile ratios by presenting analternative inequality indicator, as developed by Zenga (2007), and its decomposition by income source. While broadly confirming the distributional effect of the crisis documented in previous studies, we find that in specific countries the level of inequality since 2008 has not been as modest as previous studies would suggest. The paper further looks at how the distribution of income has evolved during the crisis by income quantile groups (i.e. zooming-in). Preliminary results point to varying contribution of labour income in 2011 compared to 2007.

## 1. Introduction

The financial crisis started in 2007-2008 marked the start of a severe and protracted recession in both Europe and the US. A number of euro area countries experienced the deepest downturn since the Great Depression; at the same time, the negative growth prospects were reinforced by the sovereign debt crisis which triggered considerable fiscal consolidation efforts in some more vulnerable economies. Not surprisingly, how these developments have affected income distribution has recently come back to the attention of academics and policy makers.

Income distribution developments are often seen as mainly relevant from a social cohesion point of view, with negligible (if any) direct impact on economic performance. Yet, a large number of theoretical and empirical studies show that income distribution does matter for subsequent growth. According to Alesina and Perotti (1996) highly unequal societies are characterised by considerable socio-political instability, as well as by high uncertainty in the protection of property rights, which discourage investment and inhibit growth (see also Keefer and Knack, 2002). At the same time, in presence of credit constraints, a higher degree of income polarisation would result in a higher percentage of individuals in the lower tail of the distribution whose income is below the cost of education, thereby reducing the incentive to invest in human capital accumulation with ultimate detrimental effects on growth. The latter effect would be significant in rich economies (see for instance Perotti 1993 and 1996) , and particularly when considering that higher levels of

inequality are normally associated with lower social and economic mobility, and therefore with lower investment in education generation after generation. Finally, in more unequal societies interests groups are more prone to engage in rent-seeking activities which are detrimental for growth (Perotti, 1996 and Benabou, 1996). At the same time, a number of studies points at a positive impact of inequality on growth prospects: according to this literature, when favouring the rich inequality would in fact spur aggregate savings and growth; furthermore, a certain degree of inequality may induce individual to increase their effort to access to a higher level of income.

Whether inequality is good or bad for growth is still a debated issue. The answer to this question is not independent on the stage of economic development: according to Galor and Moav (2004) at earlier stages of development physical capital is relatively scarce and therefore inequality would have a positive impact on growth by channelling resources towards those segments of the population with a higher propensity to save; the opposite would hold at later stages of development, in which human capital accumulation becomes the main engine of growth and inequality would exacerbate the adverse effect of credit constraints on human capital investment and growth.

At the same time, for a given level of economic development changes in overall inequality – however measured – may correspond to very different scenarios, and therefore have very different implications for growth, depending on what portions of the income distribution are affected. Based on data from the Luxembourg Income Study, Voitchovsky (2005) show that while top end inequality is positively related with economic performance, inequality at the bottom end proves to be harmful for growth. These offsetting effects may explain the fact that sometimes inequality – captured by summary statistics such as the Gini coefficient – appears insignificant in growth equations, calling for analyses looking at a wide array of indicators at a more granular level.

Based on the literature above, the aim of this paper is to look at how inequality have evolved in euro area countries since the start of the crisis and – more importantly – to shed some light on which portions of the income distribution are actually driving the observed dynamics. This will allow to identify common patterns across countries and to distinguish those cases where inequality can be considered "good" or "bad" – i.e. is likely to be conducive to higher growth or unfavourably affect economic performance. This issue appears particularly important in the current juncture, as the shape of income distribution can either reinforce the persistence of a recession phase or be among the driving forces of a faster recovery.

A growing number of empirical studies have recently explored the distributional impact of the crisis by focusing on a wide array of variables such as income, earnings, consumption expenditure and wealth (Jenkins et al. (2012), Heathcote et al. (2010), Petev et al. (2011), Perri and Steinberg (2012)); in all of these studies, developments in income distribution are normally discussed with reference to a standard set of indicators, such as the average and median income, the Gini coefficient, the poverty rate. While undeniably useful, these indicators do not allow to properly take into account the relationship between the lower tail and the upper tail of the income distribution.

Based on household level data from the EU Survey of Income and Living Conditions (EU-SILC), this paper shows a similar set of income inequality indicators - thereby allowing a comparison with the results available in the literature; at the same time, it provide the computation of the Zenga (2008) inequality index, which allows to detect, with identical receptivity, deviations from equality in any parts of the distribution (differently from what the Gini index would do). Following the approach proposed in Lerman and Yitzhaki (1985) and in Radaelli (2010), the evolution of the Gini and Zenga indexes is then further decomposed into the contribution to overall inequality coming from single income sources. This allows quantitatively assessing how

inequality is developing as a result of the economic crisis, especially in those economies which were more hardly hit. Beside an analysis on baseline disposable income, inequality is further analysed with reference to an extended income, including additional income components, some of which being particularly relevant in the current conjuncture.

The novelty of our approach stands in looking at how the distribution of income has evolved during the crisis by income quantile groups (i.e. zooming-in). In fact, movements at different extents of the distribution may not necessarily translate into higher (lower) inequality overall, especially if larger movements from people in the mid into the lower end of the distribution are compensated by a relative depletion of people at the top end of the distribution. At the same time, increases (decreases) of inequality measures, however defined, do not necessarily mean a worsening (improvement) in the distribution of income. At one extreme, inequality may increase as a result of a higher share of population moving to higher income levels, the position of the lower tail of the distribution being unchanged. Such an outcome may be actually read as a Pareto improvement. Conversely, changes in inequality over time may be driven by the poorest segments of the population. At those extremes, policy implications would be very different. It is necessary thus to take a closer look at a wide array of indicators, not only in the aggregate, but also by population sub-groups, in order to be able to capture different dimensions of inequality and their redistributive implications.

The paper is organized as follows. Section 2-3 outlines the main features of the dataset, documents the weighting scheme adopted to ensure that data are comparable across countries, and discusses the extended definition of income which will be the object of the following analysis. Section 4 presents the methodology and Section 5 outlines the main results. Section 6 concludes.

# 2. Data

We use net income flows data from the Eurostats Survey of Income and Living Conditions for the euro area 17 (henceforth EA-17) over the period 2004-2010, allowing to cover the period immediately preceding the financial crisis and the following economic downturn.<sup>1</sup>

The EU-SILC provides the longest time series of comparable and consistently defined individual level data for income and living conditions available for the euro area, and the effective sample covers the period 2004-2010. Excluding data prior to 2004 is motivated by overcoming major data missing.

One of the attractive features of the EU-SILC, compared to other surveys, is that it provides not only details on each individual and households' characteristics (i.e. family composition, etc.), but also information on the level of household income and measures of households' wealth such as households' ability to face unexpected financial expenses, mortgage burden, etc.

The EU-SILC provides longitudinal data pertaining to individual-level changes over time, observed periodically over a period of four years for the whole EU. Particularly, longitudinal data is available for total household gross and net income, defined as the sum for all household's members of gross personal income components (gross employee cash or near cash income) plus gross income components at household level. Income is available for almost all countries over the whole sample period, with the exceptions of Greece, Italy and Portugal, for which data are available since 2007.

Comparing income inequality across countries requires using scaling factors, which weight households' income according to their composition. The household weighting scheme adopted here is based on equivalence scales measures. The intuition behind using weighting schemes is that of

<sup>&</sup>lt;sup>1</sup> For data consistency and comparability, the analysis focuses on the euro area prior to its two recent enlargements, i.e. Slovakia (Jan. 2009) and Estonia (Jan. 2011).

accounting for income to grow within each additional household member in a non-proportional way (see Atkinson, 1995; World Bank, 2001). Following a standard practice, we rely on the OECD-modified scale assuming, for instance, that a household of two adults and two children has different needs (e.g., roughly twice as much) as one composed of a single person. While this choice clearly depends on technical assumptions about economies of scale, as well as on judgments about the priority assigned to the needs of different individuals - such as children or the elderly - it also allows comparability with other studies and official publications (e.g., Eurostat publications). In this way, each household type in the population is assigned a value in proportion to its (assumed) produced income, mainly taking into account the size of the household and the age of its members - whether they are adults or children (see OECD, 2008).

For each household, total disposable and gross income are imputed consistently with the underlying income components, as described in the EU-SILC User Guide.

In order to allow for a decomposition of total income (either gross or net) by components, income sources are partitioned according to (cash and non-cash) *labour income*, *cash transfers*, *other sources of income*, and *direct taxes*.

Within the labour income component, we further distinguish among income from employment, income from self-employment and non-cash labour income.

Following Jenkins *et al.* (2011) we define cash transfers, including all cash benefits from the government plus transfers such as state retirement pensions, and other income sources, mainly including income from investment and savings (see EU-SILC User Guide).<sup>2</sup>

Given the availability of new income components (2010 EU-SILC wave), the analysis is carried out on an *extended* gross and net income definition. The rationale behind referring to a wider definition of income is to account for additional income sources which may have played a non-negligible role in households' balances, particularly in the last cycle. The additional income sources relevant to this extension are (i) pensions received from individual private plans (other than those covered under the European System of integrated Social Protection Statistics - ESSPROS) and interests paid on mortgage, treated here as negative income source. Further details are provided in the Table below. In our analysis, the component of interests on mortgage is intentionally kept separate from other income sources, in order to highlight the effect of mortgages on private sector's leveraging in some countries. In both cases, those fianncial market variable would also allow evluating the extent to which financial markets may have played a role in risk smoothing over time.

Paper definition of disposable income	EU-SILC definitions
Labour income	Gross employee cash or near cash income
Labour income from self-employment	Gross cash benefits or losses from self- employment (including royalties)
Non-cash labour income	Company car (from 2007, before it is gross non-cash employee income, see Eurostat)
Cash tranfers	Unemployment benefits Old-age benefits Survivor' benefits Sickness benefits

#### Table 1 – Income definitions

<sup>&</sup>lt;sup>2</sup> A residual component is included in order to ensure consistency between aggregate income (whether gross or net) and individual income sources. Importantly, the residual component represents the part of income which is not accounted for by the available income decomposition sources in the EU-SILC. While we take the residual into account for the sake of consistency and transparency of the results, we did some robustness checks to show that this residual is proved irrelevant in the income decomposition exercise for most countries. This check is not reported here for sake of brevity. The results are however available upon request from the authors.

	Disability benefits				
	Education-related allowances				
	Family/children related allowances Social exclusion not elsewhere classified Housing allowances				
	Regular inter-household cash transfers received				
	Income received by people aged under 16				
Other income	Income from rental of a property or land				
	Interests, dividends, profit from capital investments in unincorporated business				
	Pensions received from individual private plans (other than those covered under ESSPROS)**				
Interests on Mortgages**	Interest paid on mortgage**				
Taxes	Regular taxes on wealth				
	Regular inter-household cash transfer paid				
	Tax on income and social insurance contributions				
Vate artandad definition merled with **					

*Note*: extended definition marked with **\*\***.

# 3. Standard indicators of inequality

Table 2 shows the Gini coefficient computed on the gross and disposable (equivalised) income, as defined previously, for the periods 2007 and 2011 (2010 in the case of Ireland). Countries are ranked according to the latest available year. Not surprisingly, the level of inequality in all countries is lower when after-tax income is taken into account. Interestingly, however, countries' relative position somewhat changes depending on whether their rank is based on gross or net income. Among euro area countries, Spain appears as the country with the second highest level of inequality of disposable income (after Portugal), further away from the euro area average than the same index computed on gross income; the opposite seems to hold for countries like Austria and Belgium, where redistribution policies seem to have significantly lowered the degree of inequality compared to the euro area average.<sup>3</sup> The evolution over time of the Gini index (Figure 1) shows that since 2007 in some countries inequality initially declined but then started to raise again, up to levels well above (such as in the case of Spain, Ireland, Slovakia and Slovenia) or very close (such as in Greece and Italy) to those observed at the start of the crisis. The case of France stands as the only case in which inequality has systematically increased over the entire period under analysis, while the opposite dynamics is recorded in Germany and the Netherlands.

Compared to the standard income definition from Eurostat, including the additional components of private plans and interests on mortgage seem to matter in selected countries, with inequality increasing more in Spain (and, to a lesser extent, in Belgium and Finland) and decreasing less in Portugal and Germany (see Section 5).

Summing up, since the start of the crisis inequality remained high and increased in Spain, France and Ireland, followed by Italy where a similar, although milder, dynamics was observed; inequality decreased in Portugal (but stood at very high levels), as well as in Germany and the Netherlands. It remained broadly stable in all the other countries. The evolution of the income ratio of the richest and the poorest 10% of the population provides a broadly similar picture. Note that, however, the same evolution of the quantile ratio masks rather different dynamics across countries, with potentially different implications for subsequent growth. For instance, the strong increase of the ratio in Spain reflects both a noticeable worsening in the lowest tail of the distribution as well as a

<sup>&</sup>lt;sup>3</sup> While changes in public policies may be relevant in changing economic inequality, to assess idiosyncratic tax reforms and their re-distributive effects is beyond the scope of this analysis.

significant increase of the income level of the richest; this is not the case in France, where the observed dynamics results from an improvement in both segments of the population, with the richest moving towards relatively higher levels of income (chart Annex).

In this respect, looking at the extent of inequality among specific income quantiles may provide useful information about the homogeneity of different income strata in the population, being a crucial element to consider when looking at the effect of policy interventions.

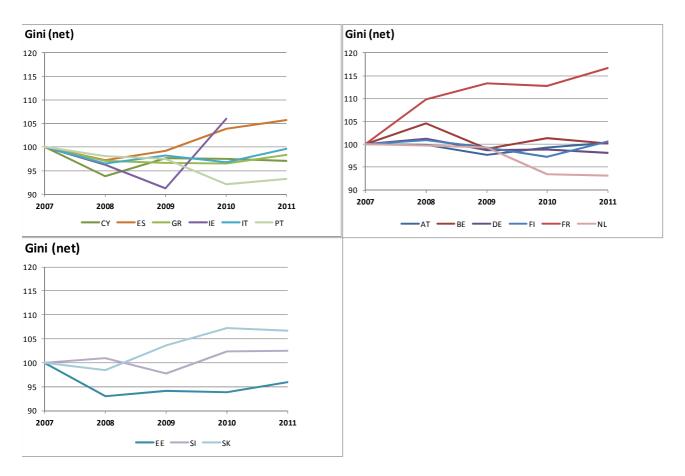
The next figure looks at the standard divide between the income of the population lying in the 10th quantile and that of the population lying in the 90-th quantile (as defined by the p90p10 quantile ratio); as a complement to the pattern of the Gini inequality index presented in earlier. The picture does not change when looking at the ratio between the income of people in the 95th quantile and that of people lying in the 5-th quantile (p95p5).

Quantile ratios are easily interpretable, as they express the income of the top, e.g., 10 percent (the "richest") as a multiple of income of those in the poorest decile. Clearly, the level of income accrues to each income level so that the decile ratio between the richest and the poorest is always greater than 1. The information provided by the quantile dispersion ratios is not always consistent with that provided by the Gini index. In particular, in the case of Spain the Gini index would show a mild increase in inequality in 2010-11, while the ratio between the number of households in the top and the bottom quantiles increased in 2010-11, well above the value observed over the period 2005-07. In particular, in Spain, the Gini index would show a mild increase in inequality between 2009-11 (+ 5%), while the ratio between the number of households in the top and the bottom deciles increased by +15% over the same period.

Analogously, in Ireland, where the the ratio between the households in the richest and the poorest ten percent has remained broadly constant until 2009, differently from the stronger decline shown by the Gini index (i.e. inequality is trending lower for most parts of the sample).

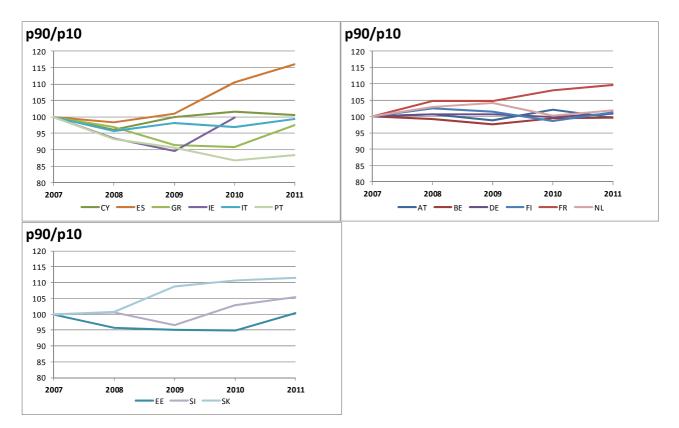
Table 2 – GINI Index - after-tax (OE	CD-equivalent) income variables
--------------------------------------	---------------------------------

	Gross income (extended definition)				Disposable income (extended definition		
	2007	2011	first diff.		2007	2011	first diff.
PT	41.8	39.1	-2.7	PT	37.3	34.8	-2.5
IE	36.1	37.9	1.9	ES	31.4	33.2	1.8
GR	38.2	36.4	-1.8	GR	33.6	33.0	-0.5
IT	35.8	35.8	0.0	IE	31.0	32.8	1.9
ES	33.7	35.0	1.3	п	31.9	31.7	-0.1
EE	36.0	34.5	-1.5	EE	33.0	31.6	-1.3
FR	29.7	33.7	4.0	FR	26.6	31.0	4.4
DE	33.6	33.2	-0.4	EA average	29.0	29.1	0.0
EA average	33.0	32.8	-0.2	DE	29.6	29.0	-0.5
BE	31.3	31.3	0.0	CY	29.8	29.0	-0.9
AT	30.6	31.0	0.5	MT	-	27.6	-
CY	31.3	31.0	-0.4	LU	27.7	27.2	-0.6
MT	-	30.8	-	AT	26.4	26.4	0.1
LU	31.6	30.7	-0.9	FI	26.1	26.3	0.1
FI	30.7	30.3	-0.4	BE	26.1	26.1	0.0
NL	32.0	30.0	-2.0	SK	24.1	25.7	1.6
SI	29.0	29.4	0.3	NL	27.0	25.1	-1.8
SK	27.0	27.6	0.6	SI	23.3	23.9	0.6



## Figure 1 - GINI Index - after-tax (OECD-equivalent) income variables

Figure 2 – p90/p10 ratio - after-tax (OECD-equivalent) income variables



While quantile ratios ignore information on incomes in the middle of the distribution - nor they use information about the income distribution within the top and bottom quantiles, these developments would suggest the tails of the distribution play a relevant role; in this case, the Gini index may not provide a reliable picture.

# 4. Methodology

In order to analyze the dynamics of the contribution of each income source to the overall inequality, we outline, in this section, two different inequality indexes and their decompositions: the Gini index and the Zenga index. We will show that the while the decomposition of both indexes provide insightful information on the inequality dynamics by income sources, the Zenga (2007) index allows also a decomposition of inequality by population sub-groups which will proved very sueful for the purpose of zoomin-in the ditribution of income before and during the crisis.

## 4.1 Measuring inequality

The Gini index is, probably, the most used and well – known index in the literature on income inequality(see Gini, 1912), and can be computed in several ways (see Yitzhaki, 1997). As discussed in earlier, the Gini index often fails to take into account the real impact of the right tail of the income distribution (i.e. the richest) with respect to the left part of the tail (i.e. the poorer).

Quantile ratios or ranges try to capture the fundamental idea that the concepts of *poor* and *rich* are intrinsically connected to each other. In order to cope with this problem along all the possible fractions of lowest (highest) incomes in the distribution, Zenga (2007) has recently proposed an inequality index based on the ratio between lower and upper arithmetic means. As it has been noted in Greselin *et al.* (2009), both indexes can be expressed as a weighted average of the so – called Gini curve: the weight function for the Zenga index differs from the one for the Gini index in that a uniform weight function is used.

The assessment of inequality in a population is hence determined by the comparison of population sub–groups: the Gini index allows for comparison between the left tail of the income distribution (the poorest) and the whole population, whereas the Zenga index compares each disjoint sub–group using the same weight for each comparison, allowing for a better comparison for each sub - groups (including a better assessment of the right part of the income distribution, i.e. the richest).

Let  $i \in [1, N]$  be the households and  $s \in [1, S]$  be the possible sources of income. Then it is possibile to define an income matrix **Y**, such that the element  $y_{is}$  represents the income of household *i* from source *s*. The variable  $y_i = \sum_{s=1}^{S} y_s$  represents the total income for household *i*. Each column vectors representing the sources and the total income can be treated as random variables in a simple linear relationship:

$$Y = \sum_{s=1}^{s} y_s$$

We assume for the remainder of this section that, without loss of generality, the total incomes are ordered such that  $0 \le y_1 \le y_2 \le \cdots \le y_i \le \cdots \le y_N$  (with at least one positive observation). Let us denote the variable total income by *Y* and the single variables representing the sources by  $y_s$ , the mean (total) income by  $\mu_Y = 1/N \sum_{i=1}^N Y_i$  and the mean income for each income source by  $\mu_{y_s} = 1/N \sum_{i=1}^N Y_{is}$ . The decompositions by income sources proposed for both indexes are then derived by applying the linearity property of the covariance (for the Gini index) and of the arithmetic mean (for the Zenga index).

The Gini index has some well-known limitations in considering the relationship between the left tail (the poorest) and the right tail (the richest) of the income distribution. It is, in fact, computed by averaging, for each quantile of the distribution (cumulated fraction of household), the sum of incomes along the left tail (cumulated income for that quantile) and then comparing it to the mean income of the whole population. As such, the Gini index *underestimates* the effect of the very poor with respect to the whole population (and the very rich) and stresses comparison between sub-groups that are more similar.

In this paper, we are mainly instead interested in a measure that can capture the increasing distance between the richest and the poorest part of the population. Hence, we resort on another (albeit less known) index of inequality (see Zenga, 2007).

For each element (household income level) *i*, let  $\overline{M}_i = \frac{1}{i} \sum_{j=1}^{i} Y_j$  be the lower mean for the income level *i* (i.e. the mean of the sub–group *poorer* than *i*) and  $\overline{M}_i = \frac{1}{N-i} \sum_{j=i+1}^{N} Y_j$  be the upper mean for the income level *i* (i.e. the mean of the sub–group *richer* than *i*). The *point inequality* for the income level *i* is then defined as follows:

$$I_i = \frac{\stackrel{+}{M}_i - \overline{M}_i}{\stackrel{+}{M}_i} \tag{1}$$

The overall inequality index *I* is computed by averaging  $I_i$  over all observations:

$$I = \frac{1}{N} \sum_{i=1}^{N} I_i = \frac{1}{N} \sum_{i=1}^{N} \frac{\overset{+}{M}_i - \overset{-}{M}_i}{\overset{+}{M}_i}$$
(2)

The properties of the curve  $I_i$  have been studied in Zenga (2007; 2007b), Greselin *et al.* (2009). As previously mentioned, due to its construction, the Zenga index allows for a comparison between each possible disjoint subgroup in the distribution: in fact the impact of an increase in income for the richest (1 - p) fraction of the population has an impact on the value of the inequality curve for the fraction of the *p* poorest. In the next section we will show how the decomposition occurs and how changes in the distribution of inequality by population sub-groups can be made.

#### 4.2 Inequality indexes decomposition

Among the many ways to compute the Gini index, we hereby refer to the geometric approach, based on the Lorenz curve L(p), which computes the Gini coefficient *G* as follows:

$$G_{Y} = 1 - 2 \int_{0}^{1} L(p) dp \stackrel{B.P.}{=}$$
$$= 2 \int_{0}^{1} pL'(p) dp - 1$$

where the last integral has been computed integrating by parts. Given two random variables *X* and *Z*, let:

$$GCov(X, Z) = cov(X, F_Z(z))$$

be the so-called *Gini covariance* between *X* and *Z*. The Gini covariance is different from the standard covariance in that it does not measure the degree of *linearity* between two variables, but the *degree of* 

*monotonicity*, making it suitable for capturing non – linear (yet monotonical) relationships. This formulation will allow to express the Gini coefficient in terms of covariance with its rankings.

After some algebra, it is then possible to express the Gini index in terms of Gini covariance between the income random variable Y and its *fractional rankings*, expressed in terms of its distribution function  $F_Y(y) = P(Y \le y)$ , as follows:

$$G_Y = \frac{2}{\mu_Y} cov(Y, F_Y(y))$$

by considering the uniform random variable  $F_Y(y) = p$ . The simply linearity property for the covariance of two variables leads to:

$$G_Y = \frac{2}{\mu_Y} \sum_{s=1}^{S} y_s GCov(y_s, Y)$$
$$= \frac{2}{\mu_Y} \sum_{s=1}^{S} cov(y_s, F_Y(y))$$

which represents the Gini coefficient in terms of the covariance of source s with the fractional rankings of the total income. The elements of the sum divided by the total  $G_Y$  represent the *relative contribution* of source s to the global income inequality.

As noted in Jedrzejczak (2008), by multiplying and dividing each income component *s* by the covariance between the same income component  $y_s$  and its cumulative distribution function, and by multiplying and diving by the  $\mu_{y_s}$ , we can rewrite the Gini coefficient as follows:

$$G_{Y} = \frac{2}{\mu_{Y}} \sum_{s=1}^{S} \frac{cov(y_{s}, F(Y))}{cov(y_{s}, F_{y_{s}})} \frac{2cov(y_{s}, F(y_{s}))}{\mu_{Y_{s}}} \frac{\mu_{y_{s}}}{\mu_{Y}}$$
$$= \frac{2}{\mu_{Y}} \sum_{s=1}^{S} R_{y_{s}} G_{y_{s}} W_{y_{s}}$$

Expression (3) is a useful way to present income inequality as the sum of the product of three quantities:  $R_{y_s}$  is the Gini correlation between income source  $y_s$  and the total income,  $G_{y_s}$  is the Gini index for the income component  $y_s$ , and  $W_{y_s}$  is the share of total income due to income component  $y_s$ . While this Gini representation is standard, it is nonteheless necessary to understand comparisons with the alternative indicator employed (the so-called Zenga index; see Zenga, 2007) and how the latter add up to a more-comprehensive analysis of inequality.

In Radaelli *et al.* (2011), a point decomposition by sources which exploits the simple linearity property of the arithmetic mean of the distribution is proposed, where the arithmetic mean of a linear combination of variables is the same linear combination of the arithmetic means of each variable. In other words, we can rewrite the lower and upper means of the distribution, as defined previously, as follows:

$$\bar{M}_{i} = \frac{1}{i} \sum_{j=1}^{i} \sum_{s=1}^{s} y_{js} = \sum_{s=1}^{s} \sum_{j=1}^{i} \frac{1}{i} y_{js} = \sum_{s=1}^{s} \bar{M}_{is}$$
(4)

10

(3)

$$\overset{+}{M}_{i} = \frac{1}{N-i} \sum_{j=i+1}^{N} \sum_{s=1}^{s} y_{js} = \sum_{s=1}^{s} \sum_{j=i+1}^{N} \frac{1}{N-i} y_{js} = \sum_{s=1}^{s} \overset{+}{M}_{is}$$

Where  $M_{is}$  and  $M_{is}$  are, respectively, the upper and lower means for income group *i* w.r.t. source *s*. In the light of the above, equation (2) can be rewritten as follows:

$$I = \frac{1}{N} \sum_{i=1}^{N} I_i = \frac{1}{N} \sum_{i=1}^{N} \frac{\frac{M_i - M_i}{M_i}}{\frac{M_i}{M_i}} = \frac{1}{N} \sum_{s=1}^{S} \sum_{i=1}^{N} \frac{\frac{M_{is} - M_{is}}{M_i}}{\frac{M_{is} - M_{is}}{M_i}} = \frac{1}{N} \sum_{s=1}^{S} I_s$$

where  $I_s = \sum_{i=1}^{N} \frac{\bar{M}_{is} - \bar{M}_{is}}{\bar{M}_i}$  is the contribution of income source *s* to the global inequality, as measured by our alternative indicator (Zenga, 2007). It is then possible to compute the *relative* contribution of each source to the global inequality:  $\beta_s = \frac{I_s}{I}$  (with  $\sum_s I_s = 1$ ). In the same vein, an inequality index can be retrieved for different segments of the population, by exploiting such a linearity property.

#### 4.4 Sample correction weights

When dealing with the estimation of the inequality indexes from survey – based datasets, it is fundamental to properly take into account sample weights. For the Gini index, the fundamental problem is to correctly compute the new weight – based fractional rankings (see Van Kerm, 2009). On the contrary, and less trivially so, for our new index (Zenga, 2007) we will need to introduce its computation in a frequency distribution framework.

In particular, let  $(y_i, w_i)_{i=1}^N$  be the representation of the *N* observations with the respective sampling weights and let  $0 \neq y_1^*, ..., y_K^*$  (with  $K \leq N$ ) be the unique observations of  $(y_i)_{i=1}^N$ . In order to compute the new fractional rankings, associated with the *K* unique values, tied values must be considered (see Van Kerm, 2009). Once the fractional rankings are computed, they can be directly used in Formula (3).

Let  $n_h$  be the frequencies associated to each unique observation  $y_h^*$ , where  $\sum_h n_h = n$ , with n being the total number of observation (e.g. the total number of inhabitants of a country) or, in other terms,  $n = \sum_i w_i = \sum_h n_h$ . Let  $N_h = \sum_{t=1}^h n_t$  be the cumulative frequencies and  $p_h = \frac{N_h}{n}$  be the cumulative relative frequencies. We can now define the lowe and upper means with respect to the cumulative relative frequencies  $p_h$ :  $\overline{M}_{p_h} = \frac{1}{N_h} \sum_{t=1}^h y_t^* n_t$  and  $\overset{+}{M}_{p_h} = \frac{1}{n-N_h} \sum_{t=h+1}^K y_t^* n_t$ . Analogously to Equation (1), the point inequality index for level  $p_h$  is then given by:

$$I_{p_{h}} = \frac{\stackrel{+}{M}_{p_{h}} - \bar{M}_{p_{h}}}{\stackrel{+}{M}_{p_{h}}}$$
(5)

and the synthetic index:

$$I = \frac{1}{n} \sum_{h=1}^{K} I_{p_h} n_h \tag{6}$$

Where equation (6) is a weighted average of the point inequality indexes with weights that can be computed from the sampling weights. The latter computation is performed as follows:

$$n_h = \sum_{i=1}^N w_i \mathbb{I}\{y_h^* = y_i\} \Leftrightarrow p_h = \frac{1}{\sum_i w_i} \sum_{i=1}^N w_i \mathbb{I}\{y_h^* = y_i\},\tag{7}$$

where  $l\{\cdot\}$  is an indicator function which takes the value of 1 whenever  $y_h^* = y_i$ .

## **5** Results

In this section we look at the extent of inequality across countries and over time based on the two inequality measures as set out in the above. Particularly, we try to understand how alternative inequality measures, capturing with different receptivity deviations from equality in different parts of the distribution, fare in practice. In Section 5.2 the analysis focuses instead on the inequality of different income sources, following the decomposition set out in the previous Section.

#### 5.1 A quick comparison between inequality indexes

Figures 3 and plots the aggregate income inequality constructed from the standard Gini coefficient, as well as the Zenga coefficient, normalized on the pre-2008 period, and based on our extended income definition. For sake of comparability, we leave in the charts the Gini and Zenga indexes based on standard income definition, where pensions received from individual private plans and interest on mortgage do not appear.

Having the pre-2008 period as a benchmark is the result of both judgment on the observed labor market slack in 2008 (i.e. labor markets reacted with some lag to the real economic downturn) and practical considerations (i.e. 2007 is the first available year for some countries). Moreover, we assume 2008 to be a sensible choice for survey data as it may take some time for individuals to gauge their reduced income availability at the household level - especially in the light of real public social spending and public social spending as a percentage of GDP effectively growing as of 2008-09 in many euro area countries (see OECD, 2012).

The two indexes qualitatively produce a similar picture. As stressed in earlier, the Gini index may however underestimate comparisons between the very poor (left-tailed) and the whole population, while emphasizing comparisons which involve almost identical population subgroups. Hence, against the backdrop of a fall in real GDP in 2009 (see OECD, 2012), inequality seemed to have increased in countries such as Greece, Italy and, to a lesser extent, Ireland and Portugal, according to the Zenga index, where the indicator has decreased less in pre-2008 terms (=100) compared to Gini.

Compared to the baseline income definitions, we show that considering extended income variables does not generally change the pattern and scale of the evolution of Zenga and Gini inequality in most countries. However, somewhat different patterns are observed in Belgium, Spain, Finland, Greece, Portugal and the Netherlands. By construction of the two indexes, this implies that some of the new variables considered may favour one tail of the distribution more than the other, having an (un)equalizing effect on total income inequality.

At this stage the interpretation of the results is certainly challenging and can be better dealt with an analysis of different income categories. However, it is intuitive to assert that such developments

in the Gini are likely to be observed when income components have important un-equalizing effect, especially increasing inequality between the lower end and the middle of the distribution.

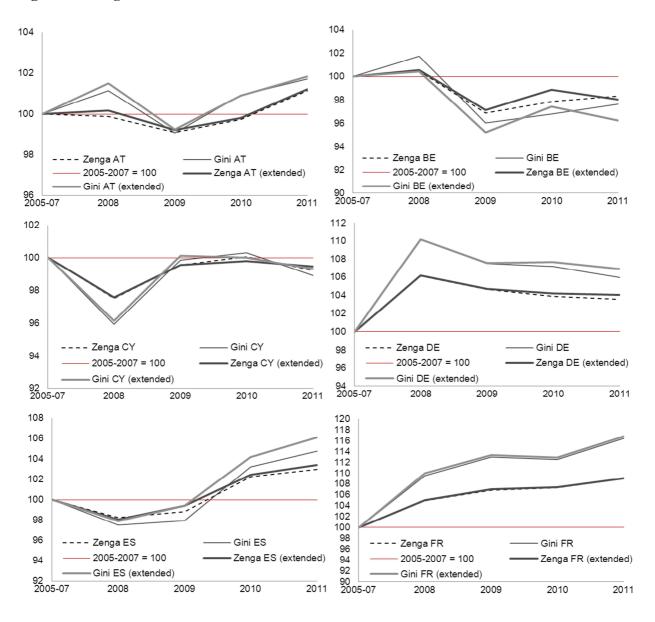


Figure 3 – Zenga and Gini coefficients - net income vs. net extended income

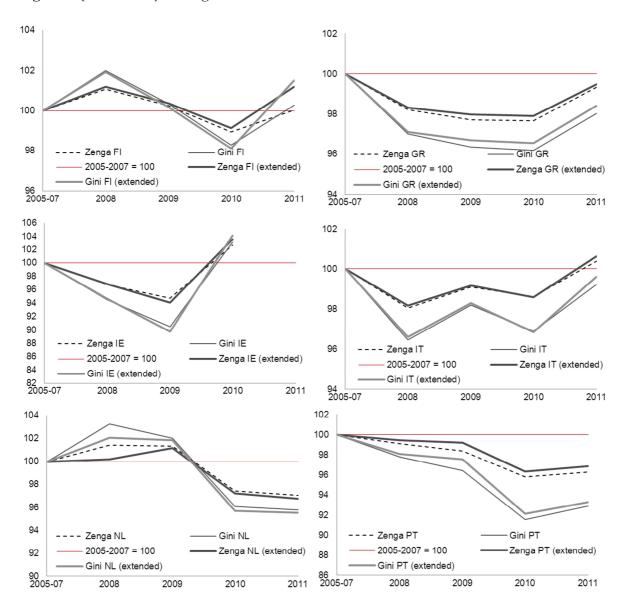


Figure 3 (continued) - Zenga and Gini coefficients - net income vs. net extended income

## 5.2 Decomposition of inequality by income sources

In order to get deeper into the drivers of the inequality developments set out in the above, following Radaelli (2007) we quantify the extent to which total income inequality (measured by the Zenga index) is explained by single income sources (Table 3). <sup>4</sup> It emerges that, between 2008

<sup>&</sup>lt;sup>4</sup> As discussed in our data Section, consistent with the assumption of income (whether gross or net) adding up to the sum of the individual income sources, a residual component is included in the contribution of income components to aggregate income. Here, the residual component represents the part of income which is not accounted for by the available income decomposition sources in the EU-SILC. There might be a number of reasons why one should expect such a discrepancy measure to appear in the data. First, survey answers may go wrong as people can forget, make mistakes or simply do not respond. Secondly, people may be reluctant to disclose the full extent of their income (e.g., coming from illegal activities, tax evasion, etc.). Finally, some parts of income, retained profits and/or related costs may be difficult to quantify (see also World Bank, 2001). In our analysis, such a discrepancy results in an observed income indicator which contains an additive random error with zero mean. This implies that the aggregate income indicators are right on average but there is an error in some individual observations. In other words, the expected value of the inequality index is likely to be unaffected by changes in the degree of error in the income variable. However, this casts some doubts on the interpretation of the income sources and their unbiasedness in explaining the observed levels of inequality. In addition, reasoning in terms of "aggregate" measurement errors, assumes that there is no corresponding

and 2010, the (positive) contribution of income from employment to overall inequality declined in all countries except in Ireland and, to a lesser extent, in Cyprus and Finland. Although less sizeable compared to dependent employment, the contribution from self-employment also declined in all countries (except Austria). At the same time, however, the share on total income of payment for direct taxes remained high while that stemming from interests on mortgage has been quantitatively smaller (i.e. taxes and interests in mortgages are treated as negative income sources). Further, both contributions declined over time.

Clearly, if an income source represents a large share on total income (and this varies over time), it may have - in principle - a strong effect on inequality. However, the extent to which this is likely to affect inequality as a whole depends on the equality of the individual source itself.

We start by looking at the pre-crisis (2005-2007). Total inequality is explained in order of importance by labour income, income from self-employment, other income, cash transfer (with the the exceptions of France, Greece, , Italy and Portugal, where cash transfers rank as third income source and, compared to the other countries, explains a much higher share of total inequality).

		2005-2007	2008	2009	2010	2011
AT	Labour income	98.8	110.4	106.4	112.7	105.4
	Self-empl. lab. income	21.2	17.4	22.9	21.0	19.2
	Non-cash lab. income (ext)	0.0	0.0	0.0	0.0	0.0
	Cash transfers	21.2	16.9	15.5	12.7	17.0
	Other income (ext)	6.3	9.5	7.2	8.8	10.1
	Interests on mortg.	-0.4	-0.6	-0.6	-0.6	-0.7
	Taxes	-47.4	-53.6	-51.3	-54.7	-51.5
BE	Labour income	128.7	118.7	125.9	122.3	129.4
	Self-empl. lab. income	16.6	22.5	13.7	11.7	16.0

 Table 3 – Contribution of income sources – net extended income (Zenga index)

error in the distribution of income, e.g., when errors occur, they are not systematically higher for one income group than for any other.

However, it is generally assumed that survey measurement errors will lead to an under-estimation of inequality, because rich people are more likely to under-declare their income. Indeed, it may well be that such omissions bring about an overestimation of the income of the poor and underestimate that of rich people (World Bank, 2001).

In order to test for the statistical significance of the residual and investigate the robustness of our results to the residual component, we estimate bootstrapped confidence bands for the Gini coefficient in each country. The bootstrapped standard errors and estimates for Gini inequality index are calculated on total income. The Gini coefficient so obtained, together with bootstrapped two-standard errors confidence bands, is plotted against the Gini coefficient calculated on the sum of the individual income components. The divergence between the two is simply explained by the existence of a residual component. Hence, the possibility that the Gini calculated on total income provides an indirect test for the statistical significance of the residual in our series. The Gini coefficient calculated on the sum of the income sources falls in between the bootstrapped confidence bands for the Gini coefficient calculated on the sum of the income sources the index calculated on total income provides an indirect test for the statistical significance of the residual in our series. The Gini coefficient calculated on the sum of the income components get, in all cases, close to the index calculated on total income series, soundly rejecting the hypothesis that the residual is statistically significant. Nonetheless, it is less so for Spain for the years 2004 and 2005, where the Gini coefficient calculated on total income and outside the estimated confidence bands.

\\Overall, the pattern that emerges from leaving the residual in the income decomposition exercise differs negligibly from an analysis where the residual is spread onto the other income components, in proportion to each component contribution to the overall income. In the presence of a statistically significant residual, keeping a residual explicit represents a necessary adjustment for sake of consistency and transparency of the results. However, that of Spain represents a unique case. For Spain, the residual on the income components is explicitly accounted for in our subsequent analysis, albeit it is proved irrelevant (albeit not statistically, in its size) in terms of marginal contribution to the income decomposition exercise.

	Non-cash lab. income (ext)	0.9	1.0	1.2	1.0	1.1
	Cash transfers	-4.4	-3.9	-1.2	0.7	-4.7
	Other income (ext)	12.8	9.3	9.7	12.9	9.0
	× /			-1.8	-2.0	-2.2
	Interests on mortg.	-1.6	-1.6			
~	Taxes	-52.9	-45.9	-47.5	-46.7	-49.5
CY	Labour income	89.7	88.5	88.5	92.7	91.6
	Self-empl. lab. income	12.6	15.3	13.0	12.4	11.0
	Non-cash lab. income (ext)	0.4	0.3	0.3	0.3	0.3
	Cash transfers	4.8	5.4	9.2	8.4	8.5
	Other income (ext)	9.1	7.6	7.2	5.9	7.6
	Interests on mortg.	-0.4	-1.1	-1.2	-1.2	-1.1
	Taxes	-16.3	-16.2	-16.9	-18.4	-18.8
DE	Labour income	101.5	101.7	107.8	110.5	109.7
	Self-empl. lab. income	25.3	28.2	23.4	19.2	16.9
	Non-cash lab. income (ext)	1.3	2.0	2.0	1.9	1.5
	Cash transfers	5.3	4.9	4.2	6.5	8.5
	Other income (ext)	8.2	8.2	7.3	11.0	9.6
	Interests on mortg.	-0.1	0.0	0.0	-1.5	-1.8
	Taxes	-41.7	-45.0	-44.6	-47.7	-45.7
ES	Labour income	34.2	103.9	99.6	94.6	92.1
	Self-empl. lab. income	2.5	7.4	7.6	10.8	11.7
	Non-cash lab. income (ext)	0.2	1.1	0.8	0.7	0.4
	Cash transfers	2.7	7.9	9.6	10.8	11.4
	Other income (ext)	2.0	5.2	5.9	5.5	4.5
	Interests on mortg.	-0.2	-1.1	-0.8	-0.9	-0.6
	Taxes	-8.1	-24.4	-22.7	-21.4	-20.6
FI	Labour income	125.8	121.2	125.1	123.5	115.5
	Self-empl. lab. income	13.3	16.1	14.2	11.5	10.7
	Non-cash lab. income (ext)	1.9	2.0	1.8	1.9	1.6
	Cash transfers	-7.8	-6.3	-6.4	-4.5	-3.5
	Other income (ext)	25.7	22.3	21.6	20.4	22.3
	Interests on mortg.	-1.8	-2.7	-2.7	-2.0	-1.3
	Taxes	-57.2	-52.5	-53.5	-50.9	-48.6
FR	Labour income	92.1	67.1	68.8	69.8	70.3
	Self-empl. lab. income	17.9	15.7	15.2	13.0	13.6
	Non-cash lab. income (ext)	0.0	0.0	0.0	0.0	0.0
	Cash transfers	20.0	19.2	15.8	19.4	18.3
	Other income (ext)	8.7	30.7	31.9	28.6	30.2
	Interests on mortg.	-1.0	-0.5	-0.7	-0.7	-0.6
	Taxes	-1.0	-0.5	-0.7	-30.0	-0.0
CD	Labour income					
GK	Labour mcome	79.5	83.6	77.3	72.1	72.7

	Self-empl. lab. income	42.8	38.9	40.2	42.9	41.7
	Non-cash lab. income (ext)	0.3	0.3	0.2	0.3	0.2
	Cash transfers	16.0	16.1	17.3	19.0	17.7
	Other income (ext)	9.5	8.5	8.2	9.1	8.4
	Interests on mortg.	-0.7	-0.7	-0.4	-0.4	-0.5
	Taxes	-47.3	-46.7	-42.9	-42.9	-40.2
IE	Labour income	101.7	105.1	114.2	106.8	
	Self-empl. lab. income	32.7	25.7	22.9	14.7	
	Non-cash lab. income (ext)	0.7	0.7	0.4	0.4	
	Cash transfers	-4.2	-2.7	-0.5	8.6	
	Other income (ext)	6.3	9.2	5.3	4.3	
	Interests on mortg.	-2.1	-2.6	-3.5	-2.2	
	Taxes	-35.1	-35.5	-38.9	-32.5	
IT	Labour income	73.4	68.6	68.1	68.3	68.1
	Self-empl. lab. income	41.6	47.8	43.4	45.4	41.5
	Non-cash lab. income (ext)	0.2	0.3	0.3	0.3	0.2
	Cash transfers	23.1	25.7	27.8	27.5	28.9
	Other income (ext)	6.4	7.4	7.5	6.5	8.0
	Interests on mortg.	-0.6	-0.4	-0.4	-0.5	-0.5
	Taxes	-44.2	-49.3	-46.8	-47.6	-47.2
NL	Labour income	118.0	117.0	113.9	122.9	124.1
	Self-empl. lab. income	19.4	27.4	30.0	28.0	28.5
	Non-cash lab. income (ext)	2.3	2.6	2.7	2.3	2.1
	Cash transfers	14.3	11.3	14.3	14.3	14.0
	Other income (ext)	13.1	21.1	18.7	11.2	12.5
	Interests on mortg.	-3.0	-6.9	-5.6	-5.1	-5.0
	Taxes	-64.0	-72.4	-74.0	-73.7	-77.3
PT	Labour income	101.2	94.9	94.3	102.4	101.1
	Self-empl. lab. income	15.9	20.5	19.9	11.9	11.5
	Non-cash lab. income (ext)	1.0	0.0	0.0	0.2	0.3
	Cash transfers	21.4	20.5	19.4	19.2	21.9
	Other income (ext)	3.2	3.6	4.1	5.3	4.4
	Interests on mortg.	-1.3	-1.3	-1.1	-1.3	-0.6
	Taxes	-41.4	-38.2	-36.7	-37.9	-39.1

*Note*: Contribution of single income sources to overall inequality (Zenga index = 100)

At the start of the crisis (2008, compared to pre-crisis) one could note a strong increase of inequality explained by labour income\_in Spain and Austria; strong reduction in labour income in France and increase in the other income.

From 2008, labour income decreased in Spain and Greece; it increased in Belgium and the Netherlands. At the same time, self-employment labour income decreased in Germany.

These results appear very much in line with the decomposition by sources of the Gini index (not reported here for sake of brevity).

Between 2008 and 2010, the (positive) contribution of income from employment to overall inequality declined in all countries except in Ireland and Autria and, to a lesser extent, in Cyprus and Finland. Although less sizeable compared to dependent employment, the contribution from self-employment also declined in all countries (except Austria) starting from 2009. At the same time, however, the share on total income of payment for direct taxes remained high while that stemming from interests on mortgage has been quantitatively smaller (i.e. taxes and interests in mortgages are treated as negative income sources). Further, both contributions declined in absolute value over time.

In the light of the above, the effect of individual income sources on overall inequality will also depends on which point of the distribution this (extra) source is earned. In other words, it may be important to asess the marginal effect of both standard and extra income sources on overall inequality measures.

In this respect, following our previous discussion in Section 4.2, the Gini decomposition allows measuring to what extent the observed contributions depend on: how (un)equal is the distribution of each income source ( $W_k$ ; the relative importance of each individual component as a share of total income ( $G_k$ ); and the correlation between the distribution of aggregate income and that of the individual income component; allowing to calculate marginal effects.

Marginal effects here account for the percentage change in inequality resulting from a small percentage change in income from a given source, all other things being equal. This corresponds to the original contribution of each source to income inequality minus each source share on total income.

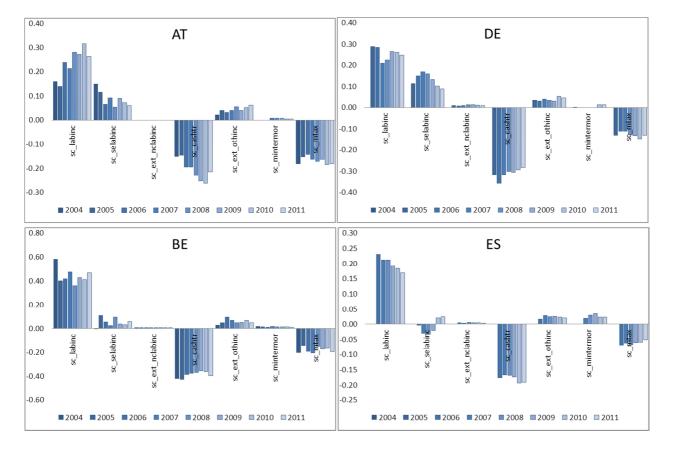
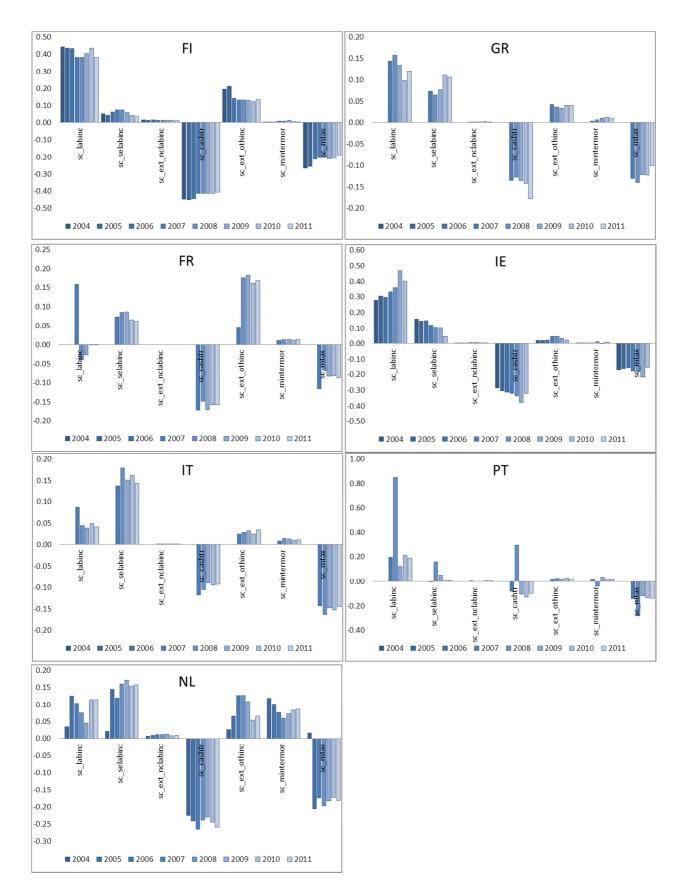


Figure 4 - Marginal effects



The results in Figure 4 show, for instance, that in country like Spain, a 1% increase in labour income increased inequality on total income by about 0.24% in 2007.

Labour income and - to a lesser extent - self-employment labour income and non-cash labour income have a strong un-equalizing effect over time in most countries (except in France and

Spain). An important un-equalising effect of income from self-employment is observed instead in Italy.

Cash transfers and taxes consistently acted by favouring people at the lower end of the income distribution. Compared the other income sources, results for the Netherlands show that interest on mortgages has a relatively strong un-equalizing effect on total income. To a much lesser extent, a similar pattern is observed in France, Greece, Italy and Spain. In the case of Finland, France and the Netherlands, and, to a somewhat lesser extent, Austria, Belgium, Germany, Spain, Ireland, Italy and Greece other income sources (including private pension plans) have an un-equalizing effect.

## 5.3 Zooming-in

The contribution of each source to the global inequality is related to specific income levels.

In what follows, we take a closer look at the decomposition of inequality by source, by considering the mean contribution for a specific pair quantile-source.

We particularly compare how the relative contribution of each income source is distributed across quantiles in 2007 (Fig. 5, left-panels) and 2011 (Fig. 5, right panels).

Overall labour income seems to play a relatively major role in the lowest percentiles (20, 40), except in Portugal (where labour income is high also in the top 80%), Greece and Spain (broadly flat).

In 2011, relative to 2007, this picture is confirmed for most countries with the exceptions of Spain and Greece where labour income is more heterogeneous across quantiles; Ireland, where labour

income becomes relatively more important in the middle of the distribution and Portugal where the weight of labour income decreases towards the right tail.

As far as "other income" is concerned important increases are observed in France in 2011, as also confirmed in the previous table with relative contributions.

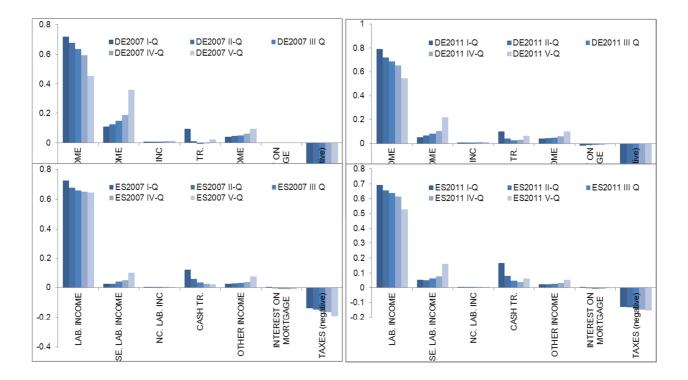
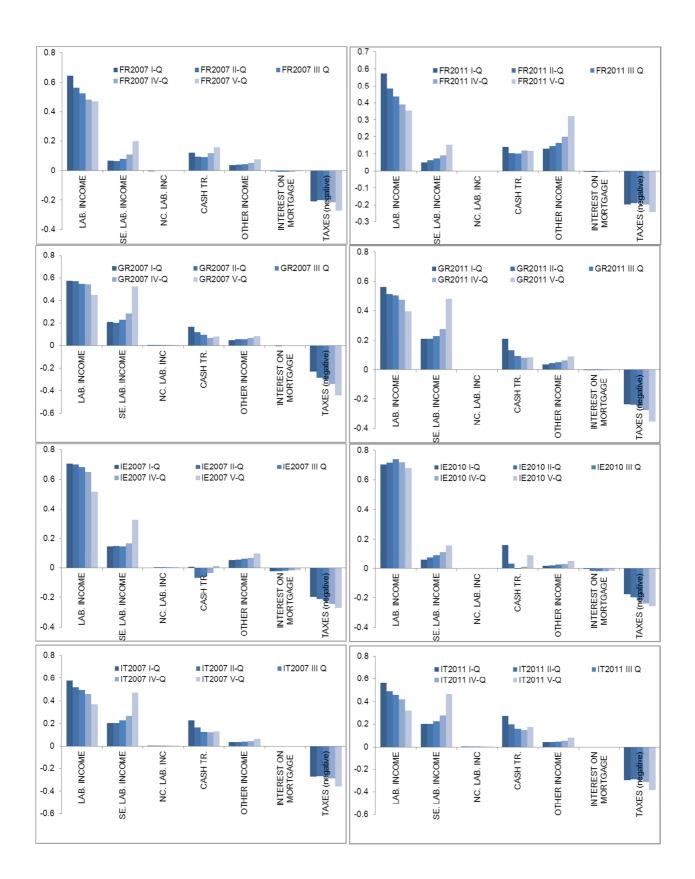
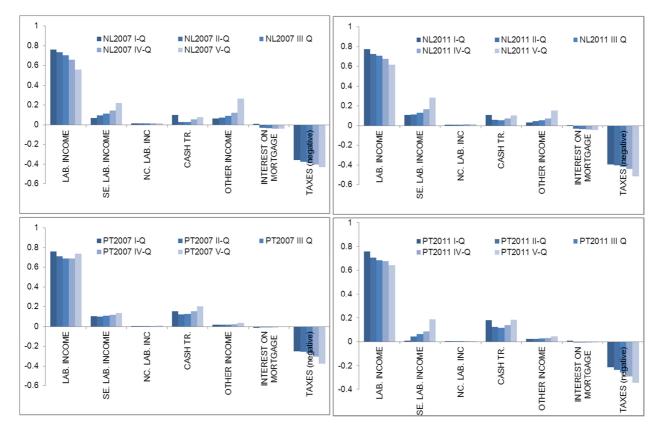


Figure 5 – Index decomposition by quantiles (based on Zenga)





With the aim of providing a richer characterization of the data, allowing to consider the impact of (some) covariates on the entire distribution of household income (by quantiles), quantile regressions are also run for each country. The dependent variable is the (log) total household disposable income for the cross sections of 2007 and 2011. This is done for a representative individual in each household (head).

Explanatory variables for each country include:

- *Partner employed* (=1 if head's partner is employed)
- No. of children
- *Part-time Job* (=1 if head has a part-time job)
- Age groups ((1) <24, (2) 25-39, (3) 40-54, (4) 55-75 year-olds)
- Housing tenure/tenure status ((1) tenant (not pays rent), (2) owner, (3) owner (with mortgage), (4) tenant)
- *Educational attainment* ((1) low, (2) medium education and (3) high education based on ISCED classifications)

In doing so, we also plot the conditional mean of the of household disposable income based on a standard ordinary least square regression, based on the same set of covariates, to show that a more complete picture of covariate effects is provided by estimating a family of conditional quantile functions. In each quantile regression, the first category (e.g., low education) is omitted, so that the coefficients may be interpreted relative to this category.

The Figure (Fig. 6) below presents a summary of quantile regression results for some selected examples. The analysis considers 10 covariates, plus an intercept.

For each of the 10 coefficients, we plot the 19 distinct quantile regression estimates with the quantile dimension ranging from 0.05 to 0.95 as the solid curve with filled dots. For each covariate, these point estimates should be interpreted as the impact of a one-unit change of the covariate on household disposable income holding other covariates fixed. Thus, each of the plots has a horizontal quantile scale, and the vertical scale indicates the covariate effect.

The dashed line in each figure shows the ordinary least squares estimate of the conditional mean effect. The two dotted lines represent conventional 90 percent confidence intervals for the least squares estimate. The shaded gray area depicts a 90 percent pointwise confidence band for the quantile regression estimates.

In the first panel of the figure, the intercept of the model may be interpreted as the estimated conditional quantile function of the household disposable income distribution of a family head whose partner is unemployed, with a full-time job, who is less than 24 years old, doesn't pay his/her rent and with low education.

We will confine our discussion to only a few of the covariates. At any chosen quantile we can ask, for example, how different is the corresponding impact on household disposable income, given a specification of the other conditioning variables. We start by interpreting the results for 2007 for Germany, Spain and Italy (Figure 7).

Having a partner employed is relevant especially at the lower end of the distribution. As it can be gauged from the second right panel in each Figure, the effect of having a partner employed is always positive, with a marginal higher effect for the I quantile. A high number of children has consistently a negative impact on household disposable income. However, this effect seem o be smaller at lower quantiles, possibily because of income effects related to child benefits (e.g., in Germany the latter could take two forms: a cash benefit or a tax allowance. Irrespective of parents' income families were entitled to  $\in$  154 for the first, second and third child and  $\in$  179 for the forth and fifth etc. child either in cash or in form of a tax allowance. In the latter case the child benefit as well as a care benefit were deducted from the family income before taxation. See Ostner *et al.*, 2003).

Having a head with a part-time job is always found to have a negative impact on household disposable income. However, the effect is particularly negative for smaller quantiles.

Moreover, compared to a person with less than 24 years old, being 25-39, 40-54, 55-75 does have a an increasing positive impact of household disposable income, possibly because of the effect of tenure. Within each age category, this effect is however downward sloping, with age being a more relevant factor at lower quantiles.

Being the owner of the dwelling (tenure status = 2) is moreover found to have a positive impact on household disposable income and this effect is found to decrease by quantiles.

Finally, compared to a head with low education, having medium or high education is always found to have a positive effect on income, and this is found to increase every time by quantile groups (the richer the household the stronger the effect from education).

When moving to the results for the 2011 cross-section, the results change quite dramatically and, albeit some patterns, as described previously, are preserved, the picture becomes much less clear (Figure 7).

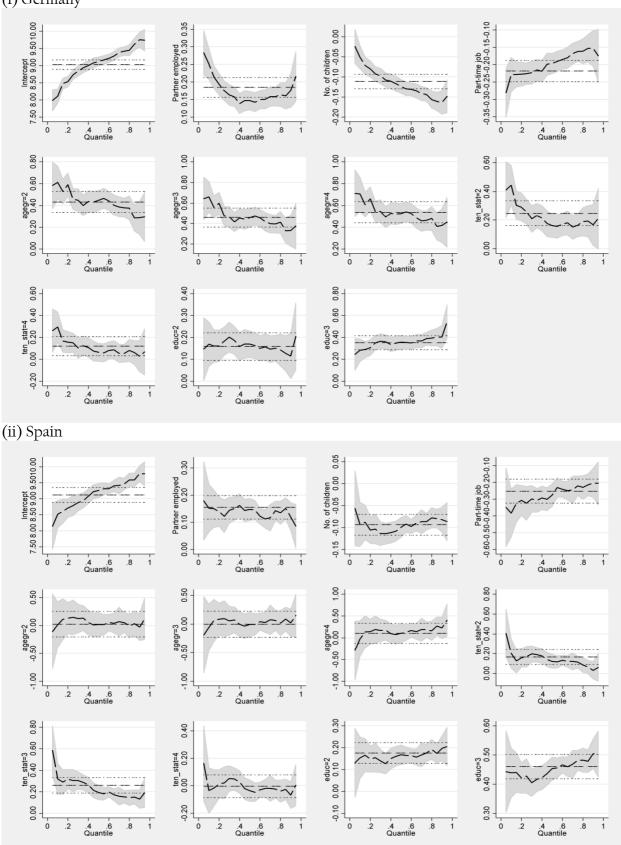


Figure 6 – Quantile regressions (2007) for selected EA countries

(i) Germany



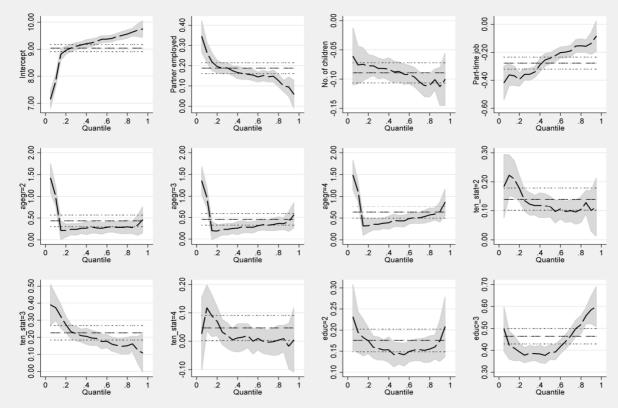
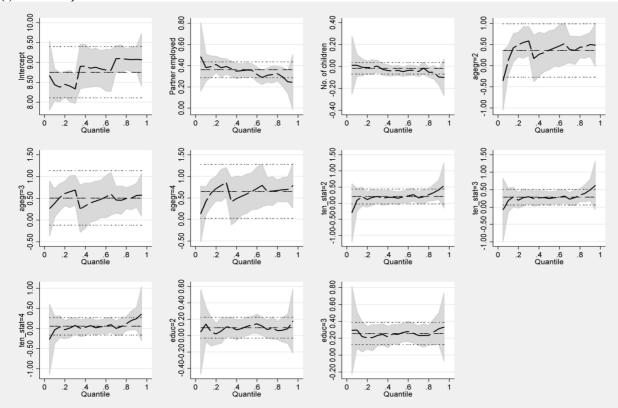
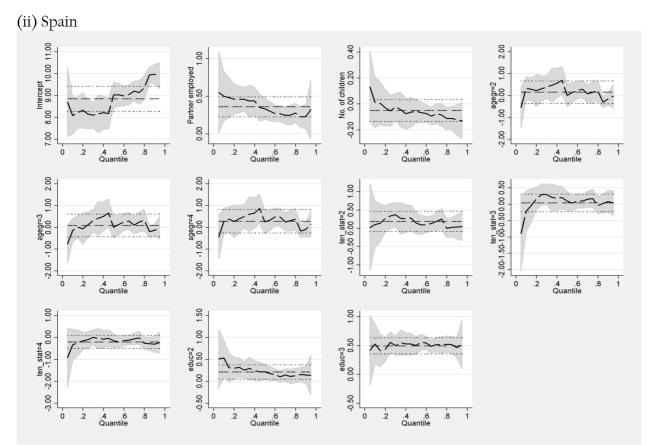


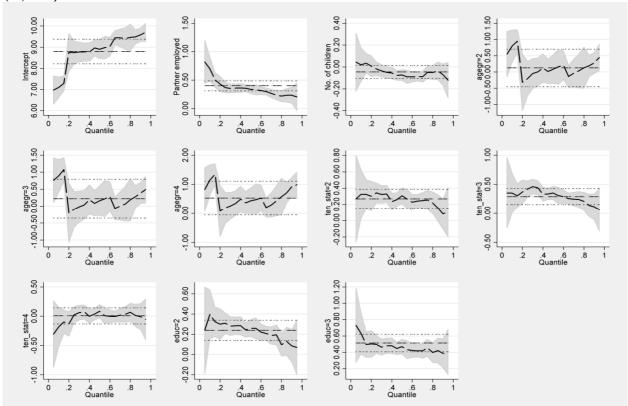
Figure 7 – Quantile regressions (2011) for selected EA countries

(i) Germany





(iii) Italy



# 6 Conclusions

[....]

## References

Alesina, A. and Perotti, R. (1996), "Income Distribution, Political Instability and Investment", European Economic Review;

Benabou, R. (1996), "Inequality and Growth", NBER Macroeconomics Annual.

Carcea, M. and R. Serfling (2013). Gini Autocovariance Function for Heavy Tailed Time Series Modeling.

Galor, O. and Moav, O. (2004), "From Physiscal to Human Capital Accumulation: Inequality and the Process of Development", The Review of Economic Studies;

Greselin, F. M. Puri, R. Zitikis (2009). L-functions, processes, and statistics in measuring economic inequality and actuarial risks.

Jedrzejczak, A. (2008) Decomposition of the Gini Index by Sources of Income. International Advances in Economic Research.

Keefer, P. & Knack, S., 2002. "Polarization, Politics and Property Rights: Links between Inequality and Growth,", Public Choice, Springer, vol. 111(1-2), pages 127-54, March

Kuan Xu (2004). How Has the Literature on Gini's Index Evolved in the Past 80 Years?

Lerman, R. I. and S. Yitzhaki (1985). Income Inequality Effects by Income Source: a new Approach and Applications to the United States. Review of Economics and Statistics 67; 151-156.

Perotti (1993), "Political Equilibrium, Income Distribution, and Growth", Review of Economic Studies; Perotti (1996), "Growth, Income Distribution and Democracy: What the Data Say", Journal of Economic Growth

Voitchovsky, S. (2005), "Does the Profile of Inequality Matter for Economic Growth?", Journal of Economic Growth, 10, 273-296;

Yitzhaki, S. and E. Schechtman (2013). The Gini Methodology: A Primer on a Statistical Methodology. Springer Series in Statistics 272

Yitzhaki, S. (1997) .More than a Dozen Alternative Ways of Spelling Gini. OECD (2012), Social spending after the crisis - Social expenditure (SOCX) data update 2012,

Zenga, M.M. P. Radaelli, Ma. Zenga (2011). Decomposition of Zenga's inequality index by sources.

#### Annex

