EUROMOD

WORKING PAPER SERIES

EUROMOD Working Paper No. EM3/10

APPROXIMATIONS TO THE TRUTH: COMPARING SURVEY AND MICROSIMULATION APPROACHES TO MEASURING INCOME FOR SOCIAL INDICATORS

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June 2010

APPROXIMATIONS TO THE TRUTH: COMPARING SURVEY AND MICROSIMULATION APPROACHES TO MEASURING INCOME FOR SOCIAL INDICATORS[1]

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Abstract

This paper evaluates income distributions in four European countries (Austria, Italy, Spain and Hungary) using two complementary approaches: a standard approach based on reported incomes in survey data, and a microsimulation approach, where taxes and benefits are simulated. Given that benefit receipts tend to be under-reported in survey data, and over-estimated in microsimulation procedures, we may expect the two approaches to generate slightly different results. In fact, we find reasonably consistent results. To the extent that the results differ, we explore why these differences occur, and suggest directions for future research, where each approach may inform improvements in the other.

JEL Classification: C81; D31; I32

Keywords: Income; Microsimulation; Poverty; Inequality; Europe

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[1] This paper uses EUROMOD version D25. EUROMOD is continually being improved and updated and the results presented here represent the best available at the time of writing. Any remaining errors, results produced, interpretations or views presented are the authors' responsibility. This paper uses EU-SILC UDB versions 2005-1 and 2005-2 obtained from the European Commission (Eurostat) under contract No EU-SILC/2007/03; the Austrian version of the EU-SILC 2004 made available by Statistik Austria; and IT-SILC XUDB 2004 – version November 2007, made available by ISTAT.

[2] This paper forms part of the ALICE (Analysis of Life Chances in Europe) project which is funded by the UK's Economic and Social Research Council (ESRC) under grant number RES-062-23-1455. The development of EUROMOD has been supported by a series of European Commission Framework Programme grants and we are grateful to all members of the EUROMOD consortium, past and present. We would like to thank participants at ALICE project meetings and at the GESIS conference 2009 in Mannheim for useful comments. The results and conclusions presented in the paper reflect those of the authors and are not the responsibility of data providers or the ESRC.

1. Introduction

This paper compares empirical estimates of income distributions and poverty rates under two analytical approaches: "classical" income analysis on the one hand, and microsimulation analysis on the other. Both approaches are subject to a degree of error: the classical approach, which relies on self-reported income in survey data, tends to underestimate the incomes of the poorest people, whereas the microsimulation approach, which simulates taxes and benefits, and which does not generally take account of benefit non-take-up, tends to overestimate them. In this paper we compare estimates from the two approaches. In this way, we are able to assess the extent to which the errors inherent in each approach are likely to present problems in the empirical analysis of incomes; we are also able to suggest directions for future research which may improve the reliability of each approach.

"Classical" income analysis is based on data from large representative samples of households, which contain detailed information on the incomes of all household members from a range of sources. In some countries, highly reliable data on incomes are available; in the Scandinavian countries, for example, earnings and benefits are available in the form of official register data. In other countries, researchers rely on survey data, where respondents report their incomes from a range of sources including employment and self-employment; state benefits; pensions; and other sources such as investments, rental incomes, and so on. There is evidence that welfare benefits may be under-reported in this type of survey (Lynn et al. 2004, Meyer et al. 2009); where this is the case, it would lead to estimates of poverty rates which are excessively high - indeed, Behrendt (2002) goes so far as to suggest that estimated poverty rates would be close to zero if full entitlement of means-tested benefits were captured by income measures in survey data.

Microsimulation models are built using the same micro-level data sets as might be used in classical income analysis, but instead of using reported data on taxes and benefits, these are simulated within the model according to prevailing rules on liability and eligibility. Because of this, microsimulation addresses the problem of under-reporting of benefit incomes. However, it does not address all the problems which may be present in survey data. For example, the under-reporting of market incomes at the top of the income distribution (Ehling and Rendtel 2004) poses exactly the same problems for microsimulation data as for survey data. Other issues relate to the fact that individuals do not always act precisely according to the rules; taxes (particularly at the top of the income distribution) may be overestimated by microsimulation models, because people may not declare their entire incomes for tax purposes, or they may exploit tax loopholes (tax evasion and tax avoidance) that cannot be captured by the microsimulation process. Lower down the income scale, microsimulation models may overestimate the means-tested benefits which poorer people receive, if they assume 100% take-up of these benefits when in reality take-up may be substantially lower than this (Mantovani and Sutherland 2003, Lietz and Sutherland 2005). In principle it is possible to take account of the effects of tax evasion and benefit non-take-up in microsimulation modelling (Sutherland et al. 2009, Matsaganis et al., 2008). However, to do this in a way which is comparable across countries and which also captures the specificity of each benefit or tax in its national context, as well as the reasons for non-take-up or evasion, is challenging to say the least (Jäntti, 2009; Sutherland et al. 2009). We do not model non-take-up or tax evasion in this paper. The only exception is represented by Italy, for which gross self-employed income has been calibrated in order to obtain an aggregate amount corresponding to that in fiscal data (Fiorio and D'Amuri 2006).

The extent to which the sources of error inherent in these two approaches present problems for the researcher is, by the nature of the problem, not precisely known. Moreover, the degree of the problem varies according to the indicator under consideration. Measures of inequality which rely on data from the whole income distribution, such as the Gini coefficient, are affected by values at both ends of the income distribution. Measures such as the 90:10 ratio, which do not rely on the highest and lowest reported incomes, are more robust to errors in the extremes of the distribution, but may still be affected. Estimates of poverty (which are based on median equivalised household incomes) are likely to be much more affected by errors at the bottom than at the top of the distribution. Even fairly large reporting errors by the very wealthy are unlikely to affect estimated poverty lines or associated poverty rates, but even relatively small errors in reporting benefit income may lead to substantial errors in estimated poverty rates.

The extent to which the two approaches are susceptible to error will also vary between countries. For example, in countries where tax evasion is common practice, or there is a great deal of scope for legal tax avoidance, the microsimulation approach, in its simpler specification without modelling tax-evasion, may simulate taxes less accurately. In countries with a complex system of state benefits, there may be a higher degree of under-reporting of benefits (leading to more under-estimation in the classical approach) but also, especially if there is greater reliance on means-testing, a higher degree of non take-up (leading to more over-estimation by microsimulation models when take-up modelling is not accounted for).

In this paper, we compare four countries – Austria, Italy, Spain, and Hungary – with very different tax and benefit systems (Schibert et al. 2009).

The Austrian welfare system is one of the more generous of the EU, being built around the main pillar of social insurance combined with the two pillars of universal state support (with recent developments in the area of family and care policies) and social assistance. Spain and Italy both provide relatively low levels of welfare compared with other European countries, with the family being relied on to provide an informal safety net. In Italy particularly, there is a generous but fragmented pension system; in Spain, quite generous unemployment benefits and regional social assistance schemes have developed in order to support to the adverse labour market situations of recent decades, The Hungarian welfare system does not closely resemble any of the welfare state models of the old Europe, but the scale of government involvement in altering incomes is above the European average, similar to that of Austria, with a relevant role for both taxes and benefits. A long tradition of pension insurance is nowadays joined by relative generous support for families with children.

As a consequence, the redistributive effects of taxes and benefits are relatively large in Austria and Hungary: the share of disposable income from benefits is among the largest of EU countries, with high reliance on non means-tested benefits. On the other hand, with some exceptions related to the generous pension system, Italy and Spain are EU countries with some of the smallest roles for cash public support (Paulus et al., 2009). Such differences in the composition of household incomes and their redistribution due to tax and benefit instruments are likely to affect the differences between reported and simulated incomes.

There currently exists very little literature in the area addressed by this paper. Pudney and Sutherland (1994) compare results using microsimulation and survey data for the UK, concluding that the basic process of microsimulation is "reasonably reliable" in terms of producing similar income distributions to survey data, although some statistics may have a wide margin of sampling error. Behrendt (2002) compares estimates of poverty rates under the two approaches for Germany, Sweden and the UK, concluding that estimated poverty rates would be close to zero if the income measures in survey data captured individuals' full entitlement to means-tested benefits. Such a conclusion is driven by the use of a fixed poverty line in order "to avoid distribution effects in the comparison of original and simulated poverty rates". However we argue that such distributional effects must be taken into account whenever poverty is measured as relative concept. We build on this with a more sophisticated analytical approach: Behrendt uses the imputed value of social assistance benefits in place of recorded incomes, where recorded incomes are lower than the income level offered by social assistance, whereas our analysis makes use of EUROMOD, a comprehensive and detailed microsimulation model, which is able to simulate the effects of the full range of benefits and direct taxes in each country. We do find evidence of under-reporting of incomes at the lower end of the distribution; however, we find that the effects of this under-reporting on estimated poverty rates are considerably smaller than the effects suggested by Behrendt.

The paper is structured as follows. In the next section, we compare the different income concepts and we present more information about the microsimulation model which we use. In Section 3, we describe our data. In Section 4 we present and discuss the results of our analysis; Section 5 concludes with some directions for future research.

2. Methods

2.1 Income measurement

In a seminal work on cross-national comparisons of income distributions, Atkinson et al. (1995) provide the following classification of income measures in order of reliability and completeness:

1. Administrative Record Income
2. Tax Reported Income
3. Edited Survey Income
4. Reported Survey Income

All these income measures are imperfect (Atkinson and Brandolini, 2001), and measurement errors in income data violate classical measurement error assumptions and may bias empirical analysis (Bound et al. 1990). For example, tax records might suffer from problems related to the coverage of those with incomes below the tax threshold and the tendency to underreport certain types of income. There may even be problems with register data: the assumption that register data can be used as a proxy for “true” income (Ehling and Rendtel 2004) is valid only where tax evasion is not a serious issue (Sutherland et al. 2009).

With survey data, a number of problems are known to arise. Total income is generally underreported comparing with national accounts (Atkinson et al. 1995); earnings from self-employment, investment income and property income are generally mis-reported (Ehling and Rendtel 2004) or are top-coded in the data (Burkhauser et al., 2008); but wages and salaries are generally well reported. Furthermore, people on very low incomes tend to under-report the benefits they receive – mainly because they fail to mention a particular benefit altogether, because they misplace in time or misclassify one of the benefits received, or because they do not report due to conscious suppression, caused, for example, by social desirability or sensitivity effects (Lynn et al. 2004). One partial solution is to combine survey and register data – for example, to combine survey data recording market incomes with register data recording benefit incomes, where this is available (Jenkins et al. 2008; Di Marco 2007). However, this is not always possible, and surveys remain the primary source of data for the analysis of poverty and income distributions.

In a situation with full compliance (i.e. 100% take-up of benefits and no tax evasion), simulating income using microsimulation models may be seen as moving away from reported survey income towards a figure which more closely represents “true” income. However, in a world with less than perfect compliance, microsimulation may replace one set of inaccuracies with another: in the case of benefit incomes, for example, it may replace inaccuracies due to non-reporting with inaccuracies arising from assuming away non-take-up. In this particular case, the inaccuracies are in opposite directions: estimates of low incomes using survey incomes would be too low, while microsimulation estimates would be too high. In the absence of other factors, such as people claiming of benefits to which they are not entitled, the difference between the survey and microsimulation approaches may be thought of as putting an upper bound on the error due to either approach. Alternatively, we may consider the microsimulation approach as measuring, rather than the *actual* effects of the tax-benefit system, the *intended* effects of the system, given the information on market income as reported in the surveys, and correcting for the misreporting of benefits and taxes.

We exploit the fact that the classical approach tends to underestimate incomes in this part of the distribution, while the microsimulation approach tends to overestimate them; by comparing the two approaches, we are able to put upper bounds on the degree to which poverty rates and other statistics are affected by these errors.

In this paper it is not our intention to compare estimates based on the two approaches with a view to deciding which is “better”. Rather, we compare the two sets of estimates with a view to establishing the extent to which they are consistent with each other, and, given that both approaches may have their shortcomings, to assess how far the differences lead to different estimates of income distributions.

2.2 Classical income analysis

The approach which we term "classical" income analysis is the familiar approach adopted by the majority of studies on income and poverty. This approach generally makes use of survey data (here, we use EU-SILC survey data), and in developed countries is based on the concept of household equivalised disposable income (see OECD (2008) for a recent comparative analysis).

Total household disposable income is calculated by adding together the incomes of all members of a household (after taxes and benefits, but before housing costs). This figure is then "equivalised" (i.e. adjusted to take account of the needs of the household) by dividing by a factor reflecting the number and ages of household members. We use the modified OECD equivalence scale, calculated as 1 for the first adult in a household, plus 0.5 for each additional adult over age 14, plus 0.3 for each child.

Having calculated household equivalised disposable income, this figure is allocated to each individual in the household; statistics on income distribution are generally calculated on the basis of individuals, using survey weights to make results representative of the population of interest.

2.3 Fiscal microsimulation: EUROMOD

Microsimulation was developed primarily not as a tool for describing income distributions, but for describing how these distributions might change if the tax-benefit regime were to change. The microsimulation approach differs from the classical approach, not in the way it calculates statistics on income and poverty, but in the way it deals with data on taxes and benefits. The microsimulation model used here is EUROMOD: a unique model which covers the countries of the EU in a comparable manner (Lietz and Mantovani 2007; Sutherland 2007). Starting with reported market incomes in EU-SILC (the identical data used in the classical approach), EUROMOD calculates direct tax liabilities, social insurance contributions and cash benefit entitlements for sample households and their members based on the information collected in the survey.

It is not possible to fully simulate entitlement to all types of cash benefits because cross-sectional surveys in general, including the EU-SILC, do not contain all the necessary information. In particular, payments that depend on past earnings and/or contribution records (such as contributory pensions), or on particular contingencies (such as disability) are not possible to simulate in full. In these cases, information on receipt of these benefits is taken directly from the survey. In our comparisons of "simulated" and reported incomes it is the effects of the distinct treatments of income taxes, social contributions and income tested and universal or categorical benefits that explain differences.

Given that the validity of findings in both approaches may be affected by measurement error inherent in survey data, one would expect extensive validation exercises and comparisons of income data with micro and macro-level data from other sources. However, very few validation studies of surveys exist, with some exceptions from the UK and the US (Jackle et al.2005, Bound et al. 2001). Tax-benefit instruments simulated in EUROMOD have been validated and tested at micro level (i.e. case-by-case validation) and macro level, comparing the aggregate indicators and distributive statistics with external sources and national microsimulation models. The results of the validation exercises are reported in the Country Reports (available on the EUROMOD web pages) and in Mantovani and Sutherland (2003) and Lietz and Sutherland (2005).

3. Data

An important feature of this paper is that our estimates of income distributions under the classical and microsimulation approaches are directly comparable, because both approaches are based on identical micro-data, namely the European Union Statistics on Income and Living Conditions (EU-SILC). We devote a section here to discussing this data source; we then explain how EU-SILC data are prepared for use with EUROMOD. See European Commission (2009) for a detailed description of the data.

3.1 European Union Statistics on Income and Living Conditions (EU-SILC)

The EU-SILC carries data on a range of indicators: income, poverty, social exclusion, labour market behaviour, health, and other personal-level information. It covers all 27 member states of the European Union, plus Turkey, Switzerland, Norway and Iceland.

Following the first year of collection (in most cases 2003 or 2004), data are collected annually. The EU-SILC is designed as a rotational panel: in most countries, sample households are retained in the survey for four years before being replaced by new households, and one quarter of the households are refreshed in this way every year. Both cross-sectional and longitudinal data files are released; there have been several releases of both cross-sectional and longitudinal data each year.

In this paper, we use only the cross-sectional files, and for each country we use data from a single release. In order to facilitate comparisons, we do not use the most recent release; rather, for each country, we take the release which has been used in EUROMOD, and use this for the classical analysis too. The year and release of data used for each country are shown in Table 1. For Spain and Hungary we use the versions of the EU-SILC data released by Eurostat; for Austria and Italy, we use national versions of the data released by these countries' own Statistical Institutes. These are based on the same sample as the other versions, and are in most respects identical to the versions released by Eurostat; however, they provide additional variables which are used by the microsimulation model.

In Table 1 we also give the policy year used for each country; that is, the year relating to the policy regime on which the microsimulation estimates are based. In most cases, this is the year prior to the year of collection of data. Income data are collected retrospectively and relate to the year prior to the date of interview, and the policy year corresponds to this. However, for Hungary, the policy year is the same as the data year; more details on the adjustment associated with this are given in Section 3.2. The final two columns in Table 1 show sample sizes for each country, both in terms of the number of households, and also in terms of the number individuals in the data.

Table 1: Data releases used in analysis

Country	Data year	Release	Policy year	Households	Individuals
Austria	2004	1	2003	4,521	11,550
Italy	2004	2	2003	24,270	61,542
Spain	2005	2	2004	12,996	37,491
Hungary	2005	1	2005	6,927	17,969

Notes: National versions of data used for Austria and Italy

The EU-SILC is not without a number of problems which affect comparisons between countries. The EU-SILC's predecessor, the European Community Household Panel (ECHP) was input-harmonised – that is, the survey questionnaires were designed to have identical meanings and to generate comparable data between countries. However, the EU-SILC is output-harmonised, meaning that the only requirement is for countries to generate a set of variables to be included in the data set, without specifying the means by which these data are gathered. In addition, the mode of data collection varies between countries: some countries have collected data via surveys, while others have used data from registers. Finally, there are differences in the way that income components have been collected. From 2007, there is a requirement for countries to report all income components as gross amounts. However, countries are allowed to collect these components as either gross or net amounts. This is not an insurmountable problem (see Section 3.2). However, all these issues, combined with the fact that the EU-SILC is a relatively recent data set which has not yet been widely used, means that there is a degree of difficulty in comparing estimates between countries. For the purposes of this study though, these difficulties are offset by a major advantage: namely, that we are able to compare results from classical income analysis with results from microsimulation analysis, using identical data sets for each country.

The measure of income which we use in this paper differs slightly from the measure of household disposable income (variable HY020) provided in the EU-SILC. Variable HY020 is constructed by adding together all the gross personal income components collected at the individual level, plus all the gross income components collected at the household level, and subtracting mortgage interest, taxes and inter-household transfers paid. In order to make this measure of disposable household income comparable to that generated by EUROMOD, we modify it slightly by adding in any income from private pensions; adding back any inter-household transfers paid; and subtracting any non-cash employment income.

In the analysis presented below, both sets of calculations make use of the cross-sectional household weights provided with EU-SILC in order to take account of differential non-response to the surveys. We do not have full information on how these weights are constructed in each country, because the national statistical institutes are not obliged to provide full details. However, because we use identical weights for both classical and microsimulation approaches, we may assert that any differences we find are not attributable to differences in the weighting of results.

3.2 EU-SILC data in EUROMOD

Survey data require a number of adjustments before they may be used as part of a microsimulation model. This section describes the ways in which the EU-SILC data have been transformed for use in EUROMOD. There are three key issues: how we calculate net incomes from gross incomes; dealing with aggregation within the household; and dealing with aggregation across benefit sources. All three of these issues may have some effect on comparisons of poverty and inequality using simulated and recorded incomes. The importance of effects will vary across countries; Figari et al. (2007) discuss these effects and provide a case study explaining the Spanish situation in some detail.

3.2.1 Net and gross incomes

Microsimulation procedures require incomes to be input as gross amounts. For the years we are considering, information on gross incomes was not provided in the Spanish or Italian EU-SILC data. Thus, for these countries it has been necessary to use EUROMOD parameters to implement a net-to-gross procedure according to the legislation for the income reference period. In Hungary and Austria information on income components is available both net and gross and we have used the gross figures provided in the EU-SILC data. However, even in these countries income data has not always been collected in gross form and in some cases it is not clear how the conversion from net to gross has been done. In the EU-SILC, information on taxes paid on each income component is not available consistently across countries. It is also unclear whether final tax liability in the year in question is captured consistently using the SILC methodology.[1]

3.2.2 Aggregation within the household

Some income is properly considered as being paid to households rather than to individuals within households (housing benefits, for example, and certain social assistance benefits). Microsimulation models are able to deal with these components reported at household level; however, in order to simulate all the components of the tax-benefit system correctly, they do require that any income components which are paid to individuals, should be reported at the individual level.

Unfortunately, this is not always the case in the EU-SILC: some income components which are paid to individuals are made available in the data only at the household level. Where this is the case, we have assigned these income components to individuals within the household, via a procedure which, while being the best available, is necessarily arbitrary in some cases. The income components affected are mainly capital income and allowances related to family and children; they do not represent a major proportion of the income of most families, but neither are they

[1] At the time of writing we are not aware of any systematic validation of the difference between net and gross incomes in the EU-SILC, with reference to administrative statistics on income tax and social contribution receipts.

negligible. The extent to which this aggregation within the household presents a problem will vary according to the tax-benefit system in each country.

3.2.3 Aggregation of income sources

EUROMOD requires each income component to be separately identifiable in the input data, even if it has a similar function to other components. There are good reasons for this: certain types of benefits cannot be fully simulated, and must be separated from benefits that can be simulated. Furthermore, different benefits may be treated differently by the rest of the tax-benefit system. However, EU-SILC provides information on benefits received, 'bundled' into a set of harmonised variables which are defined by function. Depending on the specific nature of the individual benefits in each country, the process of imputing individual income components from these aggregates may be straightforward or it may be somewhat arbitrary. In the case of Spanish benefits the necessary splitting can be done in a plausible way (Figari et al. 2007) and, to some extent, the same is true for Hungary (Hegedus et al., 2008). In the case of Austria and Italy, we have used the information on the individual benefits that is available in the national SILC databases.

3.2.4 Matching policy and income years

In the previous section, we noted that EUROMOD generally simulates policies corresponding to the income year of the underlying SILC data. For example, for Austria we use 2004 data, which collected incomes relating to 2003; we therefore use the 2003 policy year for simulations. A similar procedure has been used for Spain and Italy. In the case of Hungary, we planned to do the same, using the 2005 policy year coupled with data from the 2006 EU-SILC. However, doubts have emerged about the reliability of the Hungarian data for this particular year: our calculations, and those reported in KSH (2009), show anomalous inequality indexes for 2006, out of the trend of the available time series. As a result, we used data from 2005 (2004 income year) and uprated all income components to levels appropriate to 2005. We used a simple procedure, uprating all incomes by a factor reflecting the Consumer Price Index provided by Eurostat. For comparability, the EU-SILC disposable incomes used for the "classical" analysis are also uprated by the same index.[2]

4. Results

All the results reported in this paper are based on household equivalised disposable income, as described above. In Section 4.1 we consider six measures of income inequality (the Gini coefficient, the p90/p10 ratio, the mean log deviation index, and

[2] It would have been possible to use a more sophisticated procedure, uprating income components by appropriate and detailed indexes in an attempt to capture actual income growth in the relevant period - and in other contexts this has been done (Hegedus et al., 2008). However, in this context, the advantages of undertaking such a complicated exercise were unclear.

three variants of the Atkinson index). In Section 4.2 we also report the decile points of the distributions under the two different approaches in each country.

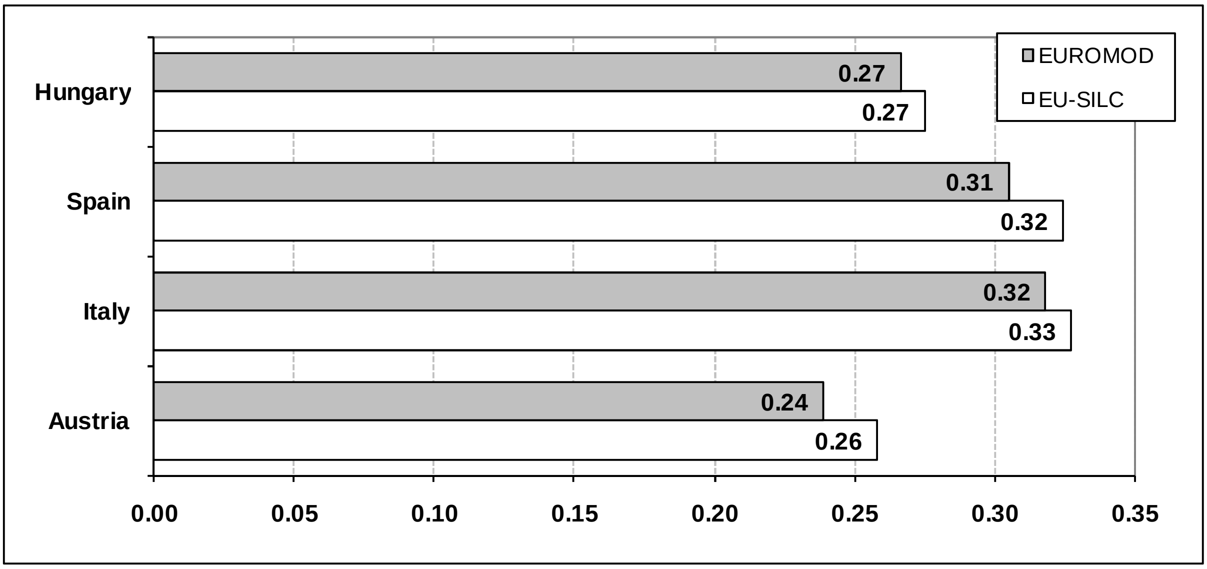
In Section 4.3 we report poverty rates under two different poverty lines (60% and 50% of national median income, again calculated using household equivalised disposable income) We do this for the full population, and also for two groups who are of particular interest in the study of poverty, namely children (i.e. individuals younger than 18 years) and older people (i.e. individuals aged 65 or more). Finally, in Section 4.4, we ask whether the same individuals are recorded as poor under the two approaches we consider.

All these indicators are familiar in the literature on poverty and income distributions (Lambert 2001). We therefore do not discuss them in detail showing only their main properties in the sections which follow.

4.1 Inequality

Figure 1 shows the Gini coefficients for the four countries, calculated from both the reported EU-SILC data and the simulated EUROMOD data. The two sets of results are similar; the EU-SILC data produce a slightly higher Gini coefficient than the EUROMOD data, but the difference is minimal in all countries except Austria, where it stands at 0.02 (a difference of around 8% of the size of the EUROMOD coefficient). The ranking of countries under both approaches is identical: under both sets of estimates, Italy and Spain have the highest levels of inequality, followed by Hungary; Austria has the lowest levels of inequality of the four countries studied.

Fig. 1: the Gini coefficient



Notes: Gini coefficients are calculated at the individual level for the whole population, based on equivalised household income. The modified OECD scale is used Observations with zeros and negative income are excluded. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

One frequently noted drawback of the Gini coefficient as a measure of inequality is that it gives equal weight to variations in income right across the income distribution, and attaches no particular importance to variations at the bottom of the distribution (which may be of much greater importance to the individuals concerned than similar variations would be to individuals at the top of the income distribution, and which may be of special interest to a society which cares about its poorer members).

For the purposes of this study, it is variations at the bottom of the income distribution which interest us most, because it is here where we expect to find a large proportion of the differences between the reported and simulated incomes in the EU-SILC and EUROMOD data sets. We therefore consider a number of other inequality indicators, which give varying degrees of weight to the lowest incomes.

We include the p90/p10 ratio as a simple, intuitively clear and commonly used measure of inequality. Being calculated as the income of the individual at the 90th centile of the income distribution divided by the income of the individual at the 10th centile, this measure is based on only two points in the income distribution, and reflects neither the distribution of income within the middle 80% of the range, nor the incomes of the very poorest.

We also consider the mean log deviation index. This is one of Theil's generalised entropy indices, where the parameter takes the value zero, and which attaches greater weight to incomes lower down the distribution. Mathematically, it may be expressed as follows, where *N* is the number of individuals in the population, y_j is the income of individual *j*, and μ is the mean income over the population.

$$GE(0) = \frac{1}{N}\sum_{j=1}^{N}\ln(\frac{\mu}{y_j})$$

Finally, we consider the class of Atkinson indices, which may be expressed mathematically as follows, where y_i is the income of individual *i*, μ is mean income, and ε is a parameter of "inequality aversion" which, as it varies, changes the importance attached to variations at different points in the income distribution. At ε = 0, the index is equally sensitive to incomes across the distribution; at ε = 1 it is more sensitive to variations at the lower end of the distribution.

$$A = 1 - \frac{1}{\mu}\left(\frac{1}{N}\sum_{j=1}^{N} y_j^{\,1-\varepsilon}\right)^{1/1-\varepsilon} \qquad with \quad \varepsilon \neq 1$$

$$A = 1 - \frac{1}{\mu}\left(\prod_{j=1}^{N} y_j\right)^{1/N} \qquad with \quad \varepsilon = 1$$

We compute the Atkinson index using three values of ε: 0.5, 1 and 2.

All the indicators of inequality, for each country and under both approaches, are presented in Table 2, with pairs of estimates where differences that are significant at the 95% level shown in bold.

Table 2: Six inequality indicators, by country and approach

	Austria	Italy	Spain	Hungary
Gini coefficient				
EU-SILC	**0.258**	0.327	**0.324**	0.275
EUROMOD	**0.239**	0.318	**0.305**	0.265
p90/p10				
EU-SILC	**3.126**	4.152	**4.634**	3.198
EUROMOD	**2.839**	4.014	**4.190**	3.117
Mean log deviation (GE(0))				
EU-SILC	**0.131**	0.199	**0.198**	0.132
EUROMOD	**0.095**	0.186	**0.174**	0.121
Atkinson index (0.5)				
EU-SILC	**0.059**	0.093	**0.088**	0.067
EUROMOD	**0.048**	0.087	**0.078**	0.061
Atkinson index (1)				
EU-SILC	**0.123**	0.180	**0.180**	0.123
EUROMOD	**0.091**	0.170	**0.159**	0.114
Atkinson index (2)				
EU-SILC	**0.935**	0.528	0.803	**0.237**
EUROMOD	**0.170**	0.509	0.724	**0.215**

Notes: Inequality indicators are calculated at the individual level for the whole population, based on equivalised household income. The modified OECD scale is used Observations with zeros and negative income are excluded. Pairs of estimates statistically different at the 95% level are shown in bold. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

Inspection of the table leads us to three main observations. First, the ranking of countries is preserved between the two approaches: Italy and Spain are the most unequal countries; Hungary follows some way behind, while inequality is lowest in Austria. This is the case for all the indicators, except for the Atkinson ($\varepsilon = 2$) index, where Austria appears as the least unequal country under EUROMOD calculations, but the most unequal under EU-SILC. This is related to the fact that the Atkinson ($\varepsilon = 2$) index weights the lowest incomes particularly heavily; we will return to this issue in detail later.

Our second observation is that all estimates of inequality are higher for the reported incomes in the EU-SILC dataset than they are for the simulated incomes in EUROMOD. For reasons we have discussed earlier, we would expect estimated inequality to be higher when using reported data. We have shown that this is indeed the case, although we have not shown whether this difference is due to benefits being under-reported in EU-SILC, or over-simulated in EUROMOD, or a combination of both.

Finally, we observe that differences between the estimates generated by the two data sets are as a rule considerably smaller than inter-country differences, and that they are only statistically significant at the 95% level in Austria, and in Spain, except for the Atkinson ($\varepsilon = 2$) index. The differences are greatest in Austria, where the differences range from 8% of the EUROMOD figure in the case of the Gini coefficient, to 38% for the MLD index, and 450% for the Atkinson (ε = 2) index. That the difference is larger in Austria, particularly for indicators which give a greater weight to the lower part of the income distribution, is not unexpected, due to the fact that Austria's benefit system contains relatively generous means-tested social assistance benefits. We return to the case of Austria later after examining some other indicators of income distribution.

4.2 Income deciles

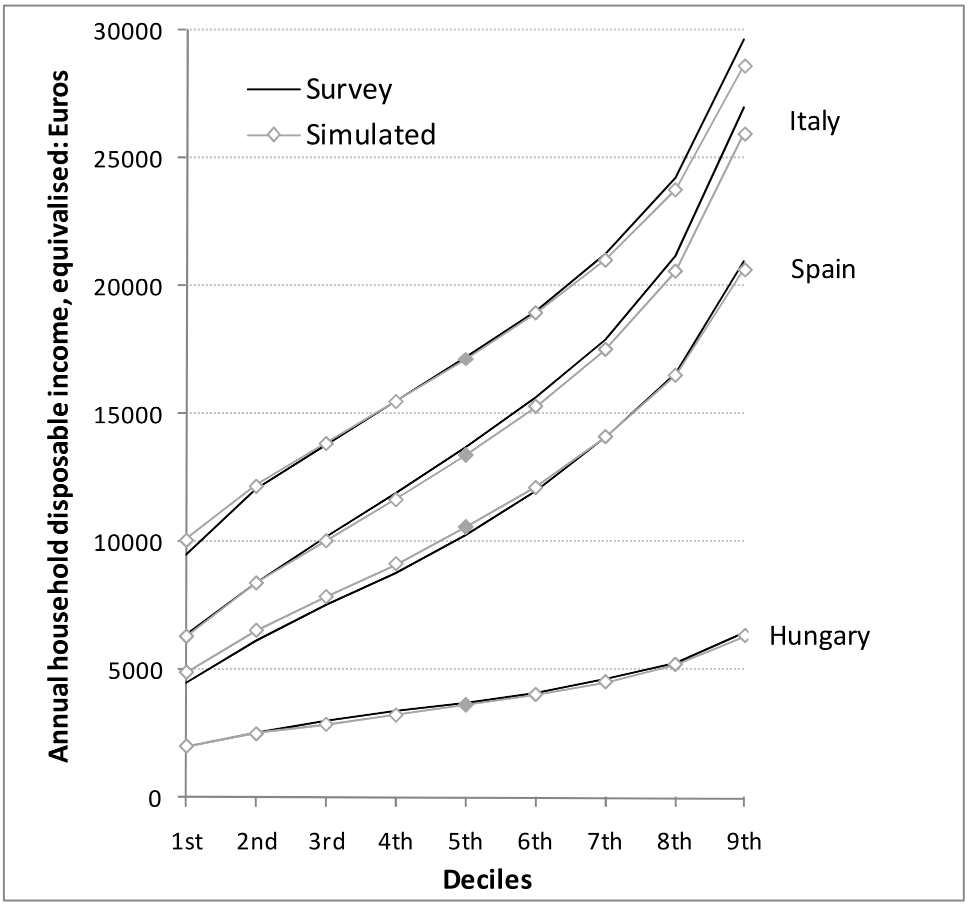
As we discussed above, different inequality indicators have their primary drivers at different points in the income distribution. Figure 2 shows the decile points for the income distributions in all countries under both approaches. The first decile point is the upper limit of the incomes of the bottom one-tenth and the lower limit of the incomes of the second one-tenth, and so on. A table containing the same information in numeric form is given in Appendix 1.

Several features of this figure stand out. In two countries – Austria and Spain – simulated incomes are higher than survey incomes at the bottom of the distribution. Austria and Spain are the two countries with social assistance benefits which are subject to non-uptake: Levy and Mercader-Prats (2003) note that in Spain old-age assistance benefit, old age pension supplement and unemployment assistance benefit are all under-reported in survey data; Fuchs (2009) reports that in Austria more than half of all households potentially entitled to the social assistance benefit do not claim.. The differences in distributions under the two approaches are not enormous, but will affect both the inequality and the poverty indicators which we estimate – as we have seen, Austria and Spain are the two countries where inequality indicators are significantly different between the two approaches. In Italy and Hungary the distributions of reported and simulated incomes are very similar, with the simulated incomes being slightly smaller also at the bottom of the distribution.

In all countries, EUROMOD simulates the top deciles rather lower than the survey data. We have already noted this as an issue, due to the difficulty in simulating (a) tax evasion, and (b) legal tax avoidance. These differences at the top end are likely to affect some inequality indicators more than others (the Gini and the P90/P10 particularly), and this effect will be most pronounced in Austria and Italy; however, they will not affect our estimates of poverty rates.

We have marked the median of the distributions with a filled marker on the graph, and will discuss the implications of the median points in the section dealing with poverty rates.

Fig. 2: Decile points by country and approach



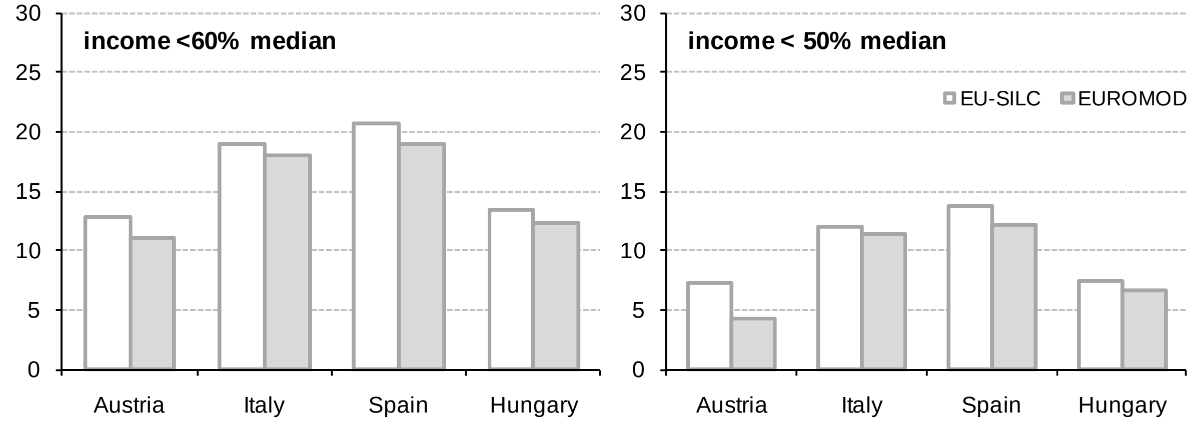
Notes: Decile points are calculated at the individual level for the whole population, based on equivalised household income. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

4.3 Poverty

Figure 3 shows poverty rates for the four countries under consideration, calculated under the two approaches (see Table A2 in the Appendix for the detailed figures). The left-hand panel shows poverty rates defined as the percentage of individuals living in households with equivalised incomes less than 60% of the national median; the right-hand panel shows poverty rates defined as the proportion of individuals with incomes lower than 50% of the national median.

The picture we observed for inequality is mirrored here: Spain and Italy, which have the highest levels of inequality, also have the highest levels of poverty; Hungary comes next; and Austria has the lowest levels of poverty under both measures.

Fig. 3: Poverty rates (percentages) by country and approach

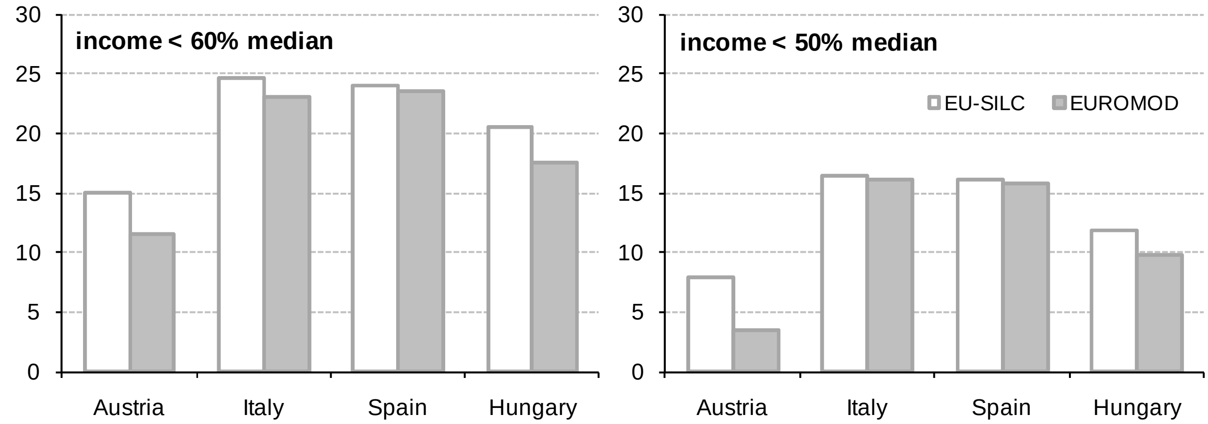


Notes: Poverty rates are percentage of individuals with equivalised household income below the poverty line set respectively equal to 60% and 50% of the median. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

Poverty rates calculated using reported EU-SILC data are higher than those calculated using simulated incomes. Most of the differences in estimated poverty rates are statistically significant. In the case of Austria and using the 50% threshold, we estimate the poverty rate at 7.3% using reported data, but only 4.3% using simulated data. This is a sizeable difference, and suggests that the difference between the two data sets occurs in the lowest 5% of incomes.

We now look at two groups who are at particular risk of poverty. Figure 4 shows poverty rates among children and young people aged under 18 years, while Figure 5 shows poverty rates among elderly people aged over 65.

Fig. 4: Poverty rates (percentages) by country and approach, among children and young people aged under 18 years

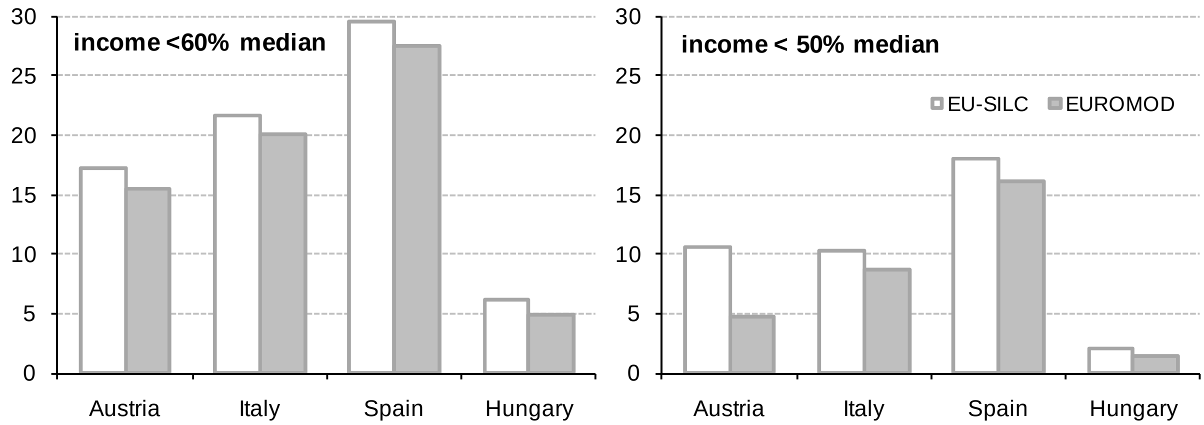


Notes: Poverty rates are percentage of individuals aged under 18 years with equivalised household income below the poverty line set respectively equal to 60% and 50% of the median. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

When we consider children and young people, we observe that the ranking of countries is as it was before, with Spain and Italy the most unequal, followed by Hungary, with Austria the least unequal. Estimated poverty rates under the two approaches are not statistically different in Italy and Spain, but they are in Austria and Hungary which rely on relatively generous public transfers not always well reported in the survey.

When we look at poverty among older people, the picture changes. Among the population in general, and among children, poverty rates are highest in Spain and Italy. Among older people, however, poverty rates remain high in Spain, but are much lower in Italy due to generosity of the pension systems which show high replacement rates; indeed, when we consider the lower poverty line, poverty rates in Italy are comparable to, or even lower than, poverty rates in Austria. Hungary also appears to have much less poverty among its older population than among its general population, and in fact has the lowest poverty rate of any of the countries considered, by a substantial margin. When we compare the two approaches, we find that poverty rates do not differ greatly, except, again, in the case of Austria, where the difference is relatively small for the higher poverty line, but very large (4.8% versus 10.5%) for the lower poverty line, due to the generosity of the Minimum Pension and Social Assistance and under the assumption of full take-up.

Fig. 5: Poverty rates (percentages) by country and approach, among people aged over 65



Notes: Poverty rates are percentage of individuals aged over 65 years with equivalised household income below the poverty line set respectively equal to 60% and 50% of the median. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

The differences shown in Figures 3-5 above, in the percentages of individuals considered poor under each approach, may arise for two reasons. On the one hand, they may arise because the incomes of certain individuals lie below a given poverty line under one approach, and above the same poverty line under the other approach. On the other hand, it may be that *the poverty line itself* is estimated differently between the two approaches.

As mentioned, both of these factors arise because of differences between reported and simulated incomes. However, the first factor arises because of differences in estimated incomes at the bottom of the distribution, while the second relates to differences in estimated incomes towards the middle of the distribution, since poverty thresholds are calculated as a percentage of median income. Figure 2, which plots the income distributions under the two approaches, supplies some of the answers to this question.

For Austria and Hungary, poverty lines are slightly lower under EUROMOD than under EU-SILC – in Austria this difference is negligibly small, while in Italy and Hungary the difference is of the order of 2%. In Italy and Spain the opposite is true: the poverty line under EUROMOD is just under 3% higher than the EU-SILC poverty line.

It appears, then, that in Austria the lower poverty rates under EUROMOD arise almost entirely because of differences between the two approaches in incomes at the lower end of the distribution, and particularly (given that poverty rates at 50% of median are particularly affected) in incomes below the lowest decile.

In Italy, the difference between estimated poverty rates under the two approaches is small and statistically insignificant. No effect is to be expected from the lowest deciles, which are estimated at almost identical levels under the two approaches; it appears that the slightly lower poverty rates estimated under EUROMOD arise from the slightly lower estimated median, which leads to a slightly lower poverty line.

In Spain, the differences between the two sets of estimated poverty rates are somewhat larger: EUROMOD generates lower poverty rates than survey data, particularly for older people. This is driven by higher estimated incomes at the lower deciles. This effect is mitigated by the higher median estimated by EUROMOD, which would tend to increase estimated poverty rates.

4.4 Who is poor?

So far in this section, we have discussed how estimates of inequality, poverty and the income distribution differ when estimated using reported and simulated income data. One question which remains to be answered is the extent to which the incomes of *individuals* within the data set are reasonably similar under the two approaches: we know that the two approaches give similar estimates of poverty rates, although with important differences, but we can only consider the approaches as somehow “congruent” if they also estimate the same *individuals* as poor.

Tables 3a and 3b present the results of this analysis, for the same poverty indicators as used previously. Table 3a shows poverty rates calculated under a poverty line set at 60% of median income; Table 3b the analogous rates calculated using a poverty threshold of 50% of median income. For each panel, the left-hand column indicates the percentage of individuals who are poor under the EU-SILC method, but not using EUROMOD. The middle column shows the percentage of individuals who are poor under both approaches, and the right-hand column shows the percentage poor under EUROMOD but not EU-SILC.

Table 3a: Percentages poor under each approach: poverty line at 60% of median

		Only poor under EU-SILC	Poor under both approaches	Only poor under EUROMOD
All				
	Austria	2.6	10.1	0.9
	Italy	2.0	17.0	1.0
	Spain	3.0	17.6	1.2
	Hungary	3.8	9.55	2.8
Children				
	Austria	4.5	10.4	1.2
	Italy	3.0	21.6	1.6
	Spain	2.2	21.9	1.7
	Hungary	7.0	13.5	4.0
65+				
	Austria	2.3	15.0	0.5
	Italy	2.0	19.6	0.5
	Spain	3.7	25. 9	1.6
	Hungary	1.9	4.1	0.7

Notes: percentages of individuals with equivalised household income below the poverty line equal to 60% of the median under different approaches. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

Table 3b: Percentages poor under each approach: poverty line at 50% of median

Poverty 50% of median income		Only poor under EU-SILC	Poor under both approaches	Only poor under EUROMOD
All				
	Austria	3.4	3.9	0.3
	Italy	1.5	10.5	0.9
	Spain	2.3	11.4	0.7
	Hungary	2.8	4.6	2.0
Children				
	Austria	4.7	3.3	0.2
	Italy	2.0	14.5	1.7
	Spain	1.3	14.7	1.1
	Hungary	5.0	6.8	3.0
65+				
	Austria	5.8	4.8	0.0
	Italy	2.1	8.2	0.5
	Spain	3.0	15.0	1.1
	Hungary	1.1	0.9	0.5

Notes: percentages of individuals with equivalised household income below the poverty line equal to 50% of the median under different approaches. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

For all countries, the results show that the two approaches overwhelmingly identify the same people as poor – the numbers in the middle column are much higher than the numbers in the right-hand and left-hand columns. As an example, looking at the top row of figures for Austria, we see that a total of 13.6% of people are identified as poor under either approach, and 10.1% are identified as poor under both approaches. Thus, almost 75% of those identified as poor under either approach are identified as poor under both approaches; 18% are identified as poor under EU-SILC but not EUROMOD, while only 7% are identified as poor under EUROMOD alone. The fact that more people are identified as poor under EU-SILC is reflected in the fact that the numbers in the left-hand column are larger than the numbers in the right-hand column. However, the numbers in the right-hand column are not zero, indicating that a small number of people are identified as poor under EUROMOD who are not identified as poor under EU-SILC.

This is entirely as expected: for reasons we have referred to, we expect more people to be poor under EU-SILC than EUROMOD. We would also expect a small number of people to be classified as poor under EUROMOD but not under EU-SILC: these would tend to be people close to, but just above, the poverty line under EU-SILC, who, with relatively minor adjustments to their incomes under microsimulation, find themselves just below the slightly poverty line under EUROMOD.

5. Conclusions

In this paper, we have analysed a range of indicators of inequality and poverty, under two approaches: the "classical" approach, using reported incomes in survey data, and the microsimulation approach, where taxes and benefits are simulated. A number of findings stand out.

We have found that for the majority of indicators, both approaches produce similar results. Although there are small differences, the ranking of countries is in virtually all cases preserved between the two approaches. Of course, we have performed this exercise for only four countries, and cannot assert that in studies with a far larger number of countries, rankings would be exactly preserved. Nevertheless, our choice of countries includes a range of different welfare systems, with substantial cash support (Austria and Hungary), very few means-tested benefits (Italy) and relatively generous benefits targeted to specific vulnerable groups (Austria and Spain), and our findings are reasonably robust.

What are the implications of this? Given that both approaches are based survey data, which are subject to a number of problems as discussed in Section 2.1, we do not claim that our findings show that either approach, or both, generates "true" estimates of poverty and inequality. But we may confidently claim that in general, both approaches lead to quite robust estimates. We *do* find some differences between the two approaches in terms of estimated poverty rates in Austria and Spain. These differences are not of the same order as those suggested by Behrendt (2002) who, under some debatable methodological assumptions, suggests that under a simulation-based approach, estimated poverty rates would be close to zero. In Spain, the differences we observe are of the order of two percentage points, whichever poverty line is used, and they appear to be driven mainly by differences in the elderly population. In Austria, estimated poverty rates using a standard poverty line of 60% of median income are one or two percentage points lower using simulated rather than survey income, but the difference is not significant. Using a lower poverty line of 50% of median income, these differences are larger: 3 percentage points for the whole population, and 4 and 6 percentage points respectively for children and the elderly population. These differences, particularly significant in the context of generally low poverty levels such as in Austria, suggest that the data must be used very carefully with reference to population subgroups whenever they have implications for policy.

In both these cases, there are good reasons why we observe these differences, namely that there is a known issue with non-take-up of social assistance in Austria (Fuchs 2009) and a number of benefits in Spain, particularly relating to older people (Levy and Mercader-Prats 2003). In these cases, the two sets of estimates are in fact providing different information. The microsimulation estimates are providing information about the intended effects of the tax and benefit systems in each country – i.e., about what poverty rates would be if everyone claimed the benefits to which they were entitled. This can be considered as a lower bound of poverty estimates. The nature of the information provided by the estimates based on survey data is a little less clear – poverty estimates are higher than the simulated estimates because the estimates take account of non-take-up (which is a good thing in that it leads to more accurate estimates) but also because of people do not report benefits they are actually getting (which is a bad thing, in that it leads to less accurate estimates).

This leaves us with a set of directions for future research which, while they are not new, are well-defined. In respect of survey data, the problem of under-reporting of benefit receipt is clear. Efforts are already under way to rectify this: they include attempts to improve questionnaire design so as to reduce the problem, and to utilise register data in conjunction with survey data in order to avoid it altogether. In the case of microsimulation, efforts are also under way to model non-take-up of benefits. This paper underlines the importance of both these fields of research, and of continuing attempts to validate, in a transparent and accessible way, both types of data against administrative aggregates.

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Appendices

Table A1: Income deciles (Annual household disposable income, equivalised; euros)

	Austria	Italy	Spain	Hungary
1st decile point				
EU-SILC	9496	6335	4476	2026
EUROMOD	10079	6305	4894	2029
2nd decile point				
EU-SILC	12040	8395	6119	2560
EUROMOD	12190	8390	6533	2506
3rd decile point				
EU-SILC	13794	10210	7519	2997
EUROMOD	13861	10038	7849	2873
4th decile point				
EU-SILC	15542	11887	8800	3376
EUROMOD	15502	11647	9139	3233
5th decile point				
EU-SILC	17220	13697	10311	3711
EUROMOD	17184	13397	10594	3616
6th decile point				
EU-SILC	19046	15672	12021	4113
EUROMOD	18973	15308	12119	4036
7th decile point				
EU-SILC	21290	17967	14065	4611
EUROMOD	21031	17537	14110	4527
8th decile point				
EU-SILC	24289	21181	16593	5269
EUROMOD	23783	20595	16512	5206
9th decile point				
EU-SILC	29680	26965	21009	6480
EUROMOD	28619	25963	20634	6325

Notes: Decile points are calculated at the individual level for the whole population, based on equivalised household income. The modified OECD scale is used. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.

Table A2: Poverty rates (percentages) by country and approach

	Poverty line at 50% median		*Poverty line at 60% median*	
Overall population				
	EU-SILC	EUROMOD	EU-SILC	EUROMOD
	7.33	**4.26**	**12.74**	**11.06**
	11.96	11.43	**18.95**	**18.02**
	13.72	**12.14**	**20.61**	**18.87**
	7.46	**6.63**	**13.36**	**12.31**
Children (<18 years)				
	EU-SILC	EUROMOD	EU-SILC	EUROMOD
	7.94	**3.47**	**14.97**	**11.6**
	16.45	16.11	24.57	23.13
	16.06	15.82	24.07	23.58
	11.82	**9.73**	**20.55**	**17.52**
Elderly (>65 years)				
	EU-SILC	EUROMOD	EU-SILC	EUROMOD
	10.52	**4.75**	17.22	15.51
	10.31	**8.7**	21.56	20.11
	18.04	**16.08**	**29.56**	**27.46**
	1.99	**1.36**	**6.09**	**4.87**

Notes: Poverty rates are percentage of individuals (by age group) with equivalised household income below the poverty line set respectively equal to 60% and 50% of the median. The modified OECD scale is used. Pairs of estimates statistically different at the 95% level are shown in bold. *Sources:* Authors' analysis of EU-SILC and EUROMOD data.