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Top Income Adjustments and Inequality: An Investigation of the EU-SILC

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Abstract

In this paper we bridge the gap between two different approaches to measure inequality: one based on household surveys and summary measures such as the Gini, and the other focused on taxable income and top income shares. We explore how these approaches adjust the Gini for equivalised household income in 26 European countries over 2003-2017 using the EU-SILC, focusing on the World Inequality Database (WID) adjustment as proposed in Blanchet et al. (2020). On average, the Gini increases by around 2.4 points as a result of the WID adjustment, for both gross and disposable income, with notable differences across countries, affecting rankings, despite limited impact on trends. We find that differences in inequality depend less on the adjustment method and more on whether it relies on external data sources such as tax data. In fact, SILC countries that rely on administrative register data experience relatively small changes in inequality after the WID adjustment. For recent years, we find that the Gini for 'non-register' countries increases by 2.8 points on average while in 'register' countries it does so by 0.9 points. We conclude by proposing ways in which household surveys can improve their representativeness of income and living conditions.

JEL Codes: D31, D63, N30.
Keywords: Inequality, Reweighting, Survey Representativeness, Top incomes.

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1 Introduction

The most striking finding from research on income inequality over the past couple of decades has been the growing share of total income going to people at the top of the distribution (Atkinson and Piketty, 2007, 2010; Alvaredo et al., 2017). Key to this burgeoning 'top incomes' literature has been the use of administrative income tax data (see Atkinson et al. (2011) for an early overview). This literature has called into question the reliance on household surveys in much of the research and official monitoring of inequality, as they may fail to capture incomes at the top of the distribution. Such questioning reflects the difficulties surveys face in capturing a relatively small group in the population, together with specific issues with non-response and under-reporting among this top group (Burkhauser et al., 2017; Hlasny and Verme, 2018; Blanchet et al., 2019). As a consequence, there are very real concerns that household surveys may mis-measure both inequality levels and trends over time.

For example, in the US, Burkhauser et al. (2012) suggest that the Current Population Survey (CPS) closely tracks tax-based top shares up to the 99th percentile but not the top 1% income share, and Atkinson et al. (2011) find that a substantial share of the growth in inequality in the US as measured by the Gini coefficient may be 'missed' by the CPS, particularly when considering capital gains after the early 2000s. This issue has grown in importance over time, with Yonzan et al. (2020) reporting that the gap between surveys and tax data at the very top has been growing in recent years. Similarly, the analysis by Morelli et al. (2015) suggests that conventional survey-based measures such as the Gini coefficient may increasingly miss the actual extent of change in income inequality. To add to these concerns, there is every reason to believe that the extent of such bias varies across countries, and this may well be the case for a given country over time: country rankings in terms of inequality levels at a point in time or inequality change over time as seen in surveys may not be reliable. The growing incidence of nonresponse and undercoverage among high-income earners —what Lustig (2019) calls the 'missing rich' problem— clearly needs to be addressed in measuring and tracking inequality by official statistical agencies.

Recent research has investigated and employed various approaches to address this problem. [1] These approaches are typically grouped into two categories. First, one can replace the top $\alpha\%$ of the income distribution in the survey with observations drawn from a parametric distribution or an imputation method. Replacement methods assume that population shares (after base survey weights are applied) are correct and focus on issues of under-reporting or under-sampling at the top. Second, assuming instead that the population shares in the survey are not correct, one can adjust the entire survey by reweighting, replacing the base weights with new weights that aim to reflect the heterogeneity in non-response rates. This the the approach following, for example, in Blanchet et al. (2019) or Muñoz and Morelli (2021). Reweighting methods are mostly focused on correcting for non-sampling issues such as low response rates among the very top, while replacement methods can also be used to address sparseness at the top, a particularly useful property when measuring income shares at the extreme right tail of the distribution (say, for the 0.1% or 0.01% of the population).

Jenkins (2017), in a study on the UK, suggests that fitting a parametric upper tail to the observed survey observations —without reference to external information— may not be an appropriate adjustment, as estimates may still fail to fully capture the 'true' upper tail. This serves to motivate the use of external information, generally from income tax data, to implement a replacement approach that Jenkins (2017) illustrates. Tax data can also provide information on the spread of incomes across much of the distribution that serves as a basis for reweighting well beyond the top. Yet, combining information from surveys and tax data is challenging in that the two sources mostly employ different income concepts and income recipient units. Survey micro-data generally include sufficient information to allow them to match the income concepts employed in external sources, most often on taxable or 'pre-tax' income among couples or individual adults (see Yonzan et al. (2020) for a detailed exercise of addressing this comparability issue). However, it has proven difficult to relate results from these type of adjusted distributions to the more standard definitions generally employed in the inequality literature, notably

[1] See a discussion on nonresponse bias and on modelling the top of the income distribution in Hlasny (2020a,b), and a extensive review of existing methods in Lustig (2019)

household income including cash transfers after direct taxes, equivalised and attributed to each person in the household (including children). This also applies when one simply compares top income shares from surveys with the ones derived from tax data (together with a national accounts denominator) in the 'top income' literature.

More recently, efforts associated to the World Inequality Database (WID) have sought to combine data from tax sources, household surveys and the national accounts to build Distributional National Accounts (DINA). The core aim of this approach is to allocate all the national income as measured in the national accounts to households. This means that items not included in the household income concept which surveys seek to measure, such as the undistributed profits of corporations and the benefits from government spending on education, health services etc., are allocated, with the resultant series being consistent with macroeconomic growth trends and account for the full distribution of national income (Alvaredo et al., 2020).

The recent study by Blanchet et al. (2020) presents DINA series for 38 European countries between 1980 and 2018, on a similar basis to the DINA estimates for the US produced by Piketty et al. (2017), for France by Garbinti et al. (2018) and for China by Piketty et al. (2019). One element in this complex exercise — before bringing undistributed profits, government spending on services, and other sources of income into the picture— is to combine data from tax data and surveys to produce an adjusted distribution of cash incomes. This is done in a two-step procedure that adjusts for both sampling errors, such as sparseness at the top of the distribution, and non-sampling errors, such as low response rates among high incomes, in a manner described in detail below. From a DINA perspective, this exercise serves as the initial building-block in the goal of distributing the entirety of national income, but differences in the income concepts and units employed once again make it difficult to assess the implications of these adjustments for the standard measures of inequality usually derived from household surveys.

This is the gap we aim to bridge for European countries, building on Blanchet et al. (2020) (hereafter the WID-adjustment). We use the micro-level adjustments they produce for 26 countries covered by the European Union Statistics on Income and Living Conditions (EU-SILC) between 2003 and 2017 to construct inequality indicators of equivalised gross and disposable household income among persons, the concepts most commonly employed for the analysis and tracking of income inequality. We explore the reweighted dataset in more depth, including its distribution across the population, as well as the impact of different units of observation and income concepts, two factors that Callan et al. (2020) showed to be crucial in explaining the differences in inequality trends in Ireland. We also compare the results we find with those of other recent studies attempting to 'adjust' such inequality measures from the EU-SILC, namely Hlasny and Verme (2018) and Bartels and Metzing (2019), to assess assessed whether the choice of adjustment method really makes a difference.

Our analysis allows us to address key concerns about the reliability of survey-based estimates of income inequality that have been highlighted by tax-based estimates of top income shares. In doing so, we also provide a bridge between the long-standing inequality research literature focused centrally on equivalised disposable cash income among persons and the emerging DINA stream of research that employs other (though of course related) income concepts and measures. To our knowledge, no other paper has delved into the reliability of the EU-SILC in such detail.

Among our key findings is that the impact of the WID-adjustment on the Gini coefficient and top income shares for equivalised disposable income among persons varies widely across the countries in EU-SILC. The Gini is increased by up to 10 points for some countries but only very modestly for others, affecting country rankings in terms of inequality levels and the gaps between them. The scale of this impact also varies from one year to the next for some individual countries, thus affecting comparisons of trends and inequality rankings, although less substantially for the former. There are also some notable differences between the impacts of the WID-adjustment and those of Hlasny and Verme (2018) and Bartels and Metzing (2019) on the Gini coefficient, demonstrating that the adjustment approach employed does indeed matter —especially the choice between methods that rely on within-sample projection versus those incorporating external information from tax data.

The remainder of the paper is structured as follows. In section 2 we elaborate on why surveys fail to capture top incomes and on the different approaches being employed to address this, and notes specific features of EU-SILC that are relevant in this context. In section 3 we summarise the WID-adjustment employed in Blanchet et al. (2020), note the distinctive income concepts on which their analysis is focused, then use their adjustment to the EU-SILC microdata to show what it means for inequality in equivalised gross and disposable income. We subsequently dig deeper into the mechanics of the reweighting, before exploring the impact of different units of observation and income concepts to measured inequality in the adjusted dataset. In section 4, we compare the extent of these adjustments to the Gini coefficient for equivalised disposable income with those presented in Hlasny and Verme (2018) and Bartels and Metzing (2019). A final section concludes with a summary and recommendations.

2 Surveys and the coverage of top incomes

Surveys fail to capture the top of the income distribution for different reasons. These reasons are typically grouped into sampling and non-sampling issues. The former reflects problems with the original design of the survey, for example how a small sample size can result in sparseness of certain population groups. The latter reflects heterogeneous response rates, for example when those at the top of the distribution decline to respond to the survey, after being included in the sample, more than those among the rest of the distribution. As a result of these problems, the gap between surveys and other more reliable sources of data is particularly large at the top (see, e.g., Burkhauser et al. (2017) for the UK, Blanchet et al. (2019) for France, the UK, Norway, Brazil and Chile, or Lustig (2019) for Uruguay) and it has been growing over time for countries like Ireland (Callan et al., 2020) or the United States (Yonzan et al., 2020).

Sampling issues are mostly associated with non-coverage error and with sampling error. Non-coverage errors happen when, by design, individuals have zero probability of being selected into the sample. Most statistical institutes design the sampling strategy so as to avoid non-coverage errors, for example by replacing the population that cannot be covered, and it is not usually a major issue. Sparseness, on the other hand, means that there is insufficient density at the top of the income distribution and therefore very few observations for that group. This might not necessarily bias inequality estimates, but will reduce their reliability. This creates a problem when estimating top income shares, particularly those at the very top (the top 0.1% or 0.001%). These issues can be resolved at the design stage, for example by over-sampling the relevant population, or subsequently by replacing the top of the distribution with estimates from a parametric model or from linked administrative data.

Non-sampling issues reflect differences in behaviour among the surveyed or in choices taken by survey administrators. It includes both unit and item non-response, as well as under-reporting and top coding. Unit non-response happens when individuals in the potential sample do not respond. Similarly, unit non-response happens when respondents opt to not answer income questions, while under-reporting happens when they do answer them but under-report the amount. Finally, top coding happens when incomes are censored above a certain threshold, usually to protect the anonymity of very high income respondents. Under non-sampling issues the final sample will differ from the original sample design and if the difference is correlated with income —for example, if high income earners are more likely to not answer the survey— inequality estimates in the survey will be biased.

Several solutions have been proposed to address these issues. Some solutions focus on adjusting inequality estimates while others aim to adjust the survey itself. The former approach combines an inequality estimate (say, the Gini index) for the poorest $1 - p\%$ with another inequality estimate for the richest $p\%$. While the former uses the survey, the latter is estimated using random draws of a Pareto distribution, estimated using either survey or tax data, resulting in a semi-parametric estimate (Jenkins, 2017). The two Gini estimates are combined following the approach of Atkinson (2007), later extended by Alvaredo (2011). As a result, this first solution provides an inequality estimate that addresses both sampling and non-sampling issues.

The second solution is to adjust the survey itself, either by replacing the top of the distribution or by reweighting the survey. Replacement, as the name suggests, seeks to replace the top of the distribution with a more representative distribution of top incomes. This could be using cell-based means drawn from tax data, as in Burkhauser et al. (2017), or random draws from a parametrised Pareto distribution, as in Bartels and Metzing (2019). While the replacement does not modify or alter the rest of the distribution, a reweighting approach by contrast adjusts the whole distribution. The reweighting approach adjusts the survey weights to address non-response rates, so that the new weights match a certain reference point. Korinek et al. (2005, 2007) use the data on average response rates by groups such as geographic areas, as does Hlasny and Verme (2018). Alternatively, Blanchet et al. (2019) and Blanchet et al. (2020) use external data on top incomes to address both non-response and under-reporting of incomes via a combination of reweighting and replacement. The resulting outcome of the replacement and reweighting approaches is an adjusted survey, including individuals and households, such that one can estimate different inequality indexes such as top income shares or the Gini index.[2]

In the specific context of top income adjustments applied to data from EU-SILC, substantial variation across countries in survey sampling, implementation and how the income data are produced must be kept to the fore. EU-SILC was launched in 2003 and extended to all EU member states and some associated countries over time so that by 2020 it was implemented in 37 countries, i.e. the 27 EU countries, Iceland, Norway, Switzerland, the United Kingdom, Albania, Kosovo, Montenegro, Northern Macedonia, Serbia and Turkey. Crucially, EU-SILC is based on a

[2] While the two approaches can result in similar outcomes (i.e., inequality levels) there are differences between the two that might be relevant, depending on what the researcher wants to estimate. For example, the reweighting approach does not modify the maximum income in the survey, while the replacement can do so. Conversely, the reweighting does not modify the number of respondents nor their individual characteristics.

common ‘framework’, as opposed to being a common ‘survey’. This framework consists of common procedures, concepts and classifications, including harmonised lists of target variables to be transmitted to Eurostat, which are made available to researchers for analysis in the form of microdata subject to restrictions and conditions. Data are collected from probability samples of the population residing in private households within the country (irrespective of nationality or legal residence status), with sampling frame and methods of sample selection differing across countries but aiming to ensure that every individual and household in the target population is assigned a known non-zero probability of selection.

Measuring income is a central aim of EU-SILC, and this is done in terms of a substantial set of specific components of income, mostly at the individual level, but some at household level. The income reference period is the previous calendar year.[3] The EU-SILC framework encourages the use of existing sources and/or administrative data, and it is key here to distinguish three different situations:

1. In the countries commonly referred to as ‘register’ countries, information on income (as well as some demographic variables) is obtained through accessing administrative registers, while other personal variables are obtained according to the ‘selected respondent model’ where only one member of the household answers the detailed questionnaire.

2. Some other countries have moved over the course of EU-SILC to retrieving at least some income information from registers, but without moving to the selected respondent model.

3. In the remaining countries all the information on income is obtained by means of survey responses.

One would expect, in general, that drawing on administrative information – for the most part from income tax and social security records – would improve accuracy

[3] Two exceptions are Ireland and the United Kingdom. In the former the income reference period is the twelve months prior to the month of the survey, while in the latter the current income is annualised and aims to refer the current calendar year, i.e. weekly income is multiplied by 52, and monthly by 12.

in the measurement of income, and this has been validated in general terms with respect to EU-SILC in for example Törmälehto et al. (2017). For example, Burricand (2013) finds that between 2007 and 2008, when France started using register data, the average disposable income increased by 15% and the Gini increased by 5 points, particularly due to differences in real estate and asset income. However a degree of complexity, and indeed uncertainty, arises when it comes to assigning participating countries to these categories.

The first category is generally referred to in the literature on EU-SILC as the 'old register countries'. This includes not only the Nordic countries –Denmark, Finland, Iceland, Norway and Sweden– which traditionally rely for many purposes on comprehensive population registers incorporating data from a variety of sources and thus are generally termed register countries, but also the Netherlands and Slovenia. Complications arise principally with respect to the second category, sometimes —though perhaps somewhat misleadingly— referred to as 'new register countries'. Over the life of EU-SILC an increasing number of countries have been combining survey data with some administrative/register data. The extent and nature of the use of administrative data varies widely, and for individual countries may differ across income components and change over time, in a fashion that sometimes cannot be traced satisfactorily from the information provided by Eurostat or national statistics offices. A particularly unclear issue is whether investment income data from tax records is also used alongside administrative data on employee and self-employed income. This all means that the correct categorisation of certain countries depends on the specific year being considered, and more generally has given rise to some confusion and variation across studies as to which countries belong in which category.

To try to clarify this insofar as possible we draw on various studies including Törmälehto et al. (2013), Törmälehto (2017) and Goedemé and Trindade (2020), from which the following information can be collated:

- For Austria the transition to using register data was fully implemented in EU-SILC 2012, and Statistics Austria subsequently revised the EU-SILC datasets for 2008-2011.

- For France the transition to register-based income data took place in 2008.
- For Italy some register information has been used since 2004.
- For Spain the use of administrative data was implemented in EU-SILC 2013.
- For Switzerland register data was being used in 2011 but the timing of introduction is not clear.
- For Cyprus, Estonia, Latvia, and Malta some register data was being used in 2018 but the timing of introduction is not clear.
- For Belgium the transition to using tax and transfer data from administrative sources has been implemented from EU-SILC 2019 onward.
- For Ireland some income data from social transfer sources has been drawn on from the start of EU-SILC where survey respondents agree, but the extent of use of register data has increased substantially over time, especially from around 2010 when administrative data on employee and self-employed income started to be drawn on.

On this basis it seems that Italy can be assigned to the second category throughout, as can Austria and France from 2008, Spain from 2013, and Belgium from 2019. Switzerland, Cyprus, Estonia, Ireland, Latvia, and Malta can also be assigned to that category for recent years but their situation in earlier EU-SILC years is unclear. Moreover, the heterogeneity among countries (or country-years) included in the second category in terms of how administrative data is actually drawn on must be emphasised. For the remaining countries —Croatia, Czechia, Germany, Great Britain, Greece, Hungary, Lithuania, Luxembourg, Poland, Portugal, Romania, Serbia, and Slovakia— it appears that use of administrative data on incomes is minimal or non-existent, though it is not always possible to be sure about this from the available documentation. The nuances of timing and variations in the nature of the use of register data will be important when we come to consider the extent to which the impact of the top income adjustment on EU-SILC data depends on the extent to which register data is drawn upon.

3 The WID-adjustment to the EU-SILC

In this section we explore the adjustment approach employed by Blanchet et al. (2020) in their analysis of inequality in Europe for the World Inequality Database (WID) (the WID-adjustment), before exploring in subsequent sections the impact this has on conventional measures of income inequality, as well as on different definitions and concepts.

This adjustment procedure addresses non-sampling error through reweighting and sampling error through replacement of the top of the income distribution. However, the replacement is only applied when estimating top income shares, to avoid issues of sparseness. This is done by increasing the number of observations within the top income group, say the top 1%, through imputation or through random draws of a parametric distribution. As our interest lies in studying different income concepts and units of observation, we focus on the reweighting adjustment they implement and its impact on inequality estimates.[4]

3.1 Survey calibration

The reweighting process calibrates the SILC weights so that they are representative of known top income shares estimated from administrative tax data. These shares are available in the World Inequality Database (WID), and in the study are complemented with additional top income share estimates from newly collected data.[5] The reweighting is based on a non-response model, where non-response creates a gap between the survey top income estimates and the tax-based estimates. The authors model non-response rates as a linear function with kinks at each relevant threshold (top 10%, top 5%, etc.), such that non-response rates increase at different rates with income. If they do not observe tax data in a country, they correct the survey based on the non-response profile of other countries. If survey data

[4] Statistically, the survey after reweighting should be indistinguishable from the tax data, which suffices for our analytical purposes. See section 2 in Blanchet et al. (2019) for details.

[5] See the extended online appendix of Blanchet et al. (2020) for a detailed description of the country-by-country adjustments.

is more up-to-date than tax data, they extrapolate top income shares based on changes in median income by decile. The resulting weights address the fact that high income earners are assumed to have higher non-response rates than those lower down the distribution. With this method the authors are able to preserve all survey covariates under the assumption of no re-ranking of survey observations. This is a necessary assumption (and thus limit) given that they cannot assess income under-reporting with the available anonymous tax data.

Correcting for survey non-sampling error involves reweighting. The problem of sampling error, on the other hand, is only addressed when replacing top incomes in the calibrated survey with those from the interpolated tax data. The authors create detailed income tabulations reporting the average income and lowest income (i.e., the threshold) for each percentile. To provide income shares at the very top, the authors create a finer grid in that part of the distribution. That is, they report statistics for percentiles 0 to 99, 99.0 to 99.9, 99.90 to 99.99, and 99.990 to 99.999. The replacement approach expands the sample size for the top 10% while keeping everything else consistent.

The WID-adjustment is a semiparametric approach, in that they combine non-parametric estimates (for the bottom 90%) with estimates drawn from a parametrised generalized Pareto distribution (for the top 10%). Once they have this distribution, they compute the corresponding statistics (average and minimum income) for each point of their percentile grid, appending them to the ones estimated for the bottom 90% in their reweighted survey. The result is a tabulation of average incomes across the income distribution with a highly detailed right tail, which they can use to compute income shares.[6]

3.2 Diverging motives, diverging concepts

Our central concern in this paper is the impact that the top income adjustment implemented by Blanchet et al. (2020) has on the standard inequality measures in the

[6]For the detailed methodology of Blanchet et al. (2020) see section A of their main online appendix.

EU-SILC used in the conventional inequality research and monitoring literatures. These are primarily measures of income shares and summary inequality indices relating to equivalised disposable household income among persons. Before producing and presenting these figures we need to explain why this cannot be simply seen from Blanchet et al. (2020). The reason is because their paper has a different core objective, namely the construction of Distributional National Accounts (DINA). Thus, all the income variables produced from the EU-SILC, including the adjustments implemented, are framed to fit with that objective. The consequence is that they differ from the income measures employed in the standard inequality literature in significant ways, in terms of both the unit of analysis and treatment of the household, as well as the income components included or excluded. These choices and the rationale for them are discussed in detail in Alvaredo et al. (2020) and summarised in Blanchet et al. (2020). Here we only provide a brief summary.

For DINA purposes the benchmark unit is "equal-split adults", whereby all the income of a household is distributed equally within couples or adults in the household. This definition is employed both for conceptual and data availability reasons, namely to align definitions with the way tax data —a key ingredient in the process— are originally structured. Individual adults then constitute the unit of analysis, with children not being included in this benchmark.[7] Furthermore, household income is not adjusted to account for the needs of children via equivalisation, nor is equivalisation employed to reflect economies of scale in consumption among adults. The main reason for not using equivalisation is that the sum of total income no longer matches national income (Alvaredo et al., 2020). Having inequality measures consistent with macroeconomic aggreagtes is the core goal of the DINA project.

Coming then to the income measures employed, the DINA framework assigns a central role to the following income variables:

[7]The DINA Guidelines in Alvaredo et al. (2020) note that alongside this benchmark '*it also makes sense to distribute it across the whole population (including children) to study the distribution of how much people can consume, which can be a better proxy for standards of living*'. This alternative is not included in Blanchet et al. (2020).

1. **Pre-tax national income:** the sum of all factor income flows, before taking into account the operation of the tax and transfer system, but after taking into account the operation of the pension and unemployment insurance systems;

2. **Post-tax national income:** pre-tax income after subtracting all taxes and adding all forms of government spending.

The pre-tax national income variable is distinctive in deducting all social contributions and adding all social insurance benefits. It also adds the undistributed profits of corporations to household incomes. In standard survey-based measures of pre-tax income that would not be the case, though the treatment of both employer and social insurance contributions and benefits with respect to pensions in particular is debated and varies across studies. Instead, this concept is closer to what is usually labelled 'gross' household income in survey-based inequality studies, which includes all cash social transfers whether social insurance-based or social assistance, but excluded undistributed corporate income.

The post-tax national income measure subtracts not only the direct taxes that would be deducted in arriving at the standard disposable income measures from surveys but also indirect and other taxes. Furthermore, it adds to household income the (assumed) benefits to households from all other elements of government spending like in-kind transfers related to health, education, public infrastructure, etc. The DINA guidelines also describe an intermediate 'post-tax disposable income' measure, in which corporate retained earnings are still distributed to individuals but government spending other than cash transfers are not included.

These income variables, like the unit of analysis and non-equivalisation of income, are framed in light of the core objective of the DINA exercise to allocate all of national income to individuals. This means, however, that results published using the DINA framework cannot be taken to apply to the conventional equivalised household income measures. Our aim is to fill this gap, by taking the top income adjustments developed by Blanchet et al. (2020) and applying them to the EU-SILC micro-data to produce series for the most widely-used income measures, namely gross and disposable income. To reiterate, compared with the DINA measures, these measures define pre-tax and post-tax income differently, equivalise income, attribute this equivalised income to all household members, and count children as well as adults in the analysis (by weighting each household by the number of persons in it).

In what follows we confine our analysis to those country-years for which both EU-SILC and top income share estimates based on actual tax data are available, in order to avoid the additional complications introduced by extrapolated top income shares. This means that for most countries our analysis does not go up as far as 2017, and for many it covers only up to EU-SILC 2012 or 2013.

3.3 Inequality using EU-SILC and WID-adjusted weights

Abstracting from differences in the role of income definitions from those of equivalisation and units of analysis, we begin by comparing the level of inequality as captured by the Gini coefficient in two income measures that we produce from the EU-SILC, equivalising and counting all individuals throughout. These are the two widely-used SILC income measures for gross and disposable income (variables hy010 and hy020 respectively).

We present inequality estimates using both the standard SILC weights and the calibrated WID weights which Blanchet et al. (2020) employ to adjust the SILC data. We report our findings concerning the Gini index in Figure 1 and the top 1% income share in Figure 2. These figures show the impact of the WID-adjustment when measured with a summary index such as the Gini as well as at the very top of the income distribution.

Figure 1 uses the Gini index to measure inequality in equivalised gross and disposable income respectively, including the corresponding figures under the SILC weights (continuous lines) and under the WID-adjusted weights (dashed lines). Dark lines are for gross income and grey lines for disposable income. On average, and for our available sample, countries increase their Gini index in around 2.4

points for gross income and 2.3 points for disposable income (as shown in Table A.3 and A.4 in the Appendix, respectively). However, the impact of the WID-adjustment is heterogeneous, with some countries showing almost no change in their inequality levels to others increasing by up to almost 10 points of the Gini index.

In terms of the Gini, Germany and Poland are the two countries with the highest increase in inequality as a result of the WID-adjustment. Germany has an average increase of 6.7 points for gross income (6.6 for disposable income), while Poland shows an increase of 6.2 points for gross income (5.8 for disposable income). Belgium, Luxembourg, Switzerland and the United Kingdom report high increases in inequality, ranging from 4.5 to 4.9 points of the Gini for gross income.[8] With the exception of Switzerland, these are all 'survey' countries or countries that do not rely on register data (with Belgium using registers since 2019). On the other extreme we have countries where the Gini almost does not change as a result of the WID-adjustment, like Denmark, Greece, Hungary, Ireland, Italy and Sweden, of which only Greece and Hungary do not rely on register data. Our findings suggest that the use of register data makes a meaningful difference on inequality estimates, with top income corrections making little difference among countries that rely on it.

Figure 2 reports the raw and adjusted top 1% income share for household gross and disposable income. The dark lines show the shares for gross income and the grey lines show the shares for disposable income. The continuous lines show the shares when using the benchmark SILC weights and the dashed lines show the share under the WID-adjusted weights, calibrated through the method described in section 3.1. Just like with the Gini, Germany and Poland are the countries with the highest increase in the top 1% share as a result of the correction, with average increases ranging from 4.8 to 5.5 percentage points. Switzerland and the United Kingdom also present high increases (3.4 to 4.2 percentages points). In addition, Romania and Serbia now appear among the countries with the highest average increases in the income share going to the top 1%, ranging from 3.7 to 4.2

[8]We exclude Iceland from this group, as its high average is driven by exceptional increase in financial earnings, as explained later in this section.

percentage points. Just as it was for the Gini, non-register countries see the highest increases in the top 1% share as a product of the calibration. As expected, countries that rely on register data such as Italy, Denmark, Ireland or the Netherlands, have relatively small differences in income shares. Interestingly, Hungary and Greece also have small differences, despite not being register countries. Overall, the WID-adjustment shows a picture of higher inequality than that provided by SILC without adjustment.

A final point to discuss is the extreme jump in inequality for Norway in 2005 and for Iceland in 2007 when using the WID-adjusted weights. These spikes appear under all income concepts, for both the Gini index and the top 1% income share, and can also be seen in the original top income shares (as reported on wid.world). For the Norwegian case, Aaberge and Atkinson (2010) trace this spike to a tax reform that began to tax dividends from 2006 onwards, giving strong incentives for higher-than-normal dividend payouts in 2005. Ólafsson and Kristjánsson (2013) attribute the spike in Iceland to the speculation bubble prior to the Great Recession, which reached its peak in 2007. As a result, the share of financial earnings in gross income grew substantially, going from 20% in 1992-96 to over 80% just before the Great Recession, where inequality in capital income accounted for half of the Gini for disposable income. These spikes reveal how using taxable income as the income concept —particularly in the context of tax policy changes— can impact the extent of these adjustments, and the importance of considering these issues when using income tax data in isolation.

3.4 Changes in inequality and concentration estimates

In this section we explore the impact of the WID-adjustment on inequality in gross and disposable equivalised income in more depth. We use three aspects of the measurement of inequality to assess that impact. First, we look at differences in levels, by quantifying the percentage change in the Gini index after the WID weights are applied. Second, we look at the differences in trends, comparing the evolution of inequality over time when using the SILC and WID weights. Lastly, we look at the change in relative positions after the reweighting by comparing the ranking of countries.

3.4.1 Differences in levels

The WID-adjustment addresses non-response by adjusting the survey based on external top income shares. We can therefore expect that the extent of the correction is larger among countries with high top income shares. Indeed, there is a positive correlation between the percentage change in the Gini and top 1% income share as reported by WID. Figure 3 shows that an increase in the top 1% share of 1 percentage point is associated with a 2.1% increase in the Gini index.

Figure 4 shows the percentage increase (or decrease) in the Gini index as a result of the WID-adjustment. The solid line is the difference for equivalised gross income and the dashed line is the difference for equivalised disposable income. Overall, the differences are quite similar for both income concepts, except for a few exceptions like Austria, the United Kingdom or Slovenia, where the percentage change under gross income is slightly higher. Excluding outliers (Iceland in 2007 and Norway in 2005), changes in the Gini range from -0.6% to 34%, with an average increase over this time period of 7.5% across all countries (and a median increase of 6%). The countries with the highest and lowest changes are the same as the ones discussed in the previous section: Belgium, Germany and Poland having the largest increases and Dermark, Greece and Italy with the smallest changes, of less than 1%.

For some countries we see an important increase in the Gini while others remain almost unchanged. One reason for this could be, as Deaton (2005) argues, that the inclusion the 'missing rich' raises the average income, such that larger absolute differences become smaller relative to the new average and inequality decreases. Figure 5 shows that it is true that most countries see an increase in average income after the adjustment. However, inequality does not respond in the same way among these countries. Czechia and Germany see a large increase in both average income and in the Gini as a result of the WID-adjustment. On the other hand, Italy and the Netherlands see a large increase in average income but no change in the

Gini. Moreover, for the few countries where the WID-adjustment decreases the average income, like Portugal and Serbia, we still observe an increase in inequality. Ultimately, whether accounting for the 'missing rich' increases inequality or not depends on the interaction between the change in average income and the change in the variance of income after the adjustment.

The interaction between changes in average income and its variance —and the overall change in inequality— appears to be mediated by the use of register data. We see larger increases in inequality among non-register countries (such as Czechia, Germany, Portugal and Serbia), as opposed to countries that rely on register data (such as Italy and the Netherlands). The use of matched register data at the individual level within the survey support seems to significantly improve the variance of income in surveys to sufficiently mitigate any initial underestimation of inequality, despite prevailing gaps in average incomes. This is consistent with the findings in Blanchet et al. (2019), which show that the most important part of a tax-based adjustment to surveys comes from what happens inside the survey support rather than what is added beyond the support.

3.4.2 Differences in trends

Figure 6 shows the evolution of inequality trends over time. We standardise the inequality level for the first year in the sample to 100, thus showing the growth rates for the Gini index over time. We report trends for both equivalised gross income (darker lines) and equivalised disposable income (grey lines), measuring inequality under both the SILC weights (continuous lines) and the WID-adjusted weights (dashed lines).

These results point to interesting time trends. One clear example includes France, where the impact of the WID-adjustment almost disappears in 2008, the year it started using register data. Interestingly, we also see a similar decrease in Spain around 2009, before they started using register data. Finland and Poland experience an increase in the gap over time, while Romania and Luxembourg (albeit with a noisier trend) have decreases over time. Great Britain shows a mixed trend, where the impact of the calibration decreased until 2011, followed by an increase for the two following years. The series also show a few one-year spikes, such as Iceland in 2007 and Norway in 2005, as previously noted. These series suggest that the impact of the calibration is not fixed over time, and changes in the distribution of taxable income (and therefore on the top income shares) play an important role in determining its extent.

Overall, trends appear to be quite similar across all four inequality estimates. The most salient exception is Poland, where inequality measured using SILC weights showed a constant decrease, being around 20% in 2017 compared to 2004. However, when looking at the WID-adjusted inequality series we see that inequality remained constant across that period. We see the opposite in France and Luxembourg, where WID-adjusted inequality remained constant while the SILC series shows an increase over time. Germany, the other country besides Poland with the largest differences due to the WID-adjustment, shows very similar trends across all inequality estimates. On the other hand, countries with small changes due to the WID-adjustment can still see differences in trends, for example in Sweden or Greece. From figure 6 we see that large corrections do not necessarily translate into different trends over time.

3.4.3 Changes in relative position

Figure 7 shows the country ranking for inequality measured for gross and disposable equivalised income, for the three years that include the largest number of countries (2006, 2008 and 2010). The ranking places the country with the lowest inequality as first, and moves up in position as inequality grows. The x-axis represents the inequality ranking when inequality is measured using the SILC weights and the y-axis shows the same for the WID weights. Countries on the diagonal line do not change their relative position, countries above the line see their position worsened (i.e., higher relative inequality) after the WID-adjustment, and the further one country is from the diagonal, the larger the change in the ranks.

We see that most countries remain in a relatively similar position after the reweighting. This is particularly true at the extremes. Low inequality countries such as Norway, Denmark and Sweden, and high inequality countries such as Romania, Portugal Poland or the United Kingdom experience small changes in their position. France, a mid-ranked countries, also sees small changes it its ranking, remaining in its position for all three years under disposable income. Overall, over half of countries remain within three spaces of their SILC position after using WID weights.

Countries that increase their inequality level after the WID-adjustment worsen their relative position, while countries where the correction makes little difference see their relative position improve (i.e., a lower WID-adjusted rank). Luxembourg, Germany, Iceland, Belgium, Poland and Finland have the higher increases in rank, of up to 12 positions. On the other hand, the Netherlands, Greece, Ireland and Estonia decrease their rank in up to 9 positions. Addressing non-response rates at the top of the distribution can make a substantial difference in cross-country rankings, especially among countries with 'middle' levels of inequality.

3.5 The importance of the income definition

We have discussed how income definitions may vary depending on choices and data limitations. In this section we compare our estimates under different units of observation and income concepts, thus contrasting the definitions used by the WID and in SILC.

3.5.1 The impact of different units of observation

The first top income series created by the WID (by then, the World Top Incomes Database, or WTID) focused on taxable income and the tax unit as the relevant unit of observation (Piketty, 2003; Piketty and Saez, 2003). Depending on the tax law, that could mean individuals or couples, resulting in an over representation of couples at the top of income distribution in joint taxation countries.

Since then, WID series have moved to account for the distribution of pre-tax and post-tax national income across individuals (as discussed in section 3.2). These series use a 'narrow' equal-split scale, such that all household income is divided in equal parts among the couple. An alternative split would be to divide income across all adults in the household, what they call a 'broad' equal-split. However, studies using tax data as their primary data source do not have information on household structure beyond the couple (see for example Piketty et al. (2017); Garbinti et al. (2018)). On the other hand, in cases where surveys are the primary source of data and household composition information is available, they have opted for a broad equal-split (Piketty et al., 2019). Whenever possible, as in the case of Blanchet et al. (2020), they opt for reporting both narrow and broad equal-split series.

While the WID series opted for dividing income equally across individuals, most economic inequality studies consider within-household economies of scale (Cowell and Mercader-Prats, 1999). These studies are concerned with individual welfare and how income can be used to satisfy needs, using equivalence scales such as the modified OECD equivalence scale to measure 'consumption units' in a household. The WID series —and more specifically, the DINA project— do not use equivalence scales because, as previously mentioned, they introduce problems when aggregating individual income such that the sum of all individual equivalised incomes does not add up to aggregate national income (Alvaredo et al., 2020, pp. 23–25). In this section we bridge the gap between these two approaches by exploring the implications of using different units of observation.

Figure 9 shows the WID-adjusted Gini index for household gross income under different scales. We include a 'per capita' scale, where household income is divided equally among all household members, a 'per adult' (or broad equal-split) scale, where household income is divided equally among all adults (i.e., aged 20 or older) in the household, the OECD equivalence scale we have used as our benchmark, a 'per couple' (or narrow equal-split) scale that divides household income in half for couples, and a taxable unit scale, where the definition varies according to each country's tax laws. We see that inequality is higher under tax units, as it is mostly a combination of individual and couples, seconded in most countries by inequality under the 'per couple' scale. The other three scales (the OECD equivalence, per adult and per capita) show relatively similar inequality estimates, as they are better at representing household composition, albeit to a different extent. Overall, we can group the scales into two groups: those that focus on the couple (taxable units and the narrow equal split) and those that include other household members (broad equal split, the OECD scale and the per capita scale).

In general, differences in these series partly have to do with the varying share of household size and composition across countries. Differences between the two groups of scale is larger in countries where household size is larger. From Table 2 we see that Serbia, Slovenia, Iceland or Poland are among the countries with the largest average number of household members, and they all show large differences between inequality under tax units and under the per capita scale. However, we also see large differences for countries with lower number of household members, such as the UK, France or Denmark.

3.5.2 The impact of different income concepts

Blanchet et al. (2020) use the income concepts defined in the DINA framework (Alvaredo et al., 2020), primarily pre-tax and post-tax national income. These are income concepts that are consistent with macroeconomic aggregates as they include information that is typically excluded from surveys, such as undistributed profits or government spending beyond social transfers and benefits. Inequality studies that use surveys such as EU-SILC on the other hand typically focus on gross and disposable household income. Here we compare the SILC income concepts to an intermediate WID income concept based on the WID definitions but that only relies in survey data. We call these concepts gross and disposable fiscal income.

Table 3 compares the make-up of total household gross income (labelled 'hy010' in EU-SILC) with total household gross fiscal income (labelled 'ginc' in WID). There are important differences between gross income and gross fiscal income: the former excludes all deductions whereas the latter includes deductions related to pensions and unemployment benefits (which is why they refer to it as 'pre-tax post-replacement' income). Similarly, gross income income excludes social allowances for education, children or housing, and inter-household cash transfers, whereas gross income includes them. While the SILC income concept of gross income includes all contributions going to unemployment benefits and pensions, the WID income concept of gross fiscal income deducts them.

Contrary to gross income concepts, the definition for disposable income is quite similar in both cases. The only difference between the SILC concept of disposable income and the WID concept of disposable fiscal income is that the income tax and social insurance contributions are treated differently. While the SILC definition uses a single variable for both (hy140g), the WID definition splits that variable into three components: income tax, social contributions, and individual contributions to private plans (using OECD social contribution tables). This is done to obtain intermediate income definitions such as pre-tax income (which includes contributions to social security). Differences between disposable and disposable fiscal income are small, and solely depend on whether the sum of the three separate components differs from the SILC variable.

Figure 10 presents the WID-adjusted Gini index series for all four income concepts. The two continuous line present the SILC income concepts of gross and disposable income (i.e., hy010 and hy020) and the two dashed lines are for the WID income concepts of gross fiscal and disposable fiscal income (i.e., ginc and ninc). As mentioned before, the differences between disposable and disposable fiscal income are negligible. However, the differences between gross and gross fiscal income can be substantial depending on the importance of the deductions. These differences can go up to 4 to 5 points of the Gini for the UK and Luxembourg, and they are also large for countries like France, Hungary, Denmark, and Ireland. On the other hand, they are less than half a point of the Gini for Italy, Spain or Greece. It is important to note that gross income, depending on whether we use SILC (or similar) income concepts or WID income concepts can vary substantially, especially in countries where social contributions and taxes are highly skewed across the income distribution.

An interesting fact of the WID income concepts is that income components are added in a step-wise manner. Starting from the income stemming from production factors, namely labour and capital, all the way to disposable income, after taxes and transfers. Figure 11 exploits that structure to report the inequality level for six different income concepts, using both SILC and WID-adjusted weights. It shows the median across all available years, as well as the 25th and 75th percentiles. As expected, all countries decrease their inequality level when going from factor income (finc) to post-tax income (ninc). In most countries, the inclusion of pension income (pinc) results in the highest drop in inequality. Germany, for example, shows a Gini of 56 (48 using SILC weights) under factor income, which drops to 44 (36.7) after removing social contributions and including pension benefits. This is true for countries like Austria, Belgium, Switzerland, Spain, France, Great Britain, Greece, Luxembourg, the Netherlands, Norway and Poland. Other countries like Czechia, Finland, Ireland or Sweden show a much more constant drop in inequality across all income concepts. Taxes on income and wealth play an important role in countries like Great Britain and the Netherlands. Social transfers also matter in these two countries, while they make little to no difference in countries like Spain, Italy, Portugal or Serbia.

These estimates point to the importance of the distribution of pension income for most countries. After including it we see the biggest changes in the level of inequality. Overall, social contributions and unemployment benefits appear to make a small difference to overall inequality, while taxes and social transfers have an heterogeneous impact across countries. However, with very few exceptions, we don't find any differential role played by the WID-adjustment across these income components.

3.6 The distribution of the reweighting

In this section we explore the WID-adjustment further to better understand the changes in inequality measures it produces by studying the extent of the reweighting procedure and how it is distributed across households. Our outcome of interest is the ratio between the new weight, adjusted using the WID-adjustment, and the original weight provided by SILC. A ratio above 1 means that an individual or household sees their weight increase as a result of the adjustment (the converse if it is below 1), while a ratio equal to 1 means that their weight has not changed. If we were to interpret the adjustment in terms of a non-response model, we can say that those with a ratio above 1 were underepresented in the original survey and now have a higher weight to address it. By construction, the overall magnitude of the increase in weights among the top of the distribution must be matched by the decrease in weights among those outside the top for the total population to remain unchanged (which is what is desired in these methods).

Figure 8 shows the median ratio, together with the 10th, 25th, 75th and 90th percentiles, for each country. The overall picture is quite heterogeneous. Countries like Belgium, Denmark, Finland, Great Britain, Iceland or Slovenia show a very symmetric reweighting structure, with increments of the SILC weights of up to 3 times joint with decreases of a similar proportion. On the other hand, other countries show much higher and asymmetric increments. For example, the 90th percentile of the distribution of the ratio for countries like France, Ireland, Italy, Poland or Romania shows the reweighting can increase the original weight by up to 6 times, while the median and the 10th and 25th percentiles are all close to 1. Roughly speaking, countries can be grouped into those with a symmetric structure and those with an upwardly biased structure. This classification appears to be independent to whether countries are 'register countries'.

To get an idea of how the reweighting distribution impacts inequality we can look at the six countries with the highest percentage increments.[9] These countries are Belgium, Germany, Iceland, Luxembourg, Poland and Serbia. Belgium and Iceland have a very symmetrical distribution, but while the ratio ranges from 0 to around 2.5 for Belgium, it ranges between 0.8 and 1.2 for Iceland. Both Germany and Luxembourg experience a strong decrease in dispersion of the ratio at the start of the series, followed by an increase in dispersion beginning in 2007 for Germany and 2013 for Luxembourg. Lastly, Poland and Serbia expierence an

[9]We define this by counting the number of times each country was among the top three post-adjustment percentage increments in the Gini index for a given year. We then select the six countries with the most years in those positions.

increase in dispersion over time – in both cases the 90th percentile of the ratio goes from around 4, when the series start, to 6 at the end. When looking at these six countries, we see there is no unique reweighting structure among them.

Contrary to the heterogeneity among countries where inequality increases, the reweighting structure is fairly similar among countries where the inequality level does not change after the calibration. Following the same criteria used to identify the countries with the largest increments, we find that Denmark, Estonia, Italy and Ireland are the four countries with smallest increments. In all four cases, which are a mix of 'old' and 'new' register countries, the 10th and 25th percentile as well as the median are close to 1, suggesting that most of the reweighting happens only at the very top.

Overall, we see that the reweighting structure is not homogeneous among countries. For some countries around a third of the sample is significantly reweighted, while others do so across the whole distribution. This structure can vary over time for a given country. The extent of the reweighting can also differ significantly, with some countries changing SILC weights less than 20% and others increasing them over 20 times. Some countries, such as those that link surveys with register data, experience small distributional changes, but their reweighting structure can still be top-heavy.

4 Does the adjustment method matter?

In this section we assess whether the adjustment method employed matters for measured inequality levels and trends by comparing results from the WID-adjustment with those from two other studies that have produced inequality estimates from EU-SILC adjusted for top income biases. These papers are Hlasny and Verme (2018) and Bartels and Metzing (2019). Both of these studies use SILC income concepts and the Gini index to measure inequality, but differ in their approaches. To briefly summarize, Hlasny and Verme (2018) assess the relative impacts of reweighting and replacement only using survey information. Bartels and Metzing

(2019) exclusively use the replacement method so as to match top income shares from WID. Here we focus on the reweighting adjustment of Hlasny and Verme (2018) and on the replacement adjustment of Bartels and Metzing (2019), so as to gauge the importance of (1) the use of external sources of data and (2) the adjustment approach.

Hlasny and Verme (2018) use reweighting and replacing methods, without recourse to external administrative data on incomes, to adjust inequality measures for top income biases. They use the EU-SILC for 2011 and the Gini index to measure inequality across 31 countries. Their outcome of interest is equivalised disposable income (hy020 divided by hx050). Following Mistiaen and Ravallion (2003) and Korinek et al. (2005, 2007), their reweighting approach uses information on regional non-response rates as well as information about the within-region distribution. Adjusting via reweighting, the Gini index increases by 3.2 points on average (with a median increase of 2.1 points).

The 'integrated approach' of Bartels and Metzing (2019) replaces the top 1% of the survey income distribution with Pareto-imputed incomes, estimated using top income shares from WID. They opt for the 1% as the cutoff as they find this is the point at which survey and tax data report a significant difference in Germany (using the German SOEP). They get the complete distribution of gross income and predicted equivalised net income (obtained through a tax-benefit system transformation) for an unbalanced panel of 11 European countries between 2003 and 2013. Inequality increases among countries that exclusively rely on EU-SILC survey data (1.7 points on average for Great Britain and Germany), as opposed to countries that link register data to their surveys, where the adjustment is negligible.

We first compare the results we have derived from the WID-adjustment in Blanchet et al. (2020) with the Hlasny and Verme (2018) adjustment, both of which use reweighting, thus allowing for an evaluation of the importance of using external data. This can only be done for the single year which the latter employed, namely 2011. We then compare the WID-adjustment with the adjustment in Bartels and Metzing (2019), both of which rely on the same external source of data for their computations over numerous years, thus allowing the impact of their adjustments on trends as well as levels to be compared.[10]

4.1 The importance of using external data sources

Figure 12 (upper panel) shows that the Hlasny and Verme (2018) adjustment results in much higher estimates for the Gini than the WID-adjustment for Great Britain and France, and higher levels for Ireland, Italy, Greece, Norway and Sweden. The WID-adjustment produces markedly higher estimates than those produced by Hlasny and Verme (2018) only for Romania, while also being higher for Germany and Poland. For the common sample of 22 countries, the Hlasny and Verme (2018) adjustment increases the Gini index in 3.3 points on average (median of 2.2), while the WID-adjustment increases the Gini by only 1.8 points (median of 1.4). The lower panel of Figure 12 shows that there is almost no correlation between the size of the two adjustments. This strongly suggests that the use of external data for the calibration in the latter is playing an important role. The magnitude of the adjustment in Hlasny and Verme (2018) is greatest for the UK, which is among the countries relying entirely on survey data, but it is also very large for France, which incorporates register data (in the year they examine). The WID-adjustment is much lower for these countries, and generally quite limited for 'old register' countries. The Hlasny and Verme (2018) adjustment is also much larger for two 'old register countries', Norway and Sweden, than the WID-adjustment, again questioning the reliability of methods that don't use external administrative information.

4.2 The importance of the method

Turning to the comparison between the WID-adjustment and that of Bartels and Metzing (2019) in Figure 13, the upper panel compares the levels of the corrected

[10]There are slight differences in the unadjusted Gini estimates across the three papers, reflecting differences in methodological choices affecting the sample employed. The increase in the Gini due to each adjustment uses the unadjusted Gini as presented in each of the three papers.

Gini estimates for each of the individual years for which both are available and the lower panel compares the size of these adjustments in each country-year. We see that the Blanchet et al. (2020) estimates and the adjustment that drive them are generally higher, especially for Great Britain and Germany, as well as for Norway in 2005 (which was anomalous in that dividend payments were exceptionally large for tax reasons), though lower in countries like Spain. However, unlike with Hlasny and Verme (2018), the size of the adjustment in Bartels and Metzing (2019) is positively correlated with that in Blanchet et al. (2020). Bartels and Metzing (2019) highlight that their adjustments are notably higher in the two countries they include that rely exclusively on survey data, namely Germany and the UK, which is the case also in Blanchet et al. (2020).

Figure 14 compares the inequality trends in the adjusted Gini series between the WID and Bartels and Metzing (2019) methods. This brings out that the gaps between the two adjusted series for Germany and the UK are wider in some years than in others, with the two UK series much closer together in later than earlier years. For Switzerland both levels and trends diverge. For Norway in 2005 the spike already mentioned is reflected in quite different adjustments as already noted, but the series are also much closer to each other in later than earlier years.

Table 1 includes all countries in 2011 with estimates from all three methodologies. On average, it is Hlasny and Verme (2018) that shows the largest increments in the Gini index after adjustment, where France, Great Britain, Norway and Sweden have increments of over 10%. The other two methods not only show lower increments, but also that the higher increments happen in different countries to those in Hlasny and Verme (2018). Both Bartels and Metzing (2019) and Blanchet et al. (2020) find that Germany has the biggest increment, of 6.2% and 20.1%, respectively, while Sweden has one of the smallest increments. Conversely, Blanchet et al. (2020) shows a high increment for Norway while Bartels and Metzing (2019) does not. Overall adjustments are the closest (both in level and direction) between Blanchet et al. (2020) and Bartels and Metzing (2019), suggesting that external data plays a bigger role in explaining the impact of the adjustment than the method itself. Regarding the size of the adjustments, Blanchet et al. (2020)

report larger increases than Bartels and Metzing (2019) but somewhat below those of Hlasny and Verme (2018), suggesting that reweighting approaches have larger impact on the Gini index than replacing the top of the distribution.[11]

5 Conclusion

The increasing availability of estimates of top income shares derived from tax data has called into question the reliance of much inequality research and official monitoring of income distribution data from household surveys, as these may fail to capture incomes at the very top and thus skew distributional results. Research has investigated and employed various approaches to adjust survey data to address this problem. The estimates of top income shares included as 'fiscal income' series in the World Inequality Database (WID) for some time now represent an extremely valuable resource in this context. More recently, the WID has turned to the production of Distributional National Accounts (DINA) series, combining data from tax sources, household surveys and the national accounts to allocate all the national income measured in the national accounts to households. An initial step in this complex exercise is to combine micro-level data on incomes from surveys and administrative records to produce a a 'corrected' distribution of cash incomes. From a DINA perspective this primarily provides a link in the longer chain building up to the distribution of overall national income, but differences in the income concepts and units employed make it difficult to assess the implications of the adjustment for the standard measures of inequality usually derived from household surveys.

This is the gap we have sought to bridge in this paper for European countries

[11]Comparing the replacement approach in Hlasny and Verme (2018) bears similar results: reweighting produces larger inequality estimates, especially when the replacement happens at the very top of the distribution, say the top 1%, instead of the top 5% or 8%. This is largely to be expected, given that reweighting is a more interventionist approach that relies on changing weights along the entire distribution, thus impacting a composite index like the Gini more than solely modifying the very right tail of the distribution. The extent of the difference depends in part on the amount of mass beyond the survey's support, i.e. beyond the maximum income reported in the survey.

in the EU-SILC. Taking the micro-level adjustments produced by Blanchet et al. (2020) for 26 countries, we have re-analysed the EU-SILC microdata applying these adjustments to produce inequality indicators for equivalised gross and disposable income. This provides a bridge between the longstanding inequality research literature focused centrally on equivalised gross and disposable cash income among persons and the emerging macro-consistent stream of research that employs other (though related) income concepts and measures. We also analysed the importance of alternative units of observation and income concepts on inequality indicators. Finally, we compared the results of this procedure with those of other recent studies attempting to adjust such inequality measures from EU-SILC, namely Hlasny and Verme (2018) and Bartels and Metzing (2019).

Our key findings are that the impact of the WID-adjustment on the Gini coefficient and top income shares for equivalised gross and disposable income among persons varies widely across the countries in the EU-SILC. The Gini for disposable income is increased by up to 10 points for some countries but only very modestly for others, affecting country rankings in terms of inequality levels and the gaps between them. The scale of this impact also varies from one year to the next for some individual countries, thus affecting comparisons of trends, though less substantially.

We also explored how the WID-adjustment, as proposed in Blanchet et al. (2020), modifies the sample weights across countries. The reweighting structure is far from homogeneous. A few countries have symmetric distributions, increasing and decreasing the weights of different individuals in an equal proportion. Others have a highly skewed distribution, substantially increasing the weights of very few households at the top, while distributing the decrease very evenly across the rest of the distribution. We found no apparent relationship between the shape of the reweighting and the size of the adjustment or whether countries use register data.

To better understand what could be driving these differences, we explored the importance of the income concept and the different units of observation. While earlier tax-based estimates relied on taxable income among couples or taxable units, 'traditional' measures of inequality have looked at household income, equivalised according household size. We found that the Gini is higher when splitting household income among taxable units or couples, and lower when splitting income among adults or all household members. As expected, these differences are stronger in countries with larger household size. We found that the choice of income concept is also important, particularly when comparing the WID and SILC definitions for gross income, as the former deducts all taxes and social contributions going to unemployment and pension benefits, resulting in higher inequality. While the unit of observation might be restricted by the type of data, the income concept is a choice made by the researchers and it is important to correctly explain its differences with more traditional definitions, as well as its impact on overall inequality.

Recently, the literature on Distributional National Accounts (DINA) has embarked on distributing national income among 'broad equal-split' adults (splitting income equally among all adults in a household). The problem, in the context of DINA, with using equivalence scales is that individual income does not add up to national income, defeating its original purpose. We find that broad split income results in similar levels of inequality to those from equivalised household income— at least for gross household income— and as such, it can be a useful compromise between capturing household needs and maintaining national aggregates.

Finally, we found some notable differences between the impacts of the WID-adjustment on the Gini coefficient and those of Hlasny and Verme (2018) and Bartels and Metzing (2019), demonstrating that the adjustment method employed does indeed matter, but only to the extent that it relies on external information from tax data as opposed to within-sample projection.

After digesting these differences, what can we conclude about the reliability of the income measures from EU-SILC? Addressing this crucial question is greatly complicated by the fact that while the EU-SILC has a common 'framework', not all countries collect and process data in the same way. In particular, in the current context, as discussed in section 2, the use of administrative register data matched to survey respondents varies considerably across countries and over time. In general, adjustment with external data has less impact on inequality measures for 'register countries'. On average, the impact of the WID adjustment on the Gini for gross or disposable income in register countries in recent years is on average about 68% of the impact in non-register countries. Nonetheless, there remains a considerable lack of clarity as to the type of register data used for each country and this merits further investigation.

Looking to the future, there are three broad courses of action that can be taken by European countries to improve representativeness of income official statistics on income and living conditions. A first option would be to maintain the SILC as it is and provide ex-post 'experimental statistics' on Eurostat (and the websites of individual country statistics offices), incorporating adjustments to the income distribution following a standard methodology. A second option would be to encourage all countries to systematically link their surveys to register data at the point of data collection. This procedure should try to link all income sources, wage and non-wage incomes alike, by matching survey respondents to comprehensive registers from the income tax data, or from the combination of administrative employment records and investment income data (in cases of dual income tax systems). Other personal variables can be obtained through the 'selected respondent model' used in 'old register' countries. A third option would be to request that countries provide a sample of their register data directly in a standard framework with all accompanying socio-demographic variables. To the extent that this is feasible, it would overhaul the EU-SILC in favour of the provision of register data with the equivalent variables, a transition that Sweden, for example, embarked on from 2013.

On the basis of the analysis in this paper, more comprehensive inclusion of administrative data on incomes is a priority for European statistics on income and living conditions. This would substantially improve assessments of distributional changes within and between countries, as seen from the existing biases currently at play in monitoring and ranking country inequality levels and trends, particularly among countries that vary in their use of income data from administrative sources. The optimal solution, in our view, would be to move progressively towards a system of register data samples, including both employment income and investment income, with equivalent variables to those that exist in the SILC to preserve its richness. For countries whose register data is not abundant in other socio-demographic information, the personal matching of register data into the SILC survey can be employed until additional information can be collated to the register data of these countries from the outset. While recognising the practical and other barriers that would have to be overcome for it to be implemented, this strategy merits serious consideration.

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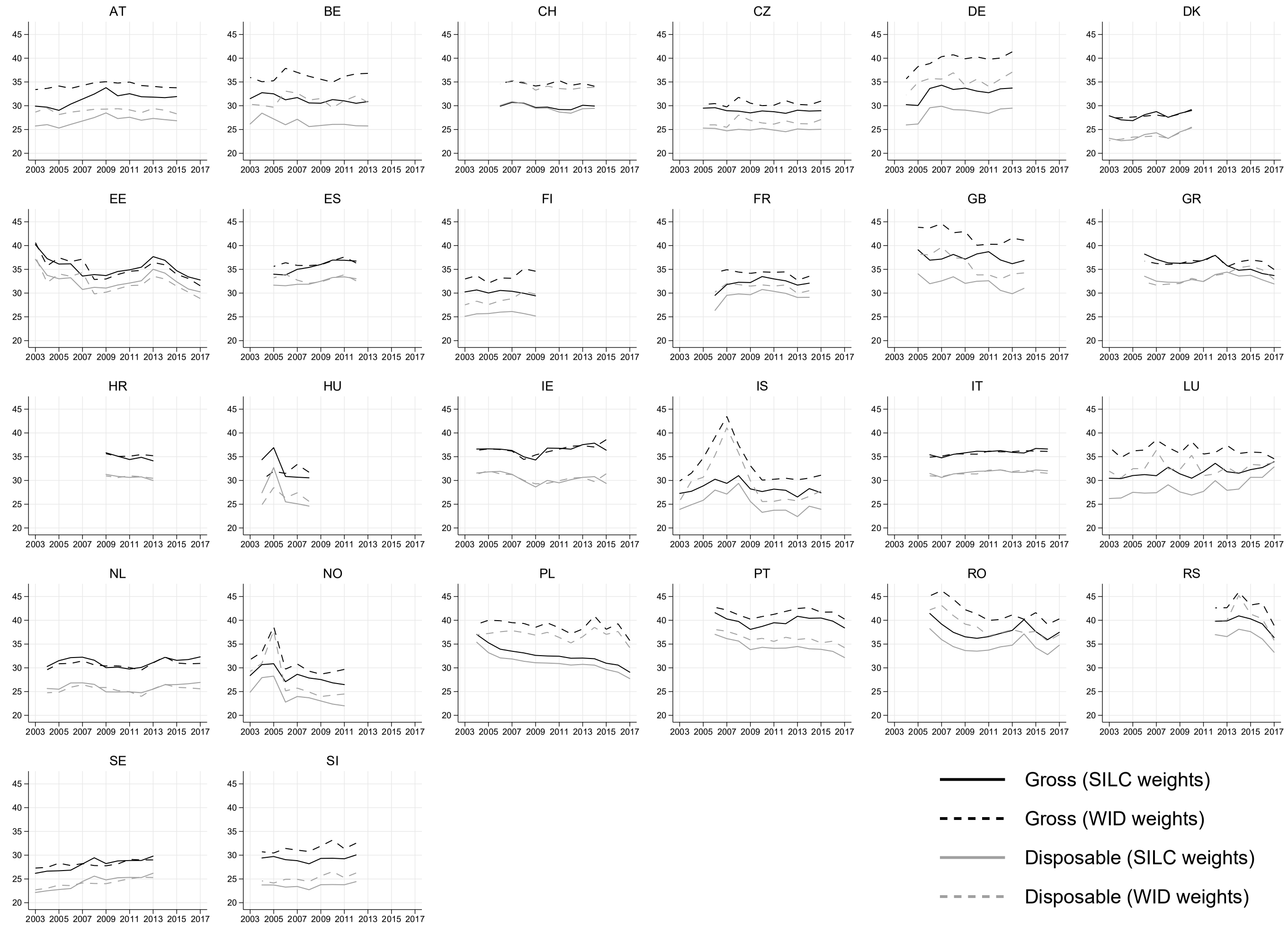
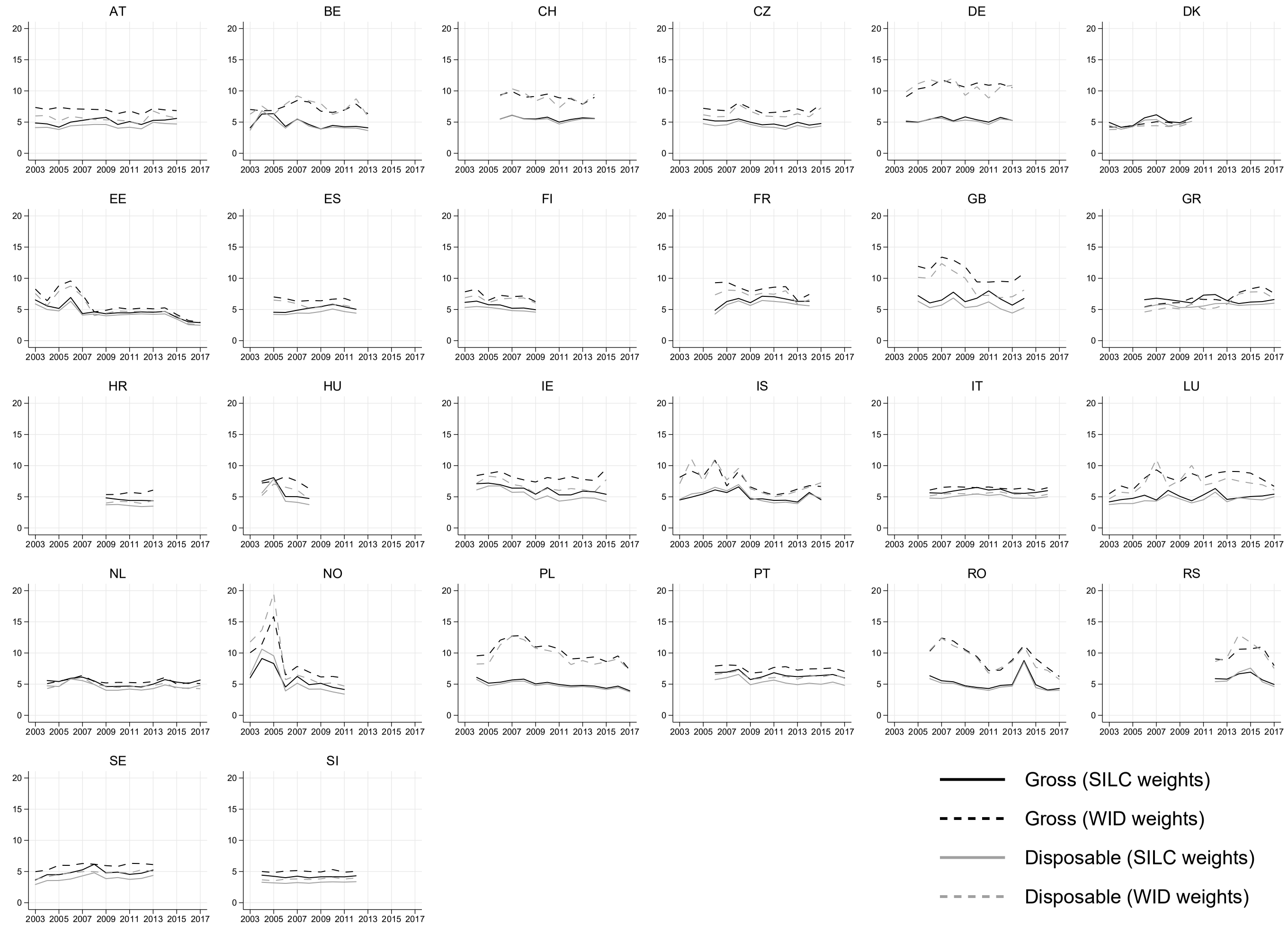
Figures and Tables

Figure 1: Gini index before and after the adjustment



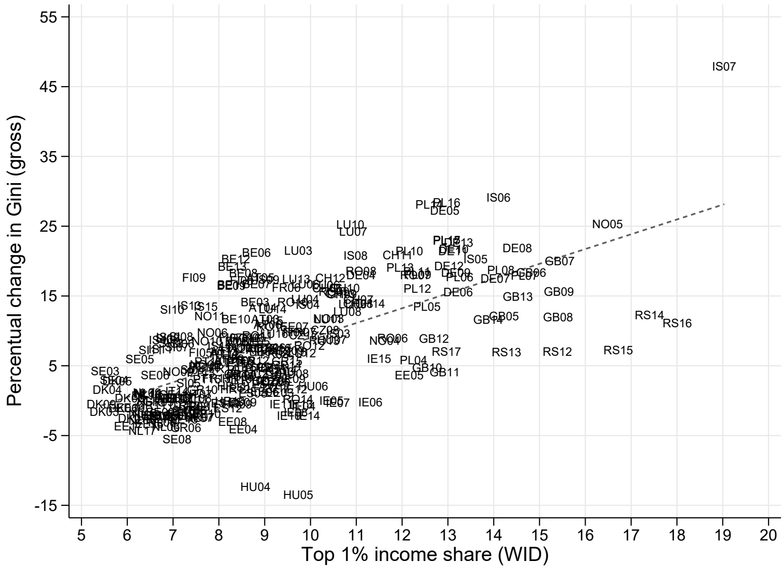
Note: Gini estimates for the SILC income concepts household gross and household disposable income (hy010 and hy020). Household totals divided by the OECD equivalence scale. SILC and WID-adjusted weights.

Figure 2: Top 1% income share before and after the adjustment



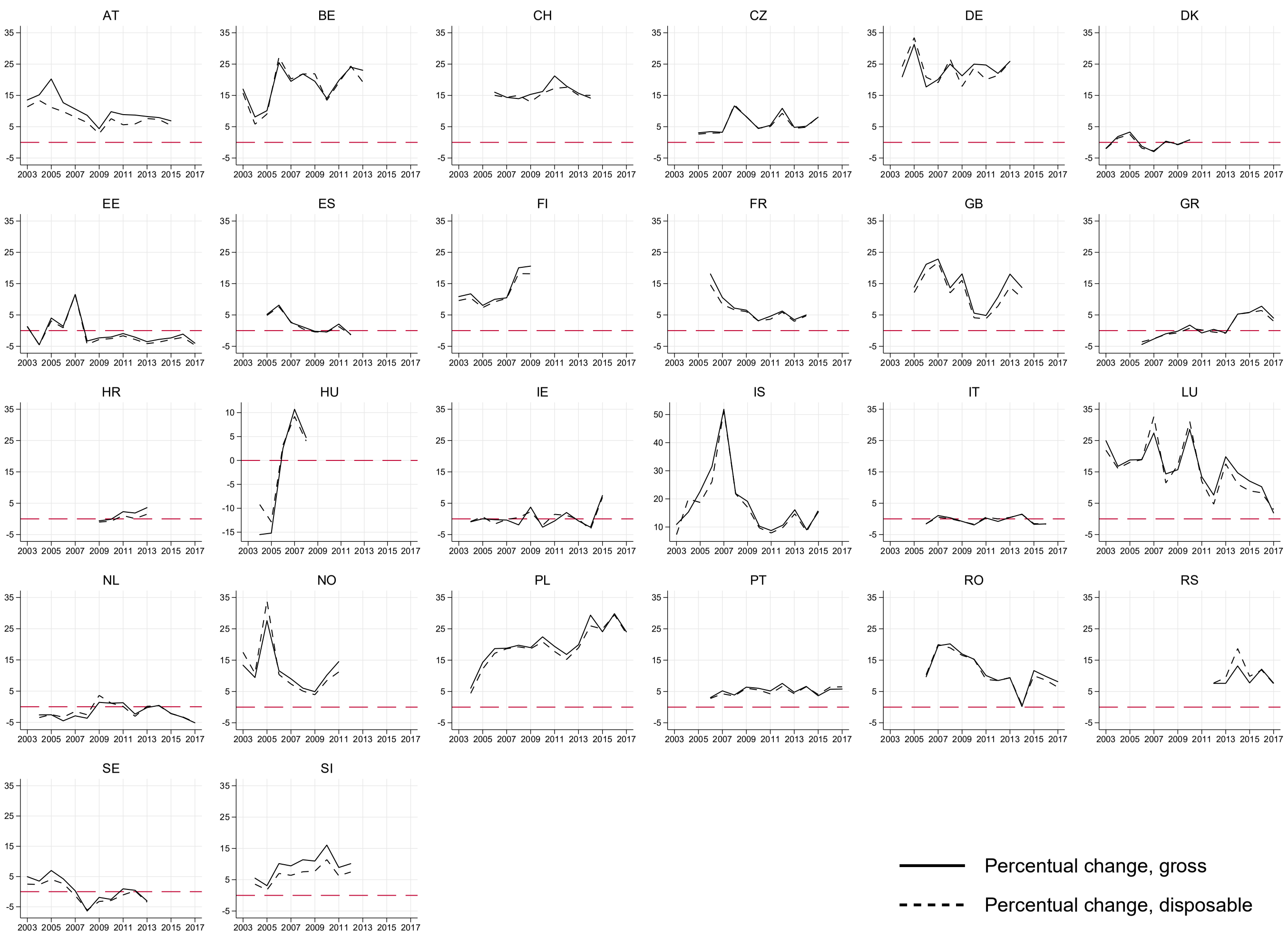
Note: Top 1% income share for the SILC income concepts household gross and household disposable income (hy010 and hy020). Household totals divided by the OECD equivalence scale. SILC and WID-adjusted weights.

Figure 3: Correlation between size of adjustment and top 1% income share



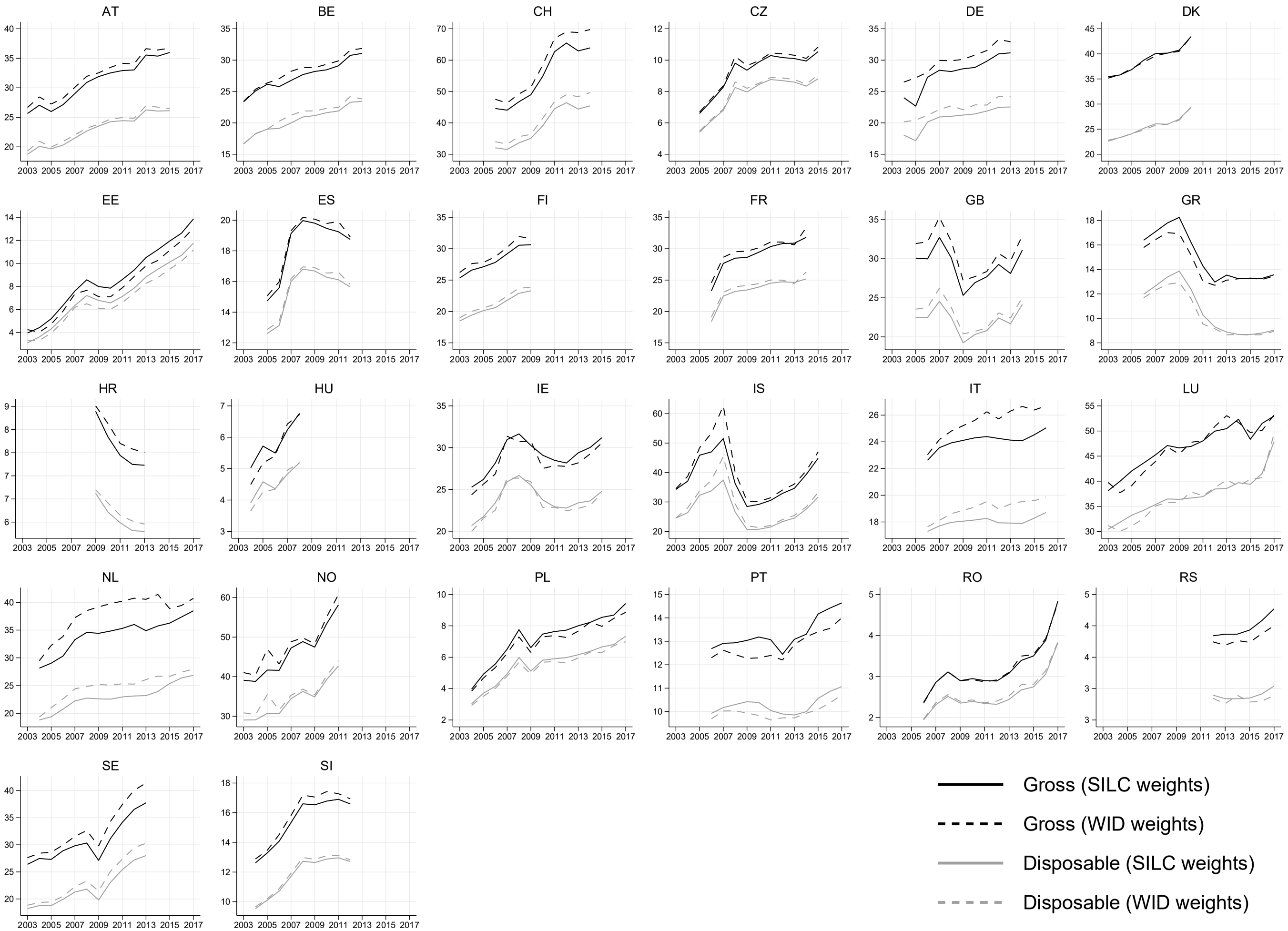
Note: Gini estimates for equivalised household gross income (hy010) using the OECD scale. Top income shares from the World Inequality Database plus the updated series in Blanchet et al. (2020).

Figure 4: Percentual change in Gini index after WID adjustment



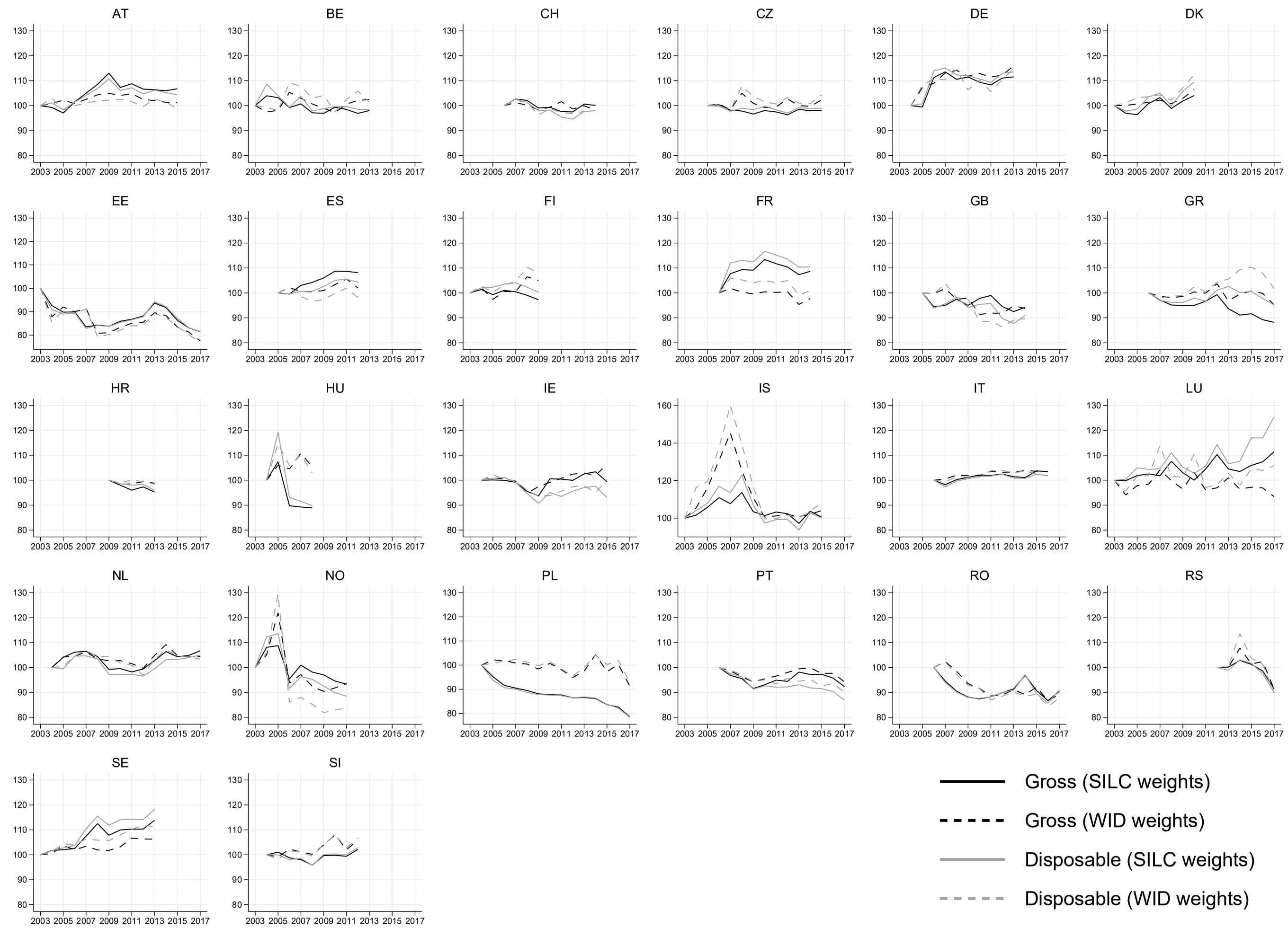
Note: Gini estimates for the SILC income concepts household gross and household disposable income (hy010 and hy020). Household totals divided by the OECD equivalence scale. SILC and WID-adjusted weights. Hungary (HU) and Iceland (IS) have a different scale in the y-axis due to, respectively, the strong drop in inequality prior to 2006 and the large spike in inequality in 2007. Horizontal dashed line set at zero (no change).

Figure 5: Average income before and after WID adjustment



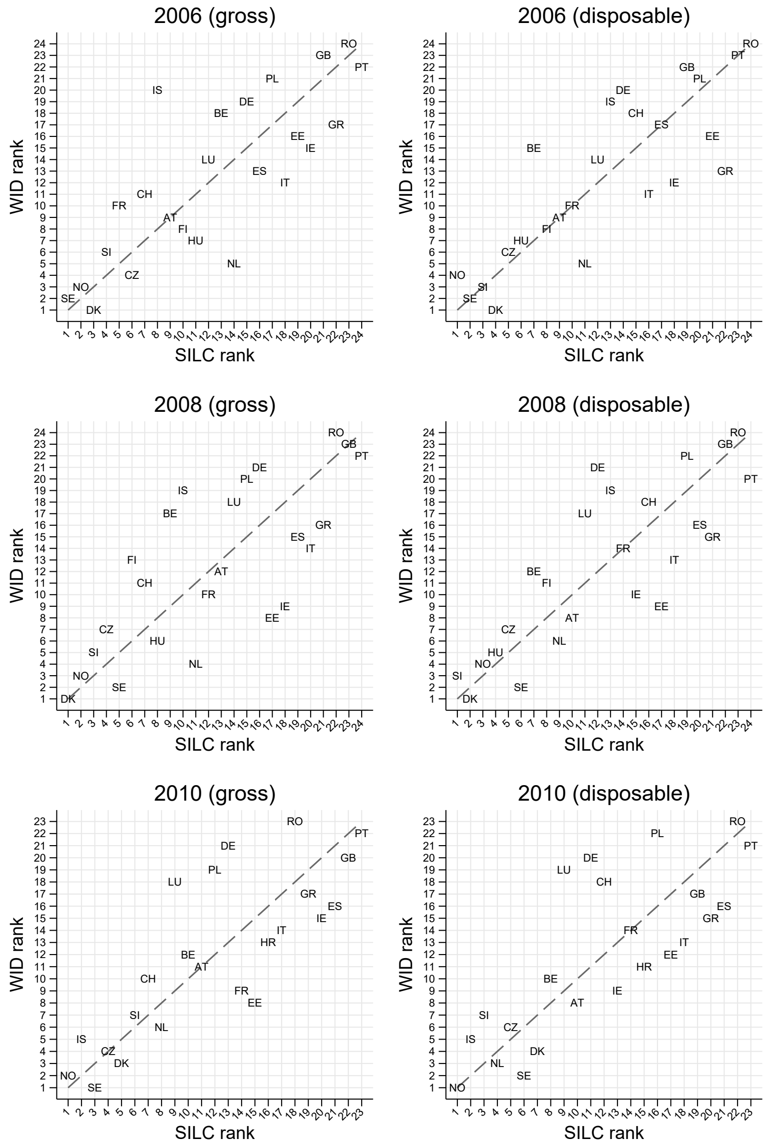
Note: Average income in thousands of Euros. Both gross and disposable income are measured as the household level and equivalised using the OECD scale. SILC and WID-adjusted weights.

Figure 6: Impact of WID adjustment – Evolution of the Gini index over time



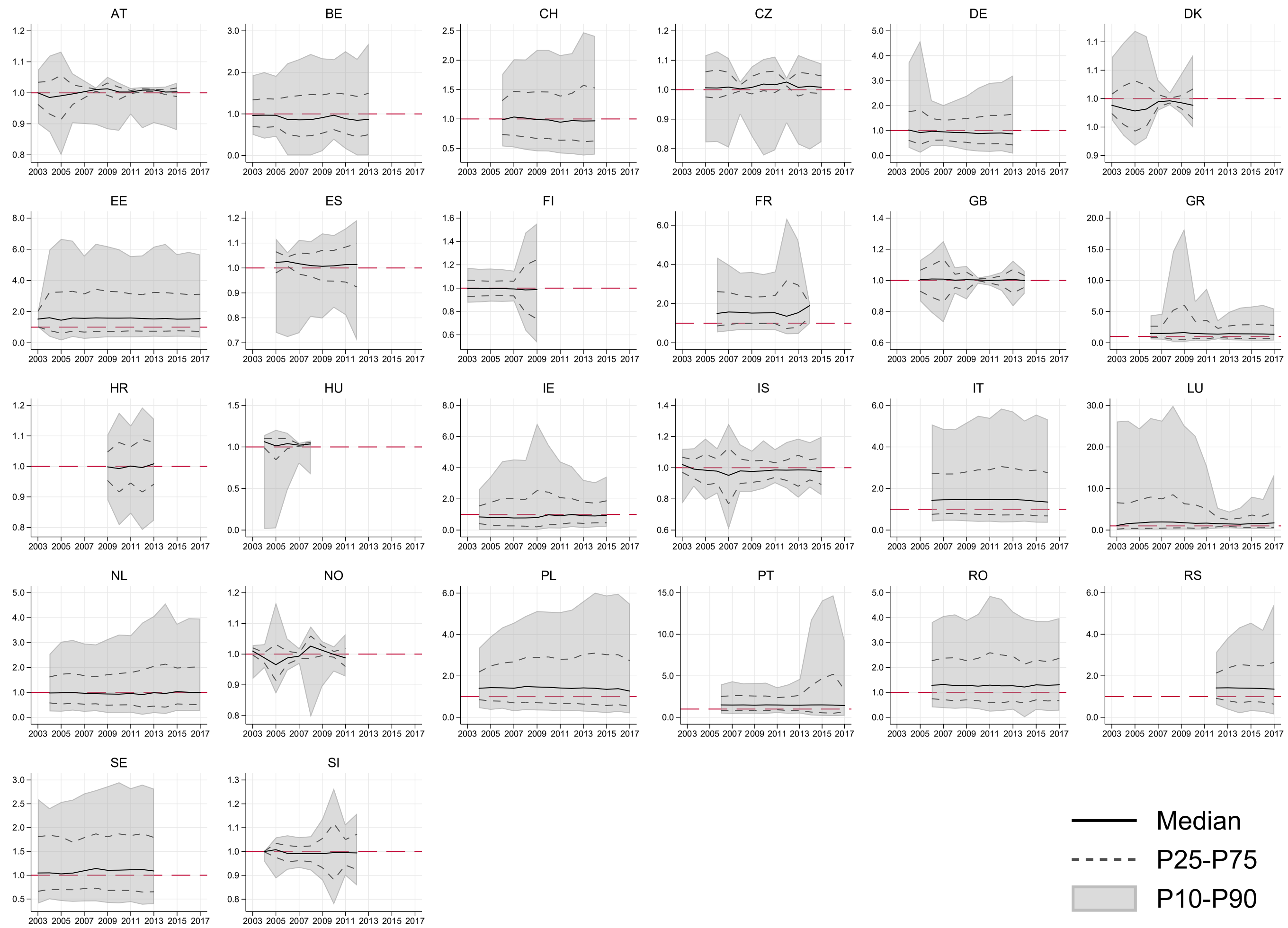
Note: Gini estimates for the SILC income concepts household gross and household disposable income (hy010 and hy020). Household totals divided by the OECD equivalence scale. SILC and WID-adjusted weights. For each country, the first year in the database is set to 100. Iceland (IS) has a different scale in the y-axis due to the large spike in inequality in 2007.

Figure 7: Impact of WID adjustment – Reranking



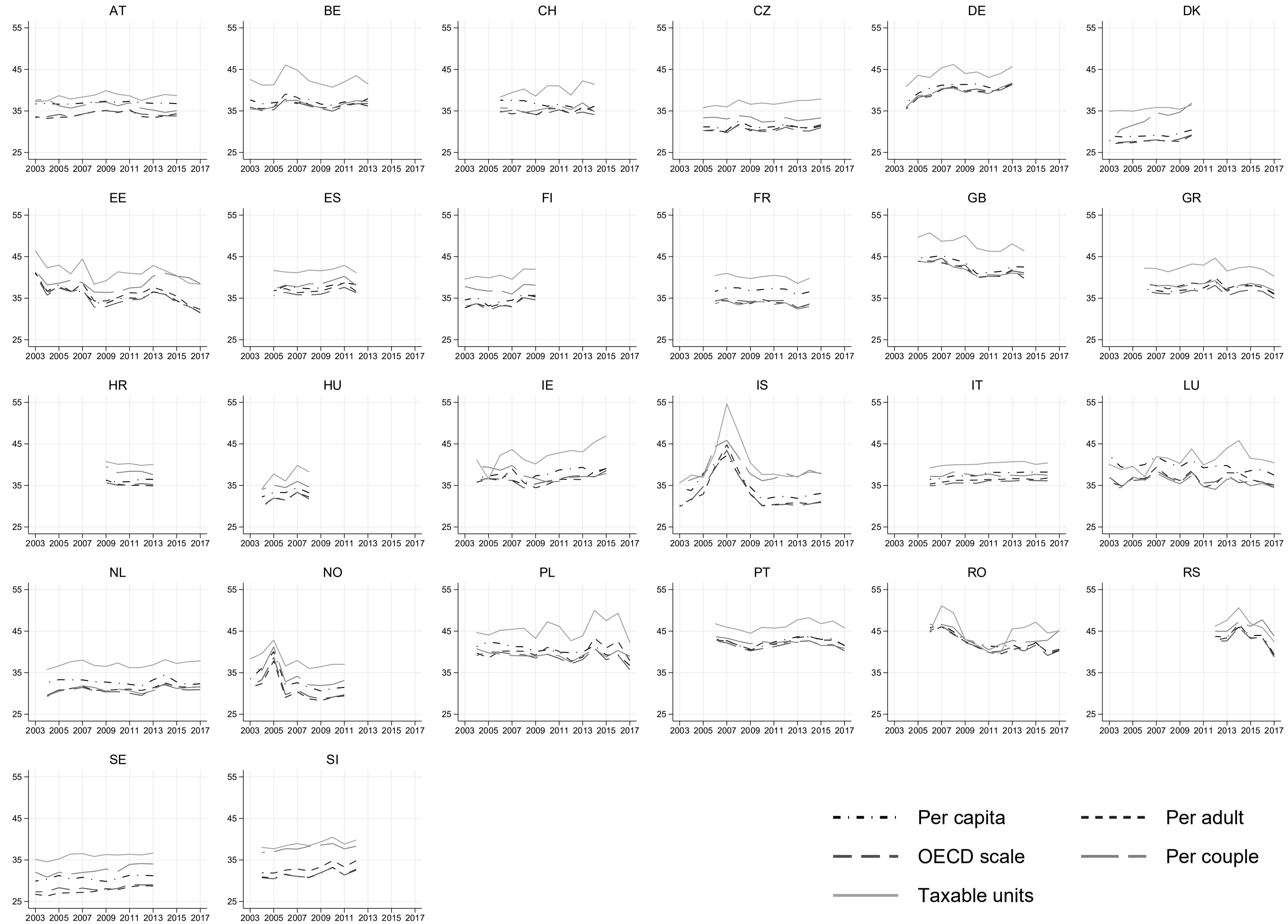
Note: Country rankings using the Gini index under SILC and WID weights (x-axis and y-axis, respectively). We look at the three years with the largest number of countries. The first column looks at equivalised gross income (hy010) rankings and the second column looks at equivalised disposable income (hy020), both using the equivalised OECD scale. Countries are ranked from lower to higher inequality. Countries below the diagonal line see their position improved (lower relative inequality) after the WID adjustment. Countries above the diagonal line see their position worsened (higher relative inequality) after the WID adjustment.

Figure 8: The reweighted distribution by year



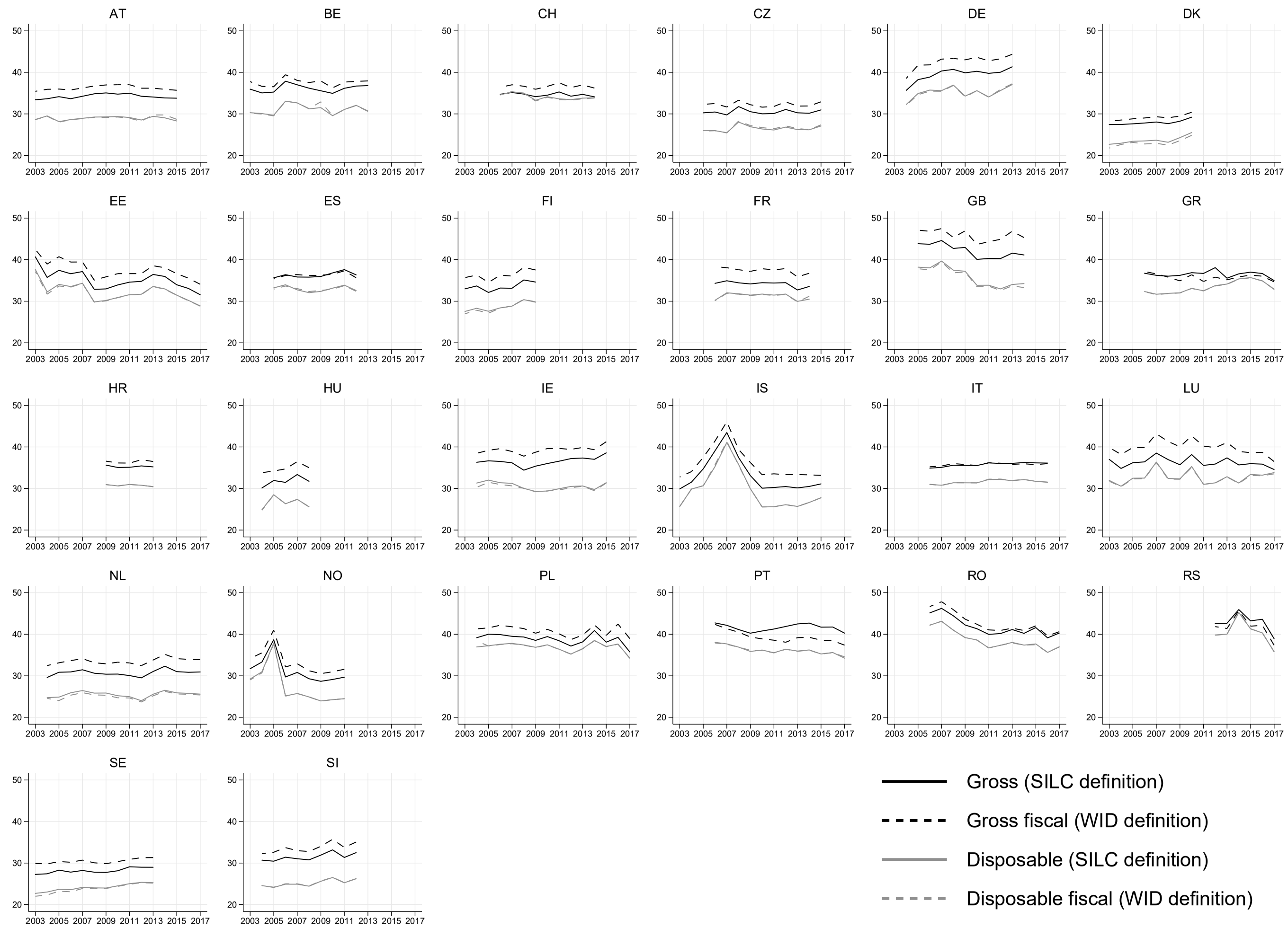
Note: Ratio between the calibrated WID weight and the original SILC weight across years. The solid line is the median for each year. The dashed lines are the 25th and 75th percentiles and the grey area represents the 10th and 90th percentiles. The red dashed line is fixed at a ratio of 1, representing no reweighting. The Y-axis differs across countries to show the extent of the reweighting.

Figure 9: Gini index under different units of observation



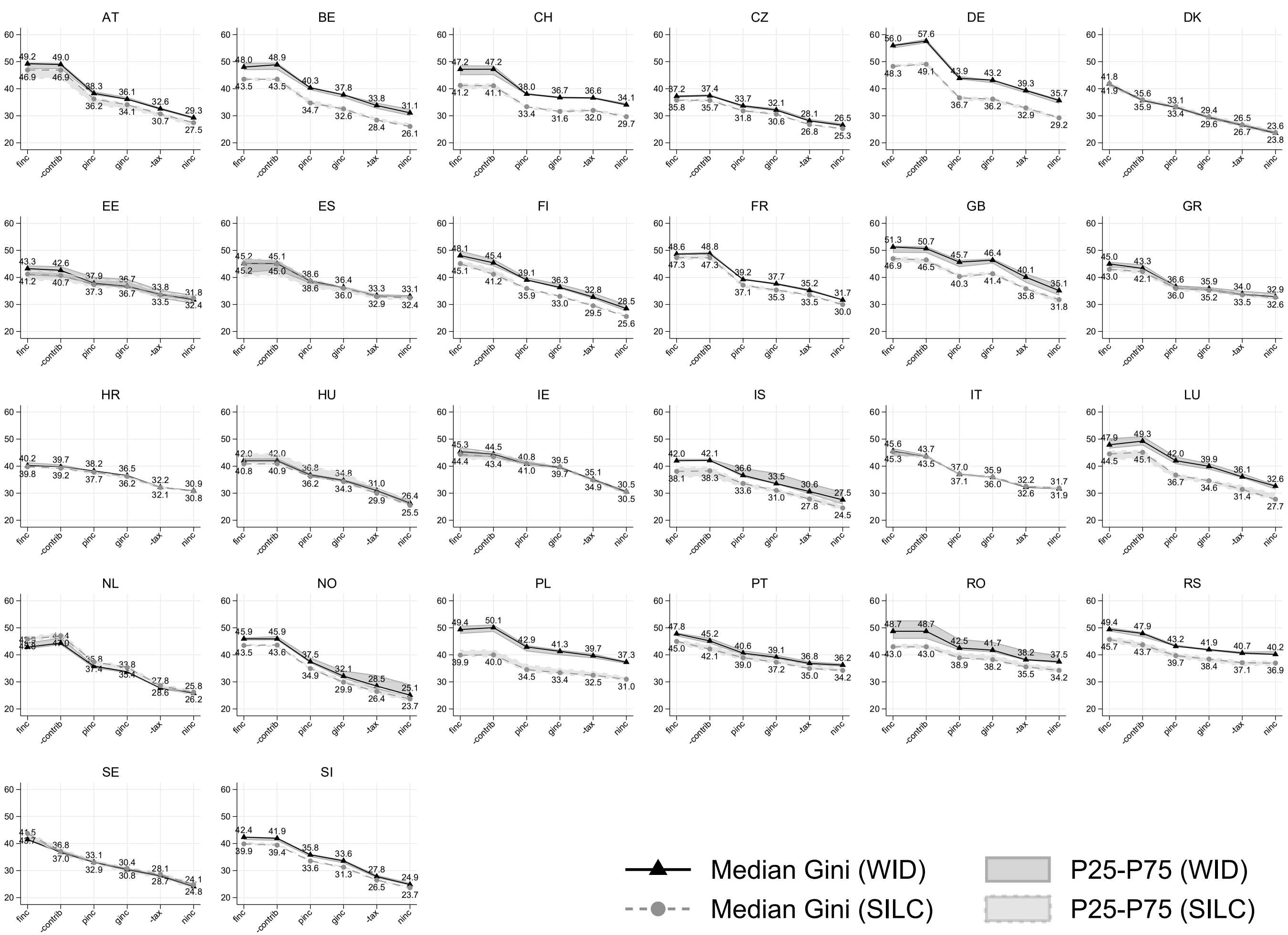
Note: Gini estimates for household gross income (hy010). The per capita scale considers all household members. Per adult excludes all household members aged less than years of age. The OECD equivalence scale is the benchmark for most of our estimates. Per couple divides household income by two if the individuals are married or in a consensual unit, while taxable units vary depending on the country's tax legislation. WID-adjusted weights.

Figure 10: Gini index under different income concepts



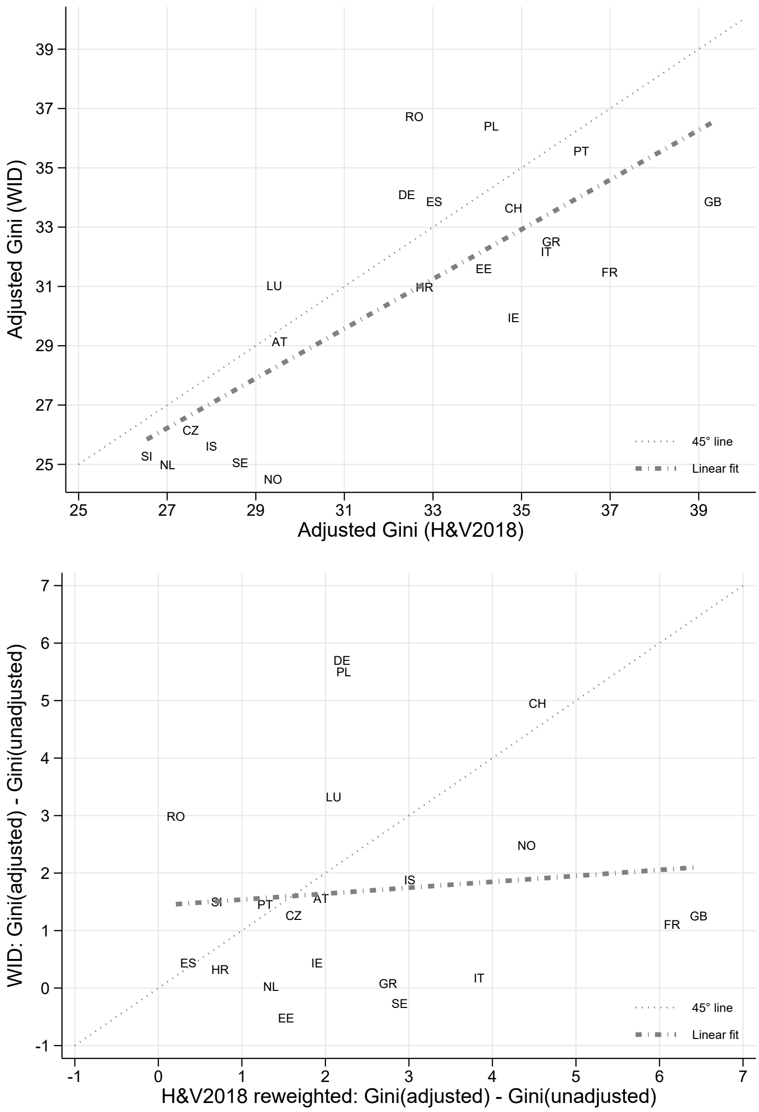
Note: Gini estimates for the two SILC income concepts household gross and household disposable income (hy010 and hy020) and for the two WID income concepts household gross fiscal and household disposable fiscal income (ginc and ninc). All income totals are divided by the OECD equivalence scale. WID-adjusted weights.

Figure 11: The influence of each income component on the Gini index (SILC and WID weights)



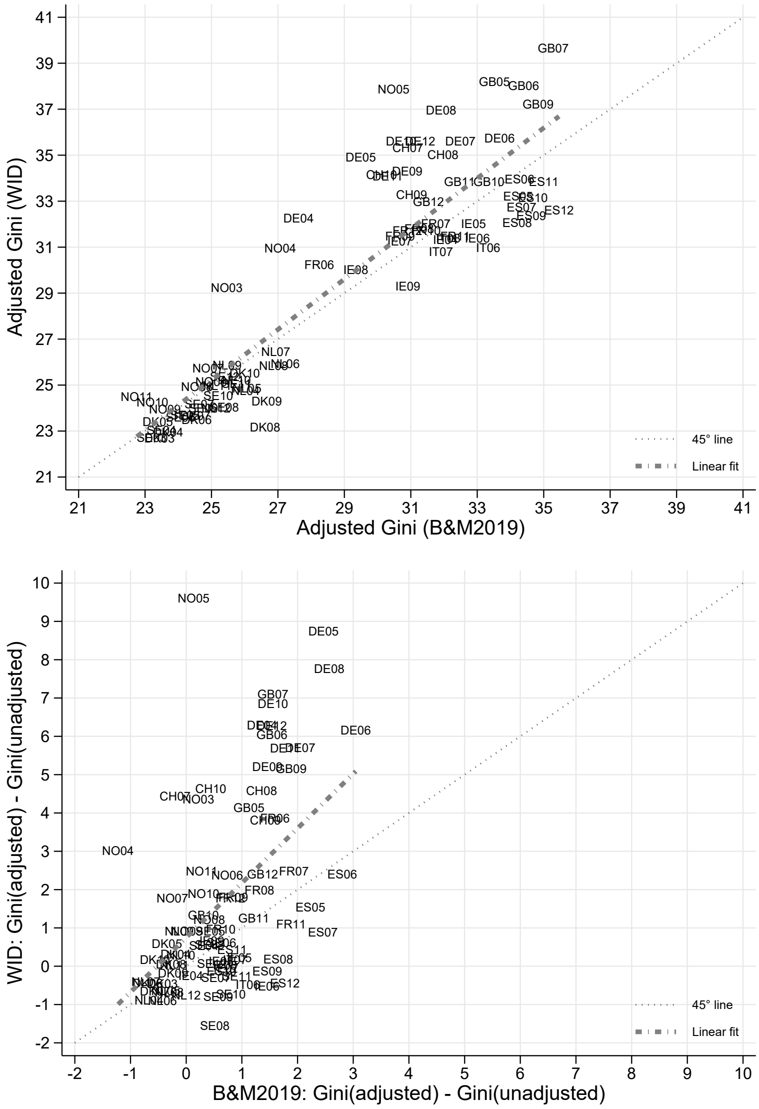
Note: Gini index for each income concept using SILC weights (in grey) and WID weights (in black). We compute the Gini for each year and report three percentiles 25, 50, and 75 for each country. The lines are the median Gini for each country. The surrounding area represents the 25th and 75th percentile for each country. All income concepts are equivalised using the OECD scale. Each income concept adds a new component to the previous one. Income concepts: (1) Factor income (finc), (2) minus social contributions, (3) plus pension benefits (pinc), (4) plus unemployment benefits (ginc), (5) minus direct taxes to income and wealth, and (6) plus direct social transfers (ninc).

Figure 12: Gini estimates – WID data vs Hlasny and Verme (2018)



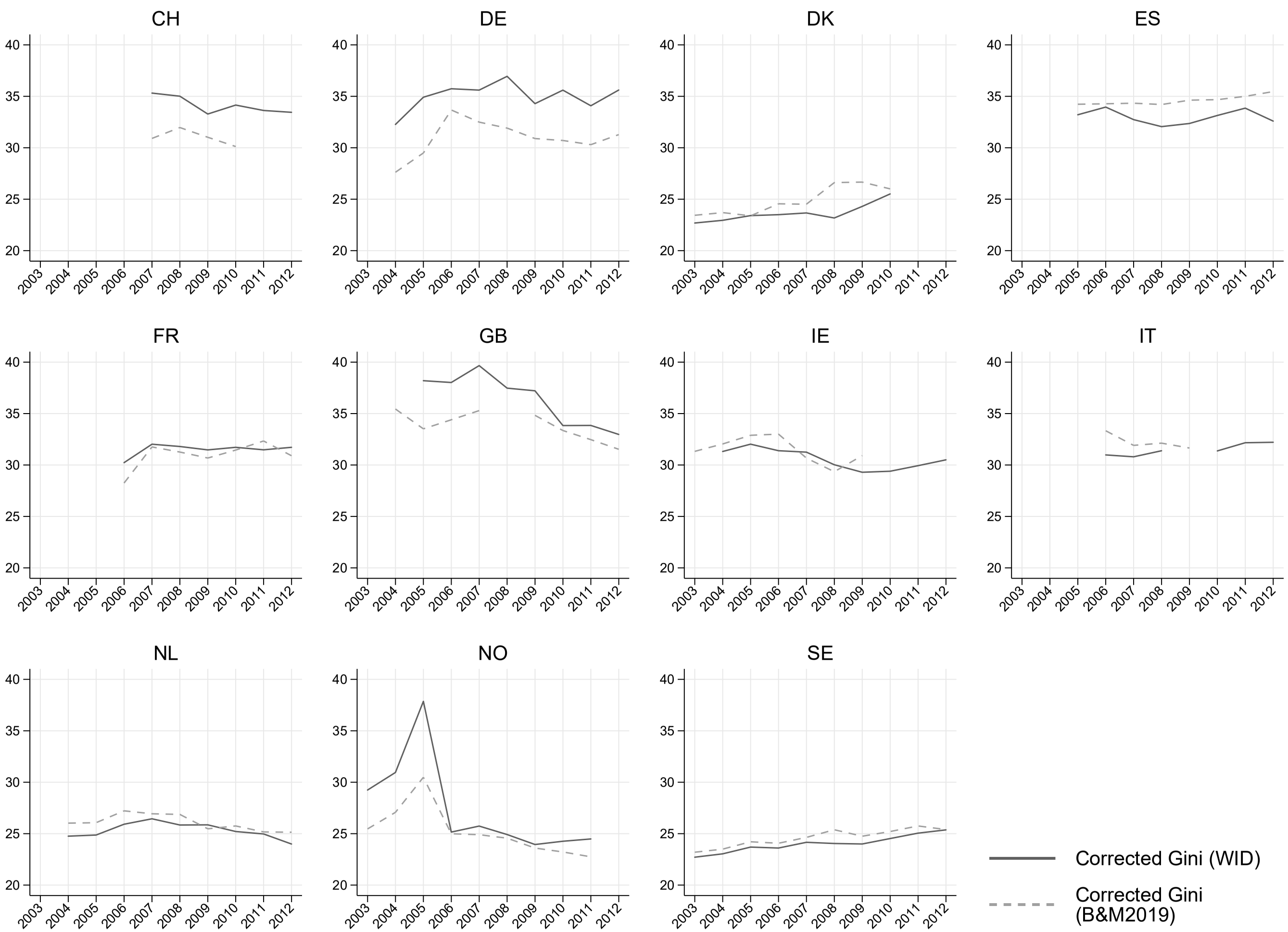
Note: 2011 Estimates for equivalised household disposable income (hy020) using the OECD scale. The first panel compares the adjusted Gini estimates in both papers, both using adjusted weights. The second panel reports the difference between the adjusted Gini and the Unadjusted Gini for each specific paper. Figure excludes Belgium as the Hlasny and Verme (2018) adjustment increases its Gini by over 20 points. The dotted line is the 45° line and the thick dashed line is the linear fit.

Figure 13: Gini estimates – WID data vs Bartels and Metzing (2019)



Note: Estimates for equivalised household disposable income using the OECD scale. The first panel compares the adjusted Gini estimates in both papers, both using adjusted weights. The second panel reports the difference between the adjusted Gini and the Unadjusted Gini for each specific paper. WID estimates for equivalised household disposable income (hy020) using the OECD scale. Bartels and Metzing (2019) estimates use predicted equivalent net household income based on the imputed (i.e., adjusted) gross household income, using an approximation of the tax-benefit system introduced by Feldstein (1969). Bartels and Metzing (2019) replace the top 1% of observations and impute synthetic values from a Pareto distribution estimated using WID top 1% and 0.1% shares. Register countries: DK, NO, SE, NL, IE, ES (since 2008), FR (since 2008), IT (since 2011) and CH (since 2007). Survey Countries: DE and UK. For Ireland and the Netherlands the Pareto α is calculated with the income share ratios of top 1% and top 0.5%, since the income share of the top 0.1% is currently not available in WID. The dotted line is the 45° line and the thick dashed line is the linear fit.

Figure 14: Gini trends – WID vs Bartels and Metzing (2019)



Note: adjusted Gini estimates. WID estimates for equivalised household disposable income (hy020) using the OECD scale. Bartels and Metzing (2019) estimates use predicted equivalent net household income based on the imputed (i.e., adjusted) gross household income, using an approximation of the tax-benefit system introduced by citeFeldstein1969). Bartels and Metzing (2019) replace the top 1% of observations and impute synthetic values from a Pareto distribution estimated using WID top 1% and 0.1% shares. Register countries: DK, NO, SE, NL, IE, ES (since 2008), FR (since 2008), IT (since 2011) and CH (since 2007). Survey Countries: DE and UK. For Ireland and the Netherlands the Pareto α is calculated with the income share ratios of top 1% and top 0.5%, since the income share of the top 0.1% is currently not available in WID.

Table 1: Comparison of the three top income adjustment methods

	Blanchet et al. (2020)			Bartels and Metzing (2019)			Hlasny and Verme (2018)		
	Gini	Increase (level)	Increase (%)	Gini	Increase (level)	Increase (%)	Gini	Increase (level)	Increase (%)
DE	34.1	5.7	20.1%	30.3	1.8	6.2%	32.4	2.2	7.3%
ES	33.9	0.4	1.3%	35.0	0.8	2.4%	33.0	0.4	1.1%
FR	31.5	1.1	3.6%	32.3	1.9	6.2%	37.0	6.2	19.9%
GB	33.8	1.2	3.8%	32.5	1.2	3.9%	39.3	6.5	19.7%
NL	25.0	0.0	0.1%	25.2	-0.2	-0.8%	27.0	1.4	5.3%
NO	24.5	2.5	11.2%	22.7	0.3	1.2%	29.4	4.4	17.7%
SE	25.1	-0.3	-1.1%	25.8	0.9	3.7%	28.7	2.9	11.2%

Note: Comparison of the adjusted Gini index from Hlasny and Verme (2018), Bartels and Metzing (2019) and Blanchet et al. (2020), all using household disposable income (hy020), equivalised using the OECD scale (Bartels and Metzing (2019) use a predicted value as their income measure, derived as a function of gross income). It includes all countries for which there is data in 2011.

Table 2: Average and median size unit of observation per country

	Capita		Adult		OECD		Couple		Tax Unit	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
AT	3.1	3.0	2.1	2.0	1.9	1.8	1.7	2.0	1.5	1.0
BE	3.2	3.0	2.1	2.0	1.9	2.0	1.8	2.0	1.5	1.0
CH	3.0	3.0	2.1	2.0	1.9	1.8	1.8	2.0	1.5	1.0
CZ	3.0	3.0	2.2	2.0	1.9	1.8	1.7	2.0	1.6	1.0
DE	2.8	2.0	2.0	2.0	1.8	1.5	1.8	2.0	1.4	1.0
DK	3.2	3.0	2.0	2.0	1.9	2.0	1.7	2.0	1.4	1.0
EE	3.4	3.0	2.4	2.0	2.1	2.0	1.7	2.0	2.0	2.0
ES	3.4	3.0	2.5	2.0	2.1	2.0	1.8	2.0	1.8	2.0
FI	3.3	3.0	2.0	2.0	2.0	2.0	1.7	2.0	1.5	1.0
FR	3.1	3.0	2.0	2.0	1.9	1.9	1.8	2.0	1.5	1.0
GB	3.0	3.0	2.0	2.0	1.9	1.8	1.7	2.0	1.4	1.0
GR	3.1	3.0	2.4	2.0	1.9	2.0	1.8	2.0	1.6	1.0
HR	3.5	3.0	2.7	2.0	2.1	2.0	1.7	2.0	1.9	2.0
HU	3.3	3.0	2.4	2.0	2.0	2.0	1.7	2.0	1.8	2.0
IE	3.4	3.0	2.1	2.0	2.0	2.0	1.7	2.0	1.6	1.0
IS	3.6	4.0	2.3	2.0	2.1	2.1	1.7	2.0	1.8	2.0
IT	3.1	3.0	2.3	2.0	1.9	2.0	1.7	2.0	1.7	1.0
LU	3.4	3.0	2.3	2.0	2.0	2.0	1.8	2.0	1.7	1.0
NL	3.1	3.0	2.0	2.0	1.9	2.0	1.8	2.0	1.4	1.0
NO	3.3	3.0	2.0	2.0	2.0	2.0	1.7	2.0	1.5	1.0
PL	3.7	4.0	2.6	2.0	2.2	2.1	1.8	2.0	2.0	2.0
PT	3.2	3.0	2.4	2.0	2.0	2.0	1.8	2.0	1.8	2.0
RO	3.2	3.0	2.5	2.0	2.0	2.0	1.7	2.0	2.1	2.0
RS	4.2	4.0	3.2	3.0	2.5	2.5	1.7	2.0	2.3	2.0
SE	3.2	3.0	2.0	2.0	1.9	2.0	1.7	2.0	1.6	1.0
SI	3.8	4.0	2.9	3.0	2.3	2.3	1.7	2.0	2.3	2.0

Table 3: Comparison between definitions of gross income (SILC) and gross fiscal (WID)

SILC income (hy010)		WID income (ginc)	
Individual income components		Individual income components	
Gross employee cash or near cash income	PY010G	Gross employee cash or near cash income	PY010G
Company car	PY021G	Company car	PY021G
		Employer's social insurance contribution	PY030G
Gross cash benets or losses from self-employment, including royalties	PY050G	Gross cash benets or losses from self-employment, including royalties	PY050G
Pensions received from individual private plans, other than those covered under ESSPROS	PY080G	Pensions received from individual private plans, other than those covered under ESSPROS	PY080G
Unemployment benefits	PY090G	Unemployment benefits	PY090G
Old-age benefits	PY100G	Old-age benefits	PY100G
Survivor' benefits	PY110G	Survivor' benefits	PY110G
Sickness benefits	PY120G	Sickness benefits	PY120G
Disability benefits	PY130G	Disability benefits	PY130G
Education-related allowances	PY140G		
Household income components		Household income components	
Income from rental of a property or land	HY040G	Income from rental of a property or land	HY040G
Family/children related allowances	HY050G		
Social exclusion not elsewhere classified	HY060G		
Housing allowances	HY070G		
Regular inter-household cash transfers received	HY080G		
Interests, dividends, profit from capital investments in unincorporated business	HY090G	Interests, dividends, profit from capital investments in unincorporated business	HY090G
Income received by people aged under 16	HY110G	Income received by people aged under 16	HY110G
Deductions:		Deductions:	
None		Income tax (contribution to unemployment and pensions benefits)	OECD data
		Social contributions (share accrued to unemployment and pensions)	OECD data
		Employer's social insurance contribution (share acrrued to unemployment and pensions)	PY030G
		Contributions to individual private pension plans	PY035G

Appendix

A Additional Tables

Table A.1: Change in top 1% share after WID-adjustment (gross income)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
AT	2.5	2.3	3.2	2.1	-	1.5	1.2	1.7	1.7	1.6	1.9	1.6	1.3	-	-	1.9
BE	2.9	0.5	0.5	3.3	3.0	3.6	2.9	2.1	2.7	3.6	2.2	-	-	-	-	2.5
CH	-	-	-	3.9	3.8	3.5	3.6	3.7	3.9	3.3	2.2	3.4	-	-	-	3.5
CZ	-	-	1.7	1.8	1.6	2.6	2.2	1.9	1.9	2.4	2.1	2.0	3.1	-	-	2.1
DE	-	3.9	5.3	5.2	5.9	6.0	4.8	5.9	5.9	5.4	5.3	-	-	-	-	5.4
DK	-0.7	0.0	0.1	-0.9	-1.1	-0.1	-0.3	-0.3	-	-	-	-	-	-	-	-0.4
EE	1.7	0.8	3.6	2.7	3.0	0.0	0.6	0.8	0.6	0.6	0.6	0.6	0.4	0.2	0.0	1.1
ES	-	-	2.5	2.2	1.4	1.2	0.9	0.8	1.3	1.1	-	-	-	-	-	1.4
FI	1.7	2.0	0.7	1.5	1.9	1.9	1.3	-	-	-	-	-	-	-	-	1.6
FR	-	-	-	4.4	3.1	1.8	1.7	1.2	1.5	2.0	0.2	1.1	-	-	-	1.9
GB	-	-	4.7	5.4	6.9	5.1	5.6	2.6	1.4	2.8	3.7	4.0	-	-	-	4.2
GR	-	-	-	-1.2	-1.0	-0.6	-0.2	0.8	-0.7	-0.8	-0.1	1.8	2.1	2.4	1.0	0.3
HR	-	-	-	-	-	-	0.5	0.8	1.3	1.1	1.7	-	-	-	-	1.1
HU	-	-0.3	-0.6	3.2	2.5	1.6	-	-	-	-	-	-	-	-	-	1.3
IE	-	1.3	1.6	2.2	1.8	1.3	2.0	1.6	2.5	3.0	1.9	1.8	4.1	-	-	2.1
IS	3.6	4.2	2.9	4.8	1.1	2.5	2.0	1.1	0.8	1.1	2.1	1.1	2.1	-	-	2.3
IT	-	-	-	0.5	0.9	0.7	-	0.0	0.5	0.1	0.6	0.9	0.3	0.5	-	0.5
LU	1.3	2.2	1.4	2.7	4.9	2.1	2.4	4.4	2.7	2.4	4.5	4.2	3.8	2.7	1.3	2.9
NL	-	-0.5	0.1	-0.1	0.3	-0.1	0.6	0.6	0.6	0.7	0.4	0.3	-0.3	0.1	-0.6	0.1
NO	4.0	2.3	7.5	1.9	1.6	2.0	1.0	1.7	1.8	-	-	-	-	-	-	2.7
PL	-	3.5	4.6	6.7	7.0	7.0	5.9	5.9	5.7	4.3	4.4	4.7	4.3	4.9	3.3	5.2
PT	-	-	-	1.1	1.2	0.6	1.0	0.8	0.8	1.5	1.0	1.1	1.1	1.0	1.0	1.0
RO	-	-	-	3.9	6.9	6.5	5.8	4.9	2.9	2.5	4.0	2.5	4.2	3.5	1.9	4.1
RS	-	-	-	-	-	-	-	-	-	3.1	3.0	3.9	3.7	5.3	3.0	3.7
SE	1.3	0.7	1.5	1.2	1.0	0.0	1.2	0.9	1.8	1.6	0.9	-	-	-	-	1.1
SI	-	0.6	0.6	1.1	0.9	1.0	0.8	1.2	0.7	0.7	-	-	-	-	-	0.8
Mean	2.0	1.6	2.3	2.5	2.5	2.2	2.1	2.0	1.9	2.0	2.1	2.2	2.3	2.3	1.4	2.1

Table A.2: Change in top 1% share after WID-adjustment (disposable income)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
AT	1.9	1.9	1.3	1.5	-	0.8	0.7	1.3	1.0	0.7	1.8	1.3	0.9	-	-	1.3
BE	2.6	0.8	0.7	3.9	3.7	4.1	4.1	2.0	2.8	4.7	2.2	-	-	-	-	2.9
CH	-	-	-	3.7	4.2	4.2	3.0	3.6	2.6	3.7	2.3	4.0	-	-	-	3.5
CZ	-	-	1.4	1.4	1.3	2.6	2.1	1.8	1.7	2.0	1.9	1.8	2.9	-	-	1.9
DE	-	4.9	6.2	6.3	5.6	7.0	4.0	5.5	4.2	5.2	5.6	-	-	-	-	5.5
DK	-0.7	0.0	0.0	-0.9	-1.0	-0.1	-0.3	-0.2	-	-	-	-	-	-	-	-0.4
EE	1.7	0.6	3.2	2.4	3.0	-0.2	0.4	0.6	0.5	0.4	0.5	0.4	0.5	0.1	0.1	0.9
ES	-	-	2.3	2.2	1.5	0.8	0.7	0.7	1.0	0.9	-	-	-	-	-	1.3
FI	1.6	1.8	0.8	1.6	2.0	2.1	1.5	-	-	-	-	-	-	-	-	1.6
FR	-	-	-	3.1	2.3	1.6	1.5	1.2	1.1	1.9	0.1	1.0	-	-	-	1.5
GB	-	-	3.8	4.7	6.7	4.3	4.7	1.7	1.0	1.8	2.6	2.8	-	-	-	3.4
GR	-	-	-	-0.7	-0.8	-0.5	-0.2	0.5	-0.5	-0.7	-0.1	1.8	2.0	2.0	0.8	0.3
HR	-	-	-	-	-	-	0.3	0.5	0.6	0.5	0.9	-	-	-	-	0.6
HU	-	-0.4	-0.8	2.3	2.0	0.9	-	-	-	-	-	-	-	-	-	0.8
IE	-	1.1	1.6	1.4	1.3	0.9	1.0	1.2	1.7	1.8	1.3	1.0	3.5	-	-	1.5
IS	2.5	5.6	1.7	4.5	1.7	2.6	1.5	1.3	1.0	1.2	2.0	1.1	2.5	-	-	2.2
IT	-	-	-	0.4	0.7	0.5	-	0.0	0.4	0.4	0.6	0.7	0.3	0.4	-	0.4
LU	0.9	1.8	1.6	2.7	6.7	1.3	3.0	6.0	2.3	1.5	3.8	2.7	2.6	2.4	1.1	2.7
NL	-	-0.4	0.1	-0.1	0.5	0.0	0.7	0.4	0.4	0.6	0.5	0.3	-0.2	0.1	-0.6	0.2
NO	5.2	3.1	10.0	1.8	1.3	1.7	0.8	1.4	1.3	-	-	-	-	-	-	3.0
PL	-	2.5	3.6	6.3	7.3	6.6	6.0	5.4	5.3	3.6	4.2	3.8	4.4	4.6	3.4	4.8
PT	-	-	-	0.8	0.8	0.6	0.9	0.6	0.4	1.1	0.9	1.3	1.2	1.2	1.2	0.9
RO	-	-	-	4.6	7.2	6.0	5.8	4.9	2.8	3.1	3.9	2.5	3.3	3.2	1.7	4.1
RS	-	-	-	-	-	-	-	-	-	3.2	3.8	6.0	4.1	5.0	2.9	4.2
SE	0.8	0.6	1.0	1.0	0.7	0.2	0.9	0.9	1.0	1.4	0.7	-	-	-	-	0.8
SI	-	0.4	0.4	0.7	0.6	0.6	0.5	0.7	0.5	0.6	-	-	-	-	-	0.5
Mean	1.8	1.6	2.2	2.3	2.6	2.0	1.9	1.8	1.5	1.8	2.0	2.0	2.2	2.1	1.3	2.0

Table A.3: Change in Gini after WID-adjustment (gross income)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
AT	3.5	4.0	5.1	3.3	-	2.4	1.2	2.7	2.4	2.4	2.3	2.1	1.9	-	-	2.8
BE	4.5	2.3	2.8	6.6	5.3	5.6	5.0	3.7	5.2	6.2	5.9	-	-	-	-	4.8
CH	-	-	-	4.8	4.4	4.2	4.5	4.8	6.1	5.1	4.6	4.2	-	-	-	4.8
CZ	-	-	0.8	0.9	0.8	2.9	2.0	1.1	1.4	2.7	1.2	1.3	2.0	-	-	1.6
DE	-	5.4	8.2	5.2	6.0	7.3	6.2	7.2	7.0	6.5	7.6	-	-	-	-	6.7
DK	-0.4	0.4	0.8	-0.3	-0.7	0.1	-0.2	0.2	-	-	-	-	-	-	-	0.0
EE	0.5	-1.5	1.3	0.5	3.6	-1.0	-0.7	-0.6	-0.3	-0.7	-1.2	-1.0	-0.8	-0.3	-1.2	-0.2
ES	-	-	1.6	2.6	0.8	0.4	-0.1	-0.1	0.7	-0.4	-	-	-	-	-	0.7
FI	2.7	3.0	2.1	2.6	2.7	5.2	5.2	-	-	-	-	-	-	-	-	3.4
FR	-	-	-	4.8	3.1	2.1	1.9	1.0	1.4	1.9	1.0	1.5	-	-	-	2.1
GB	-	-	4.7	6.8	7.4	4.6	5.8	1.8	1.6	3.3	5.4	4.3	-	-	-	4.6
GR	-	-	-	-1.5	-0.9	-0.3	-0.1	0.6	-0.2	0.1	-0.2	1.8	2.0	2.6	1.3	0.4
HR	-	-	-	-	-	-	-0.2	0.0	0.7	0.6	1.1	-	-	-	-	0.4
HU	-	-4.2	-5.0	0.6	2.7	1.2	-	-	-	-	-	-	-	-	-	-0.9
IE	-	-0.3	0.0	-0.1	-0.1	-0.6	1.1	-0.8	-0.2	0.6	-0.2	-0.8	2.2	-	-	0.1
IS	2.6	3.8	5.9	8.8	14.1	6.4	4.9	2.4	2.1	2.5	3.6	2.2	3.7	-	-	4.9
IT	-	-	-	-0.5	0.3	0.1	-	-0.6	0.1	-0.3	0.1	0.5	-0.6	-0.5	-	-0.1
LU	6.5	4.4	5.2	5.2	7.5	4.2	4.3	7.7	3.7	2.3	5.5	4.1	3.7	3.2	0.6	4.5
NL	-	-0.7	-0.7	-1.2	-0.8	-1.0	0.4	0.3	0.3	-0.6	-0.1	0.1	-0.6	-0.9	-1.4	-0.5
NO	3.3	2.6	7.8	2.6	2.2	1.4	1.1	2.3	3.2	-	-	-	-	-	-	3.0
PL	-	2.1	4.7	6.0	6.0	6.2	5.9	7.0	6.0	5.1	6.1	9.0	7.1	8.7	6.7	6.2
PT	-	-	-	1.1	1.9	1.4	2.2	2.1	1.8	2.6	1.6	2.3	1.2	1.9	1.9	1.8
RO	-	-	-	3.7	7.0	7.0	5.7	5.1	3.4	2.9	3.3	0.1	4.0	3.2	2.8	4.0
RS	-	-	-	-	-	-	-	-	-	2.8	2.8	5.0	2.9	4.4	2.6	3.4
SE	1.1	0.8	1.6	1.0	0.1	-1.6	-0.5	-0.6	0.2	0.1	-0.8	-	-	-	-	0.1
SI	-	1.3	0.7	2.4	2.2	2.6	2.6	3.8	2.1	2.5	-	-	-	-	-	2.2
Mean	2.7	1.6	2.6	2.7	3.3	2.5	2.5	2.2	2.2	2.2	2.5	2.3	2.2	2.5	1.7	2.4

Table A.4: Change in Gini after WID-adjustment (disposable income)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
AT	2.9	3.5	2.8	2.6	-	1.7	0.8	2.1	1.6	1.6	2.1	2.0	1.5	-	-	2.1
BE	4.1	1.7	2.5	7.1	5.5	5.6	5.7	3.5	5.0	6.3	5.0	-	-	-	-	4.7
CH	-	-	-	4.5	4.4	4.6	3.8	4.6	4.9	5.0	4.4	4.4	-	-	-	4.5
CZ	-	-	0.7	0.7	0.8	3.0	2.0	1.1	1.3	2.3	1.1	1.2	2.0	-	-	1.5
DE	-	6.3	8.7	6.2	5.7	7.8	5.2	6.8	5.7	6.3	7.6	-	-	-	-	6.6
DK	-0.5	0.3	0.6	-0.4	-0.7	0.1	-0.2	0.2	-	-	-	-	-	-	-	-0.1
EE	0.5	-1.5	1.0	0.3	3.6	-1.4	-0.9	-0.8	-0.5	-0.9	-1.5	-1.3	-0.9	-0.7	-1.4	-0.4
ES	-	-	1.5	2.4	0.9	0.2	-0.1	-0.1	0.4	-0.4	-	-	-	-	-	0.6
FI	2.4	2.7	1.9	2.4	2.7	4.7	4.6	-	-	-	-	-	-	-	-	3.0
FR	-	-	-	3.9	2.5	2.0	1.8	1.0	1.1	1.8	0.9	1.4	-	-	-	1.8
GB	-	-	4.1	6.0	7.1	4.0	5.2	1.3	1.2	2.4	4.2	3.3	-	-	-	3.9
GR	-	-	-	-1.2	-0.8	-0.4	-0.2	0.2	0.1	-0.2	-0.3	1.8	1.9	2.1	1.0	0.3
HR	-	-	-	-	-	-	-0.3	-0.2	0.3	0.0	0.5	-	-	-	-	0.1
HU	-	-2.5	-4.2	0.8	2.3	1.0	-	-	-	-	-	-	-	-	-	-0.5
IE	-	-0.3	0.2	-0.5	0.0	0.1	0.7	-0.6	0.4	0.3	0.0	-1.0	2.0	-	-	0.1
IS	1.8	5.0	4.8	7.3	13.9	6.4	4.4	2.3	1.9	2.3	3.3	2.1	3.8	-	-	4.6
IT	-	-	-	-0.5	0.2	0.0	-	-0.6	0.2	0.0	0.1	0.5	-0.5	-0.5	-	-0.1
LU	5.7	4.2	5.0	5.2	8.9	3.3	4.7	8.4	3.3	1.4	4.9	3.1	2.7	2.6	1.0	4.3
NL	-	-0.9	-0.6	-0.9	-0.4	-0.7	0.9	0.3	0.0	-0.8	0.0	0.1	-0.6	-0.9	-1.3	-0.4
NO	4.4	3.0	9.6	2.4	1.8	1.2	0.9	1.9	2.5	-	-	-	-	-	-	3.1
PL	-	1.6	4.0	5.5	5.9	6.0	5.8	6.5	5.5	4.7	5.8	7.9	7.4	8.6	6.5	5.8
PT	-	-	-	1.0	1.5	1.3	2.0	1.9	1.4	2.3	1.5	2.2	1.4	2.1	2.1	1.7
RO	-	-	-	4.0	7.2	6.5	5.6	5.1	3.0	2.9	3.3	0.3	3.4	2.8	2.2	3.9
RS	-	-	-	-	-	-	-	-	-	2.9	3.4	7.1	3.7	4.3	2.5	4.0
SE	0.6	0.5	0.9	0.6	-0.3	-1.5	-0.8	-0.7	-0.3	0.1	-0.9	-	-	-	-	-0.2
SI	-	0.9	0.4	1.6	1.5	1.7	1.8	2.7	1.5	1.8	-	-	-	-	-	1.6
Mean	2.4	1.6	2.4	2.5	3.2	2.4	2.3	2.0	1.8	1.9	2.3	2.2	2.2	2.3	1.6	2.3