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DISCUSSION PAPER SERIES

IZA DP No. 12734

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ABSTRACT

Reevaluating Distributional Consequences of the Transition to Market Economy in Poland: New Results from Combined Household Survey and Tax Return Data*

We use Pareto imputation, survey reweighting, and microsimulation methods applied to combined household survey and tax return data to reevaluate distributional consequences of the post-socialist transition in Poland. Our approach results in the first estimates of top-corrected inequality trends for real equivalized disposable incomes over the years 1994-2015. We find that the top-corrected Gini coefficient grew by 14-26% more compared to the unadjusted survey-based estimates. This implies that over the last three decades Poland has become one of the most unequal European countries among those for which top-corrected inequality estimates exist. The highest-income earners benefited the most during the post-socialist transformation: the annual rate of income growth for the top 5% of the population exceeded 3.5%, while the median income grew by about 2.5%.

JEL Classification: D31, D63, C46, P36

Keywords: income inequality, Gini index, top income shares, tax record, survey data, Pareto distribution, Poland

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1. Introduction

Recent economic literature provides convincing evidence that the standard approach to measuring income inequality – relying on household survey data – significantly underestimates the true level of income disparity in the population (see, e.g., Burkhauser et al. 2012, 2017; Bartels and Metzing 2018; Jenkins 2017). The major determinant of the downward bias in survey-based inequality estimates is under-coverage of top incomes in survey data, related to relatively high rates of survey non-response and income under-reporting among high-income earners. One of the ways to address this problem has been to use tax return data with better coverage of the upper tail of the income distribution.[1] Empirical studies have found that inequality estimated from administrative data such as individual tax returns (or aggregated income tax statistics) often displays significantly different levels and trends over time compared to survey-based estimates. For example, Jenkins (2017) reports that the Gini coefficient for individual gross income in the UK estimated on tax data rose by 7-8% between 1996/7 and 2007/8, while it fell by about 5% in the same period when estimated using survey data. Top 1% income shares for fiscal incomes were found to be higher in tax data than in surveys by 3-6 percentage points (p.p.) in Germany (Bartels and Metzing 2018), by about 6 p.p. in the US (Burkhauser et al. 2012), and by as much as 12-14 p.p. in Russia (Novokmet et al. 2018).

Several methodological approaches have been developed to produce more reliable inequality estimates using advantages of both household survey and tax return data (Alvaredo 2011; Jenkins 2017; Bartels and Metzing 2018). This literature produces top-corrected inequality estimates by integrating survey and tax data with harmonized income definitions and reconciling units of observations (households versus tax units) in both data sources. So far however, largely due to data availability, the research in this area has mainly concentrated on developed countries with notable exceptions by Novokmet et al.'s (2018) on Russia, by Bukowski and Novokmet's (2017, 2018) on Poland and Piketty et al.'s (2018) study about inequality in China. These studies show in general that survey-based inequality estimates for transition and emerging economies are substantially lower than top-corrected estimates exploiting additional information from tax data. However, most of these works estimate income inequality in terms of gross (pre-tax) income distributed among tax units or only among adult individuals. This kind of income concept deviates considerably from the primary measure of the standard of living analyzed in income distribution and welfare economics literature, namely disposable equivalized household income defined for the entire population. In practice, both levels and trends in inequality of gross incomes distributed among the adult population may be significantly different from those derived from equivalized disposable incomes for the entire population.

In this paper, we fill a gap in the literature by providing first top-corrected inequality estimates for real equivalized disposable (post tax and transfer) household incomes in Poland over 1994-2015.[2] We combine survey income data from the Polish Household Budget Survey (PHBS)

[1] Obviously, tax data have also their limitations. Usually the definitions of income and observation unit in tax data are different from those used in household surveys. Tax data are also very sensitive to tax avoidance and evasion, as well as to legislative changes in the income tax law (Atkinson et al. 2011).

[2] This is the longest period for which consistent series of household survey data with individual incomes (required for microsimulation analysis, see section 2.1 and Appendix A) can be constructed. However, this may be less of a problem for two reasons. First, income data from the Polish Household Budget Survey (PHBS) for the first years of post-socialist transition are of limited reliability due to enormous economic uncertainty and volatility in this period, as well as because of the significant methodological changes in the survey design introduced in 1993. Second, Keane and

with information from tax-based top income shares (Bukowski and Novokmet 2017) and use microsimulation modelling (Bargain et al. 2007; Morawski and Myck 2010) to reconcile differences in income concepts and observation units between the two data sources. We account for under-reporting and under-coverage of top incomes in the PHBS data by Pareto imputation of the highest income observations (see, e.g., Jenkins 2017) and survey reweighting techniques (Creedy 2004; Myck and Najsztub 2015).

Our analysis reevaluates distributional consequences of post-socialist transition in Poland using combined income data from household surveys and tax returns. The existing research on this problem has traditionally relied only on survey data and painted an optimistic picture of the Polish transition as almost an unqualified success story. This standard view suggests that Poland managed to achieve fast and stable economic growth (around 4.3% per year since 1994) that was at the same time broadly inclusive and shared relatively equally by various social classes and segments of income distribution. This view can be found in a number of influential works. For the early transition period of 1989-1996, Keane and Prasad (2002) have adjusted PHBS data to account for changes in survey design and found no increase in income inequality at all. Mitra and Yemtsov (2007) have contrasted smaller and gradual growth in income inequality in Poland with a sharper and larger inequality increase in Russia. In his comprehensive overview of inequality evolution in European countries, Tóth (2014) observed that the Gini coefficient for Poland grew by 5 p.p. between early 1990s and the mid-2010s and classified this increase as relatively modest by 'eastern standards'. Similar views were offered in recent book-length studies devoted to explaining Poland's successful transition to high-income status authored by the World Bank (2017) and Piatkowski (2018). The former work argues that income inequality in Poland is low and that the Gini coefficient for income distribution did not increase during the post-socialist transformation. The latter study claims that throughout the transition Polish economic growth has been inclusive and that income inequality as measured by the Gini index increased over 1989-2015 only by 3 p.p. – the smaller amount than in most of other transition countries. In opposition to the standard view, Bukowski and Novokmet (2017, 2018) use combined data from surveys, tax returns, and national accounts to show that income inequality in Poland as measured both by top income share and the Gini coefficient has increased during the transition much more than previously thought. For example, according to their results the Gini coefficient grew from about 0.28 in 1989 to almost 0.45 in 2015 (Bukowski and Novokmet 2018).[3] However, Bukowski and Novokmet's results are given in terms of fiscal (pre-tax) incomes distributed among tax units or among the adult population and therefore are hardly comparable with previous survey-based literature dealing with equivalent disposable (after tax) incomes examined on the whole population.

Our paper makes two major contributions. On the substantial level, we provide first estimates of the top-corrected distribution of the living standard (real equivalent disposable household income) of the entire Polish population for the period since early 1990s to 2015. Our main empirical result shows that contrary to the results based on unadjusted survey data which suggest no inequality increase, the top-correction procedures show that inequality of living standards as measured by the Gini coefficient increased substantially in Poland in the range from 14 to 26%. Our revisions imply that both the inequality trend and its level are significantly underestimated. While according to the unadjusted data the Gini coefficient in 2015 is at a relatively moderate level (30.1), the top

Prasad (2002) show that there is no evidence of an increase in income inequality in Poland over 1989-1996, when accounting for changes in the PHBS survey design and using equivalence scales in a consistent way.

[3] On the other hand, their survey-based estimates show an increase in Gini from 0.27 to 0.33 over the 1989-2015 period.

corrected estimate is 28% higher and equal to 38.4. We also show that the highest-income earners benefited disproportionately from the post-socialist growth process compared to the middle income groups and the poor. For instance, the annual rate of income growth for the top 5% of the Polish population has been within 3.5-5% range, while the median income grew by about 2.6% per year. Our top-corrected estimates suggest also a sharp decline in the progressivity of the social insurance and direct taxation system in Poland.

Second, we make a methodological contribution to the literature by showing that two techniques of adjusting income distributions (Pareto imputation of top incomes and survey reweighting) that have been so far applied separately can be implemented jointly to produce top-corrected inequality estimates that provide best fit to the data. To this end, we integrate the methodology of imputing to household survey data top incomes from Pareto models fitted on tax data (Bartels and Metzing 2018) with microsimulation-based survey reweighting approach using tax and other administrative information (Myck and Najsztub 2015).

Section 2 presents our income data from household surveys and tax records. In section 3, we introduce the methodology of top-correcting survey-based income distribution using Pareto imputation, reweighting and microsimulation modelling. Section 4 provides our empirical results on top-corrected income inequality in Poland over 1994-2015, as well as the comparison of top-corrected inequality levels and trends for Poland and other European countries. In this section we also discuss how different segments of income distribution in Poland benefited during the process of post-socialist transformation by looking at top-corrected rates of income growth by percentiles of income distribution and indicators of redistributive effect and progressivity of direct taxation. The last section concludes.

2. Data

2.1. Polish Household Budget Survey (PHBS) data

Our survey income data come from the Polish Household Budget Survey (PHBS) conducted annually by Statistics Poland since 1957. The PHBS is the main representative source of information on household incomes in Poland.[4] Since 1993, the methodology of collecting data in the PHBS is fairly constant (Keane and Prasad 2002; Kordos 2002). The sample size since 1993 is more than 30,000 households and 100,000 persons. We use the PHBS data for 1994-2015 as the pre-1994 surveys do not contain data on individual incomes (required for our microsimulation modelling) and 2015 is the last year for which estimates of tax-based top income shares are available (Bukowski and Novokmet 2017).[5] Kordos et al. (2002) provide comprehensive information about sample design and other features of the PHBS. The survey contains detailed data on monthly income from various sources for households as well as for individuals within households. Beside data on incomes, the PHBS provides information on household size and structure, economic activity of household members, housing conditions, detailed household expenditure, and others.

In order to account for survey non-response, Statistics Poland provides sampling weights that correct for inclusion of the households in the sample in accordance with the sample design. The sampling weights computed as inverse of selection probabilities are adjusted by post-stratification based on census data on place of residence (rural or urban) and size of the household. The

[4] The PHBS has been previously used to study income distribution in Poland by, among others, Szulc (2000), Keane and Prasad (2002), Podkaminer (2003), Brzeziński and Kostro (2010), Myck and Najsztub (2016).
[5] Note that the modern personal income tax was introduced in Poland only in 1992.

post-stratification does not use any information on sex, age or education of household members. We refer to these weights as 'baseline' PHBS weights. Myck and Najsztub (2015, 2016) show that using the baseline weights leads to significant under- or over-representation of several age groups. For example, compared to administrative statistics the PHBS results obtained with baseline weights overestimate the population of children aged 0-15 by more than 1.4 million in 2014 and underestimate the adult population by the corresponding amount. Similar discrepancies were found in case of subpopulations defined with respect to the education level, employment type or type of household residential area. Following Creedy (2004) and Deville and Särndal (1992), Myck and Najsztub (2015) propose to address this problem by calibrating the PHBS baseline weights using information from various administrative sources. This reweighting approach leads to adjusted weights that allow for obtaining weighted PHBS estimates corresponding closely to values taken from administrative sources (such as the official number of children in the population or people with higher education).

In this paper, we follow Myck and Najsztub (2015) in using the reweighing approach to adjust the baseline PHBS weights. In particular, we use two types of weight calibration. The first of these adjusts the baseline weights by calibrating them to match the census-based number of males and females in several age groups (see Appendix A for details). We refer to these weights as "population weights". Secondly, we further calibrate population weights to match the number of PIT payers in each tax bracket based on official information from Ministry of Finance reports.[6] These weights are henceforth referred to as "tax weights". We expect that using tax weights will lead to a significantly better coverage of the upper tail of the Polish income distribution as compared with raw PHBS data.[7] However, since the value of income in the higher tax brackets is heavily underestimated even using tax weights (see Appendix A) it is necessary to adjust for missing top incomes using other methods.

Our main income variable is real equivalized household disposable (post-tax, post-transfer) income.[8] We obtain it from the Polish microsimulation model SIMPL (Bargain et al. 2007; Morawski and Myck 2010) applied to the PHBS data. Using income obtained from tax and benefit microsimulation procedure has several advantages over relying on raw data declared in the survey. The simulated household income correctly captures all social transfers paid to the household. It is also adjusted for seasonality with respect to income from agriculture. In particular though, using the microsimulation model, we are able to construct gross (before PIT and employee SSCs) income distribution among the tax units, which is unavailable in the raw PHBS data (see Appendix A for details). This is crucial as it is the gross income distribution between tax units to which we impute top incomes from the Pareto distribution estimated using tax-based statistics (see section 3). Similarly, the microsimulation model allows us then to express imputed gross incomes in terms of their net values.

[6] The number of PIT payers is computed based on gross incomes simulated using the SIMPL microsimulation model.
[7] Myck and Najsztub (2015) show that calibrating the baseline PHBS weights with respect to the total number of PIT payers significantly increases the level of income inequality in Poland over 2006-2011 as measured by the Gini index and other indices.
[8] We use the modified OECD equivalence scale.

2.2. Top income shares from tax return data

Bukowski and Novokmet (2017) provide top income shares series for Poland between 1892 and 2015.[9] In this paper, we focus on the period 1994-2015 for which we can construct reliable and consistent series of household survey data on income (see section 2.1). For this period, Bukowski and Novokmet (2017) estimate top income shares using tabulations on the settlement of the PIT published annually by the Ministry of Finance.[10] The tabulations contain information on the number of taxpayers, the amount of income, and tax paid by income brackets as defined by the tax rate schedule. This information is highly grouped as limited progressivity of the Polish income tax system implies that the number of income brackets in the tax rate schedule is small (three for 1994-2008, and only two after 2008). For this reason, Bukowski and Novokmet (2017) estimate only income shares of those top percentile groups that are close to the percentage of taxpayers in the top income bracket (i.e. the top 5% and top 1% income shares). The top income shares, as standard in the literature, are calculated in terms of gross (pre-tax) income distributed among tax units. The income concept used covers income from employment, pensions, nonagricultural business activity, special departments of agricultural business activity, self-employment income, rental income, capital gains and income from other sources. Capital income is not included. The estimates are adjusted for the several changes in the tax code that were implemented since 1994. In order to estimate top income shares, Bukowski and Novokmet (2017) apply the standard Pareto interpolation techniques (see Atkinson 2007; Atkinson et al. 2011).

3. Top-correcting of income distribution using combined household survey and tax return data

Jenkins (2017) provides a recent comprehensive review of approaches to correct the income distribution for under-coverage of top incomes in survey data. There are three main approaches to estimate inequality indices that account for under-reporting of high incomes and under-coverage of high-income respondents in surveys. The first one (Approach A in Jenkins' terminology), which relies only on survey data, fits Pareto models to high-income observations from the survey and derives inequality estimates by combining survey information and values from the fitted models. Alfons et al. (2013) used this approach to correct income distributions for Austria and Belgium, while Burkhauser et al. (2012) applied it to the US. Brzezinski and Kostro (2010) used a variant of this method to adjust the income distribution in Poland. However, while this approach may address the issue of high-income under-reporting, it does not deal with the problem of under-coverage of high-income respondents in surveys. It produces top income shares that are several p.p. lower than those derived from tax return data. For these reasons, Jenkins (2017) considers it less reliable than other alternatives.

The two remaining approaches to deal with under-coverage of high incomes in surveys make use of tax return data. Approach B in Jenkins' (2017) terminology, replaces the highest incomes in a survey with cell-mean imputations based on the corresponding observations in data from tax returns. It has been applied by Burkhauser et al. (2017) to correct the income distribution in the UK and by and by Bach et al. (2009) for Germany. In principle, Approach B requires access to individual tax return data.. The last method, Approach C, combines inequality estimates from

[9] Kośny (2019) provides top income shares estimated from individual tax returns for Lower Silesian Voivodeship in Poland.

[10] Information from individual tax returns from Poland is not at present available to researchers.

survey and tax data (and not data from the two sources as the Approach B does). It was developed in Atkinson (2007) and applied by Atkinson et al. (2011) to the US. Alvaredo (2011) extended the approach and used it to correct inequality estimates for Argentina and the US. Other applications include Lakner and Milanovic (2016) and Anand and Segal (2017) to global income inequality, Jenkins (2017) to the UK, and Bukowski and Novokmet (2017) to Poland. Approach C combines inequality estimates for the 'non-rich' households computed in the standard way from survey data with inequality estimates for the 'rich' calculated from tax return information, either non-parametrically or by fitting Pareto models to tax data and deriving parametric inequality estimates.

Recently, Bartels and Metzing (2018) proposed a flexible, integrated methodology for top-correcting income distributions, which can be considered as a combination of Jenkins' B and C approaches. The methodology has three important advantages. First, it can be used when micro-data from tax records is unavailable and only aggregated tax-based statistics (such as publicly available top income shares) are at researchers' disposal. Second, it produces top-corrected distributional results for any distributional measure (i.e. inequality, poverty, middle class indices, etc.) as well as for any income definition. Third, in contrast to most of the previous approaches, Bartels and Metzing's (2018) framework produces distributional indices not only for the population of taxpayers, but also for the full population. This allows for obtaining estimates of inequality in terms of the most common measure of the standard of living, namely disposable (post-tax post-transfer) equivalized income for the entire population.

The methodology of Bartels and Metzing (2018) involves the following steps. First, survey and tax data are reconciled with respect to differences in income definitions, observation units, and the coverage of top incomes. Second, the appropriate share of top incomes in gross (pre-tax) household survey data is replaced with Pareto-imputed incomes estimated using information from tax-based top income shares. Finally, top-corrected gross income distribution is "netted down" to obtain net (after-tax) equivalent household income distribution, which is used to compute final estimates of inequality and other measures. This approach, modified to account for several specific conditions, is applied in our paper to Polish incomes data.

In order to impute top incomes estimated from tax-based statistics, Bartels and Metzing (2018) follow most of the literature in using the Pareto Type I model (Atkinson et al. 2011; Alvaredo 2011).[11] The Pareto I distribution for income variable x can be defined through its survival function $S(x)$, which is equal to 1 minus the cumulative distribution function $F(x)$:

$$S(x) = 1 - F(x) = \left(\frac{x}{x_m}\right)^{-\alpha}, \tag{1}$$

where $x \geq x_m > 0$, and $x_m > 0$ is the threshold above which the data are Pareto distributed. Parameter α is known as Pareto tail index and describes the heaviness of the right tail of income distribution. The lower the tail index, the heavier the right tail and the more unequal Pareto distribution. Following Atkinson (2007) and Bartels and Metzing (2018), we estimate the tail index as:

$$\alpha = \frac{1}{\left(1 - \frac{\log(S_j/S_i)}{\log(P_j/P_i)}\right)}, \tag{2}$$

where P_i and P_j are the population shares of group i and j, and S_i and S_j are the income shares of these groups estimated using tax data. In practice, the indices i and j denote given fractiles of the population with i being a subgroup of j. Most of the literature uses 0.10, 0.05, 0.01, and 0.001 fractiles of the population. For Poland, the only existing top income shares are for the 0.05 and

[11] Jenkins (2017) carefully studies the problem of fitting various Pareto models to income tax data. He finds that Pareto Type II (generalized Pareto) model provides a better fit do data than Pareto Type I model. According to his results, the threshold above which Pareto models fit income data well is the 99th or 95th percentile.

0.01 fractiles (Bukowski and Novokmet 2017), which means that we estimate the Pareto tail index using population and income shares for the top 5% and 1% of the population.

After estimation of α , the threshold x_m can be obtained from equation (1) as follows:

$$x_m = x(1 - F(x))^{1/\alpha}, \tag{3}$$

where $F(x)$ and x are estimated using survey data. The value of x is implied by the proportion of survey incomes to be replaced with Pareto-imputed values. In this paper, we experiment both with replacing top 1 and 5% incomes from survey data and correspondingly set x to the 99th and 95th percentile of the survey income distribution, respectively.[12] In the final step of top-correcting gross income distribution, we replace the top 1% (or 5%) of tax unit incomes observed in our survey data with incomes implied by the Pareto distribution characterized by our estimates of α and x_m.

The full methodological approach taken in this paper is composed of the following steps..[13] We use detailed year-specific information on the Polish tax-benefit system parameters and the SIMPL microsimulation model to cross-walk from the PHBS household net income to gross income distributed among tax units (individuals). In the next step, we use data on top income shares from Bukowski and Novokmet (2017) to estimate the parameters of the Pareto distribution (equations 2-3) for tax units' gross incomes.[14] Then, we replace the top 1% (or 5%) of tax units' incomes with incomes implied by the Pareto distribution characterized by our estimates of α and x_m. The resulting imputed gross distribution is subsequently reweighted using either population or tax weights in order to ensure that our survey data are representative with respect to age and sex distribution in the population and – in the latter case – that they match the number of PIT payers in each tax bracket based on official information from Ministry of Finance data.[15] After imputing top incomes, we again use the microsimulation approach to compute top-corrected net incomes by applying the tax schedule on the imputed incomes within tax units as defined in the PHBS data. . The resulting top-corrected net income distribution, combined with other sources of income in the data, is used as a measure of disposable income to compute our final distributional indices. The procedure is performed separately for each year between 1994 and 2015.

4. Empirical results

4.1. Estimating the under-coverage of high incomes in household survey data

We start by looking into the degree of under-coverage of high incomes in the PHBS. Figure 1 compares estimates of top income shares from tax records (Bukowski and Novokmet 2017) and

[12] Bartels and Metzing (2018) set x_m to the 99th percentile, while Jenkins (2017) finds that the appropriate value of the threshold is between the 99th and 95th percentile.

[13] Appendix A provides a more detailed description of our top-correction procedure.

[14] Our estimates of α and x_m are provided in Table A2 in Appendix A. The goodness-of-fit of Pareto models to data can be assessed using the so-called Zipf plots (which plot $\log(1 - F(x))$ against $\log(x)$). If data follow a Pareto model, the Zipf plot should produce a straight line with the slope equal to $-\alpha$. Figure A2 in Appendix A shows that in general the unadjusted PHBS data do not follow Pareto distribution. For the top-corrected data, lines on Zipf plots are much flatter implying lower tail exponent and more unequal income distribution.

[15] We have considered also an alternative procedure according to which we first reweight the PHBS data to match target statistics from official sources and in the second step we impute top incomes to the reweighted distribution. The two approaches are compared in Appendix B (Figures B1-B2) in terms of discrepancy between top income shares estimated from top-corrected survey data and from tax records. The approach of imputing top incomes first and reweighting the imputed distribution next seems to provide slightly better results and we rely on it in the reminder of the paper.

from the PHBS data (with population weights). The series are based on reconciled income definition (gross income) and refer to the distribution among tax units (individuals). We observe that there is relatively little discrepancy between the two series for the period 1994-2004. In case of the top 5% income share, the discrepancy does not exceed 2 p.p. The top 1% income share is underestimated in survey data in this period more significantly by between 2 and 3.5 p.p. Since 2005 the gap between the estimates grows sizeably reaching in 2015 as much as 8.8 p.p. in case of the top 1% income share and 6.5 p.p. in case of the top 5% income share. The top 1% share in the last year of our series is thus higher compared to the estimates for Germany (3-6 p.p., Bartels and Metzing 2018) and the US (6 p.p., Burkhauser et al. 2012), but still lower compared to Russia (12-14 p.p., Novokmet et al. 2018).

[Please insert Figure 1 around here]

As we can see from the income shares from tax records displayed in Figure 1 the highest incomes in Poland grew particularly fast between 2003 and 2008 and this change in the top shares is completely missed in household survey data. In our view both of these facts may provide interesting clues as to the reliability of the income series to inform us about the true nature of inequality dynamics. Using individual panel tax return data for 2002-2005, Kopczuk (2012) argues that the increase in top tax incomes is related to the 2004 tax reform in Poland which introduced an optional flat tax for non-agricultural business income. This reform reduced the marginal tax rate for the highest income taxpayers from 40% to 19%. Before 2004, business income was taxed according to the progressive scale with three marginal tax rates of 19%, 30%, and 40%. The reform introduced an option of taxing business income using the flat rate of 19%. Kopczuk (2012) shows that the reform was associated with a dramatic increase in the amount of reported business income in tax returns. Gross income reported by taxpayers affected by the reform grew by 48% over 2003-2004. Kopczuk (2012) suggests that although this increase may partly reflect the rise in real economic activity, it is likely to be largely driven by reduced tax avoidance or tax evasion. Figure 2 plots year-to-year changes in the GDP per capita and total reported gross income between 1995 and 2015. The figure shows that for most of the 1995-2004 period reported total gross income of taxpayers grew more slowly than the GDP per capita, which might suggest that before the 2004 reform the problems of tax evasion and avoidance could have been more pronounced compared to later years. This change in the scale of tax avoidance calls for two notes of caution. First of all, correcting survey data with official tax information might still fail to capture the true extent of inequality. Second, in particular in the context of developing countries and emerging economies and in studies covering longer time periods, alternative approaches are called for to address the potentially changing degree of income underreporting (or non-reporting) in tax data. While under-reporting of top incomes in surveys can be addressed by adjusting survey data with imputation from Pareto model estimated on tax data, the under-coverage (the fact that some of the top incomes were likely not reported at all) cannot be probably corrected using this method. A more promising approach to address the under-coverage of top incomes in tax data is to adjust survey weights with tax weights. We explore this approach in the next section, and show that it can provide an alternative set of reference values for a consistent long-term series of inequality measures. .

It is also worth noting that, as shown in Figure 2, while reported gross income subject to the linear 19% tax grew exceptionally fast over 2005-2008 period, this was also accompanied by strong growth in gross taxable income taxed according to the progressive scale. The two series seem to reflect the soaring real economic activity driven by fast economic growth in that period and may cast some doubt over the interpretation that the strong growth the top 1% and top 5%

share (Figure 1) only reflected a structural shift in tax avoidance. [16] Taxable incomes taxed in the linear 19% systems grew very fast not only right in the follow up of the reform, but continued for a number of years later and reflected overall trends in the economy.[17] This interpretation is shared by Bukowski and Novokmet (2017) who argue that since top shares grew strongly not only over 2003-2004 but also over the extended period up to 2008, the major underlying cause of this inequality spike is probably not related to the 2004 tax reform. They also show that the sharp rise in top income shares over 2003-2008 was exclusively due to the rise of business incomes and that since 2005 most of the top 1% income consists of business income.

[Please insert Figure 2 around here]

Bukowski and Novokmet (2017) suggest several economic mechanisms to explain the substantial growth in top income shares in Poland over 2003-2008, other than increased tax compliance. It could be driven by a cyclical expansion of the Polish economy (caused by the global economic boom of 2001-2007) that increased top business incomes disproportionately more than top labor incomes. The growth of top income shares over 2003-2008 could also be a result of a long-term capital deepening and growing capital income share (declining labor share) in the Polish national income (Growiec 2012; Gradzewicz et al. 2018).[18] Growing capital share could be in turn driven by capital-augmenting technical change or by globalization through trade-induced shift toward capital-intensive sectors. Additionally, monopolistic markups adjusted for cyclical effects increased substantially in Poland over 2004-2009 (Hagemejer and Popowski 2014) and the markups were significantly higher for manufacturing and non-exporting firms. Nolan et al. (2018) suggest that higher markups and associated increased product market power could make income distribution more unequal through higher firm profits and higher incomes of the richest firm owners, or through negative impact on interest rates that leads to increased asset prices favoring richer individuals.

However, since none of the above hypotheses can be formally tested we still need to treat the continuity of the tax series across the years 2003-2008 with some caution, which is an argument in favor of an approach which may to some extent address this problem.

4.2. Income inequality levels and trends

Based on the results presented in Figure 1, we examine several imputation approaches - imputing either top 1% or top 5% of incomes in the PHBS data. We also use survey reweighting based either on population or on tax weights (see section 2.1). This gives four alternative combinations for top-correcting the PHBS data which we apply below. Figure B1 in Appendix B compares the four methods in terms of the gap between top income shares estimated from tax records and from top-corrected survey data. It seems that neither approach reduces the gap in a satisfactory way for the whole period under study. Up to 2005, the smallest gap for both top percentile groups is obtained for imputing top 1% incomes and applying population weights. However, after 2005 this approach is dominated by imputing top 1% and reweighting with tax weights or imputing top 5% and apply-

[16] The surge in business income over 2004-2008 can be also a result of shifting top labor earnings to business income (see Bukowski and Novokmet 2017 for further discussion).

[17] The GDP per capita growth amounted to 5.3% per year over 2005-2008, and to 6.7% over 2006-2007.

[18] The relationship between capital share and income inequality is complicated and depends, among others, on inequalities of capital and labor income and on the correlation between capital and labor income. Bengtsson and Waldenström (2018) show that empirically there is a strong positive link between capital share and top personal income shares, which is increasing for recent periods and in Anglo-Saxon countries.

ing population weights. Imputing top 5% and reweighting with tax weights significantly overestimates top income shares, especially in the case of the top 5% share. The trend in tax-based top income shares after 2005 seems to be best captured by the approach of imputing top 1% incomes and reweighting with tax weights. Confidence intervals for this series cover point estimates for tax-based top income shares in almost each year over 2006-2015. The alternative approach – imputing top 5% incomes and reweighting with population weights – significantly underestimates top 5% shares in each year over the 2009-2015 period. For this reason, our preferred top-correction procedure for post-2005 period is based on imputing top 1% and using tax weights. On the other hand, for the pre-2005 period we rely on two series using imputation of top 1% incomes and either tax or population weights. While the series using population weights tracks tax-based estimates of top income shares in the pre-2005 period quite closely (cf. Figure B1), as we argued in Section 4.1, the tax series up to that point, i.e. prior to the 2004 tax reform, may suffer from a higher degree of tax avoidance or evasion.. Therefore, we for the pre-2005 period we consider also the same method as our preferred method for the post-2005 years, i.e. imputing top 1% and using tax weights. The use of tax weights in this approach addresses the potential higher degree of tax avoidance by reweighting a greater proportion of the population than the 1% for which incomes are imputed.

Figure 3 provides estimates of top-corrected top income shares using our preferred approaches. The gap between tax-based estimates from Bukowski and Novokmet (2017), labelled as "Income tax records" on the Figure, and survey-based estimates (the two "Top corrected PHBS series") becomes much smaller for our top-corrected series (cf. Figure 1). The top-corrected series using tax weights overestimates the top 5% income share before 2005, but it can be considered as a plausible estimate of an upper bound on top income shares adjusted for higher top incomes underreporting in the pre-2005 period. The good performance of this approach in the post-2005 period reinforces our premise that this kind of correction can serve as a satisfactory upper bound on our estimates for the pre-2005 period. Point estimates for the top 5% income share are slightly higher than the tax-based figures since 2009, but our confidence intervals contain tax-based estimates for most of this period. Overall, our preferred methods of top-correction seem to successfully reduce the gap between tax-based and survey-based estimates and shows advantages of combining Pareto imputation and survey reweighting.

[Please insert Figure 3 around here]

Figure 4 shows the evolution of income inequality in Poland over 1994-2015 as measured by the Gini coefficient, using both unadjusted and top-corrected series. Until 2005, our two correction procedures show similar inequality trends, but somewhat different levels. The correction using tax weights suggests that the Gini index is about 4 p.p. higher than that implied by the method using population weights. Since we are unable to decide which series gives more plausible Gini estimates for the 1994-2005 period, we conclude that the series present upper and lower bounds on the "true" Gini. After 2005, our single preferred correction method shows systematic and high divergence between unadjusted and top-corrected Gini indices ranging from 4 to 8 p.p. The spike in the top-corrected series observed in 2009 results from a slight overestimation of top income shares in this year and should be treated with caution. The point estimate for the Gini index for unadjusted data remains mostly stable over time and even declines somewhat after 2013, while it surges significantly for the top-corrected series from about 0.3-0.34 in 1994 to around 38-40 p.p.

in the period between2010 and 2015.[19] The top-corrected Gini indices increase by between 14 to 26% over the 1994-2015 period.

[Please insert Figure 4 around here]

It should be stressed that the confidence intervals for the top-corrected Gini series are much wider than those for the unadjusted series. For example, in 2015 they range from 36.5 to 40.2. However, even accounting for the uncertainty associated with our estimates, the top-corrected Gini indices suggest that at least since 2005 income inequality in Poland is substantially higher than previously thought.

Bukowski and Novokmet (2018) also provide top-corrected Gini coefficients for Poland over the 1983-2015 period. However, their results are not strictly comparable to ours as they compute the indices in terms of fiscal income (gross income before personal deductions and income taxes), while our final estimates are for disposable incomes, net of taxes and transfers. In addition, Bukowski and Novokmet (2018) apply the distributional national accounts methodology of Alvaredo et al. (2016). For the period 2006-2015, their Gini coefficients lie within a range from 43 to 45% and are 6-7 p.p. higher than our estimates.

4.3. Inequality in Poland in the light of results from other counties

We now turn to the implications of our results for the comparison of inequality trends and changes in Poland versus other countries. We focus mainly on the countries for which top-corrected inequality estimates have been obtained using methods similar to those used in this paper. Bartels and Metzing (2018) provide such results for a number of European countries using survey data from the German Socio-Economic Panel (SOEP) and EU Statistics on Income and Living Conditions (EU-SILC). Their results show that the gap between survey-based inequality estimates and top-corrected inequality estimates is negligible for countries that have a long tradition of exploiting administrative sources in collecting income information in EU-SILC (e.g. Scandinavian countries, the Netherlands and Ireland).[20] The gap is somewhat larger, but still relatively small for the 'new register countries' that started using income data from register relatively recently (France, Italy, Spain, Switzerland). Not surprisingly, the largest gap is found by Bartels and Metzing (2018) for countries that collect income information in the EU-SILC using household surveys only (Germany and the UK). The top-corrected Gini indices for net income distribution are higher than those for unadjusted net income distribution by 5-9% for Germany and 2-5% for the UK (see Figures B3-B4 in the Appendix).

The comparison of our results with those of Bartels and Metzing (2018) for the EU-SILC 'survey countries' and Spain indicates that for the unadjusted data the Gini index for Poland takes only a moderately high value – it is higher than for Germany, but in general lower than for Spain and the UK.[21] However, the comparison of top-corrected estimates leads to a strikingly different

[19] Our results for the unadjusted data are in line with those from the Luxembourg Income Study (LIS), which is most widely used cross-country database of harmonized income microdata. The Gini for real equivalized net disposable income from LIS is 0.318 for 1995 and 0.316 for 2013.

[20] The administrative sources include population registers, tax registers, social security data, and health and education records. See, for example, Jäntti et al. (2013) for more information.

[21] We add Spain to the comparison despite the fact that it is a 'new register country' rather than 'survey country' since it has the highest level of income inequality (as measured by the Gini index) among the EU countries studied by in Bartels and Metzing's (2018).

conclusion. Since 2005, the top-corrected Gini indices for Poland exceed substantially and significantly those for the comparator countries. Our results suggest therefore that the standard view implying that income inequality in Poland is close to the average EU level is probably wrong.

After 2005, the increase in the Gini index resulting from our top-correction procedure for Poland is dramatically higher than the sizes of analogous top-corrections for other countries analyzed by Bartels and Metzing (2018). It ranges from 15 to 30% of the Gini estimate, while the top-corrections for other EU countries are always smaller than 10%. This result suggests that the under-coverage of top incomes in the PHBS data may be significantly more severe than in household surveys used in other countries.[22] The substantially larger size of top-correction for Poland is probably related to the observation of Bukowski and Novokmet (2017) that in Poland most of the top 1% income consists of business income, while in most of other countries the dominant source is labor income. Business owners may be harder to reach in household surveys and they may have more incentive to refuse to participate in surveys or to under-report their incomes.

Our top-corrected estimates suggest that the standard view maintaining that the post-socialist transition in Poland was associated with a modest rise of inequality of household disposable incomes has been overly optimistic. This view was widely accepted in academic publications and policy reports (see, e.g., Mitra and Yemtsov 2007; Tóth 2014; OECD 2015; Perugini and Pompei 2015; World Bank 2017; Piatkowski 2018). However, all these publications were based on income data from household surveys (usually from the PHBS). Our results call this previous literature into question by showing that between early 1990s and mid-2010s income inequality in Poland grew faster than survey data alone would suggest. In particular, our top-corrected Gini index for net disposable equivalent incomes increased over 1994-2015 within a range from 5 to 8 p.p. (14-26%).

The divergence between inequality in terms of unadjusted survey data and inequality measured for top-corrected income distribution in Poland is replicated for other inequality indices. Figures B5-B7 in Appendix B present our estimates of the three Generalized Entropy (GE) inequality measures (mean log deviation, the Theil index, and half the squared coefficient of variation). The results show that our top-correction procedure (with tax weights) leads to an increase in the point estimate for the mean log deviation index by about 35% over 1994-2015. The corrections are even larger in case of other GE measures. This is not surprising as the GE indices are more sensitive to extreme observations than the Gini coefficient (Cowell and Flachaire 2007).

We study also the impact of imputing top incomes and survey reweighting for the trend in relative poverty in Poland during the post-socialist transition. Figure B8 in Appendix B compares evolution of relative poverty rate (the proportion of population with income less than 60% of the median income) for the unadjusted and top-corrected income distributions. While the relative poverty rate for unadjusted distribution increased from about 14.7% in 1994 to 16.5% in 2015, the results for the top-corrected distribution (using tax weights) show that poverty rose over the same period by 13.4% to 17.1%. The adjustment due to the top-correction, although significant, is therefore much less pronounced for relative poverty than for income inequality. This is not surprising as our top-correction approach is designed mainly to adjust the upper end of income distribution, while the relative poverty rate is sensitive mainly to the shape of lower end of the distribution.

4.3. Growth rates by percentiles

[22] The estimates of the Gini index for net incomes in Poland based on the unadjusted PHBS data are not significantly different in general from those based on EU-SILC data (results available upon request). Therefore, the severe under-estimation of top incomes is not specific to the PHBS data but seems to be a universal feature of household surveys in Poland.

We now turn to the analysis of income gains for various segments of the Polish population using growth incidence curves (GIC) of Ravallion and Chen (2003). GIC provides graphical depiction of annualized growth rates for every percentile of income distribution between two points in time. Figure 5 computes GICs for the unadjusted and top-corrected data between 1994 and 2015. The GIC for unadjusted distribution is fairly flat suggesting that real incomes for most of the Polish population, irrespective of their position in income distribution, grew by about 2.5% per year over 1994-2015.

[Please insert Figure 5 around here]

The overall picture is strikingly different for the top-corrected GICs. Both have strictly positive slope implying that higher income groups experienced higher income growth. According to the corrected estimates, the poorer part of the income distribution (up to about 15th percentile) experienced lower annual rates of income growth compared to the unadjusted estimates. However, our correction for the bottom decile group does not exceed one half of a p.p. on average. We observe much bigger discrepancy between unadjusted and corrected data for the upper part of the income distribution (above 65th percentile). The top-corrected estimates suggest that annual income growth of the rich has been underestimated from about 0.4-0.8 p.p. (at the 90th percentile) to 1.5-2.4 p.p. (at the 99th percentile). In other words, cumulative growth in real income over 1994-2015 for the top 1% of Poles reached 122-167%, while for the bottom 10% the corresponding number is at most 57%.[23] This is consistent with the observed rise in overall income inequality as measured by the Gini index (cf. Figure 4). Our estimate of the income growth rate for the 99th percentile (about 4.8% per year) is relatively high by regional standard. For example, Novokmet et al. (2018) estimated that the annual rate of growth for the 99th percentile of pretax national income distribution in Russia in 1989-2016 was slightly lower than 3.5%.

It is at the same time worth noting that even looking at the top-corrected GIC for Poland for the 1994-2015 period that each segment of disposable income distribution in Poland gained in absolute terms between 1994 and 2015.[24] The upward-sloping shape of our GIC for net income distribution is similar to that of the GIC for the fiscal income distribution obtained by Bukowski and Novokmet (2018) for Poland the period 1989-2015. The only major difference is that their estimates suggest negative rates of growth for the bottom few percentiles. This can be explained with reference to differences in income definitions and time coverage of the studies.

4.4. Redistribution and progressivity

This section investigates how our top-correction of household survey data affects measures of redistribution and progressivity of social insurance and direct taxation (income taxes, employees' mandatory social security contributions, and health insurance) in Poland. The system of social insurance has been reformed multiple times during our period under study. The modern social insurance system with social security contributions (SSC) paid partially by employees and employers was introduced in 1999. Before that, all SSCs were paid by employers only.[25] For these reasons, our analysis of redistribution and progressivity due to social insurance and direct taxes covers the period 1999-2015. In 2007 and 2008, the SSC rates were reduced by 7 p.p. Major reforms have

[23] The cumulative income growth at the median income reached 75%.
[24] On Figure 5, we do not show estimates for the two lowest percentiles which are slightly negative. However, this may result from measurement error and noisiness of income distribution at the very lower end.
[25] See, e.g., Goraus and Inchauste (2016) for a detailed description of the Polish public finance system.

taken place also in the system of personal income tax (PIT). Before 2005, there was a single progressive PIT schedule with three tax brackets and marginal tax rates of 19%, 30% and 40%. As described in Section 4.1, a reform in 2004 provided an option of choosing between the progressive tax rate schedule and the flat rate (19%) for non-agricultural business activity. Since 2009, the number of tax brackets and marginal tax rates in the progressive schedule was reduced from three to two (18% and 32%). About 95% of PIT payers were in the first tax bracket in 2015 (see Table A1 in Appendix A).[26]

To measure redistribution, we use the most popular redistribution measure, the Reynolds-Smolensky (RS) index of redistribution (Reynolds and Smolensky 1977), which in our context is defined as the percentage difference between the Gini coefficient for gross income (before income taxation, SSCs and health insurance) and the Gini coefficient for net income (after income taxation, SSCs and health insurance). Figure 6 (panel a) presents the evolution of the RS index for the unadjusted and top-corrected survey data.[27] Both series indicate that the redistributive effect diminishes over time, which reflects declining marginal rates of PIT and falling SSC rates. The top-corrected estimates show that the percentage reduction in the Gini index due to social insurance contributions and PIT has fallen from 19.2% in 1999 to 11.6% in 2015. Our estimates suggest that in 2005 Poland reached comparatively low level of redistribution due to direct taxes and social insurance contributions. Verbist and Figari (2014) show that the average RS index for the 15 "old" EU members was 15.3% in 2008 with only three countries (Italy, Spain, France) having a lower level of redistribution than Poland in 2015.

[Please insert Figure 6 around here]

Finally, we consider the problem of tax progressivity using the Kakwani (1977) index defined as the difference between the concentration coefficient of the tax and the Gini coefficient of gross income.[28] Figure 6 (panel b) plots our estimates of the Kakwani index for the unadjusted and top-corrected income distributions. Even the unadjusted estimates rank Poland as the country with the lowest PIT and SICs progressivity in the EU (Verbist and Figari 2014; Mantovani 2018). While the unadjusted series suggest that the progressivity of the Polish system of PIT and social insurance contributions has decreased only mildly over time, the top-corrected estimates point to a much steeper fall, especially during 2005-2009. Without the top-correction, the progressivity in 2015 is overestimated by 2.3 p.p. (or by 40%). Much of the decline in tax progressivity over 2005-2009 is due to the reduction from three PIT brackets and marginal tax rates to just two brackets and rates (18% and 32%) in 2009. According to the top-corrected estimates, the Kakwani index fell from 7.5% in 1999 to 3.4% in 2015. Thus, the results suggest that top-correcting of survey data leads to lower estimates of the redistributive effect and progressivity of direct taxation system in Poland. In particular, the corrected estimate of PIT and SICs progressivity is reduced by as much as 40% compared to estimates based on unadjusted household survey data.

5. Conclusions

[26] Kopczuk (2012) and Bukowski and Novokmet (2017) provide more details of the Polish PIT system.

[27] Since both our adjustment procedures give very similar results for redistribution and progressivity analysis, we treat them in this section as a single top-corrected series.

[28] The Kakwani progressivity index reflects the departure of tax system from proportionality to the gross (pre-tax) incomes. If the tax system is proportional, the concentration curve for the tax (showing the cumulative proportion of taxes versus position in the gross income distribution) should coincide with the Lorenz curve for pre-tax income. See, e.g., Lambert (2001) for more details.

This paper uses combined household survey and income tax data to reevaluate distributional consequences of the post-socialist transition in Poland from early 1990s to the mid-2010s. We correct for the problem of survey under-coverage and under-reporting of top incomes by using Pareto imputation, survey reweighting and microsimulation methods. We present first top-corrected trends in inequality of the standard of living in terms of real equivalized disposable (post-tax post-transfer) household incomes. In contrast to the prevailing literature based on unadjusted household survey data, we find that inequality in Poland rose sharply between 1994 and 2015. The top-corrected Gini coefficients calculated using equivalized disposable household incomes grew by 4-8 p.p. or by 14-26% over the analyzed period. Our estimates suggest that while Poland was already a relatively unequal country in early 1990s, it has become one of the most unequal European countries (outside Russia) among those for which comparable estimates exist. The top-correction to the Gini index that we estimate is 2-3 times larger than those obtained using similar methods for other (mostly advanced) European countries. We also find that it is the highest-income earners who benefited most from the post-socialist transformation in Poland. What's particularly striking is the fact that incomes at the top end of the income distribution grew also as a result of government tax policies. Our top-corrected estimates show that progressivity of direct taxation and social insurance has fallen by 40% over the 1999-2015 period.

On the methodological level we show the advantages of combining Pareto imputation with survey reweighting methods to further improve survey-based top income shares in Poland. Relying only on Pareto imputation without survey reweighting can substantially underestimate income inequality levels and changes in survey data. Survey reweighting with weights estimated using administrative tax data have been shown to be especially useful in recovering bounds on inequality levels when there is a risk that top incomes in the tax data also suffer from underreporting. We believe that our methodology can be usefully applied in the context of top-correcting income distributions in other countries and can be successfully applied in particular to data from emerging economies.

Our results have important implications for the literature evaluating distributional consequences of major socio-economic transformations and modernization processes in emerging economies. We have shown that using income tax data and imputation or reweighting techniques to account for the problem of missing top incomes in survey data can significantly alter the picture of inequality levels and trends. Although the literature on correcting income distributions in emerging economies (see, e.g., Bukowski and Novokmet 2017, 2018; Novokmet et al. 2018; Piketty et al. 2018) seems to be growing fast, clearly more data (especially individual income tax microdata) and research are needed. This would contribute not only to a better understanding of the underlying processes but could also shed light on recent political developments in many countries (such as Turkey, Hungary or Poland). As suggested recently by Bussolo et al. (2018), the growing distributional tensions in emerging countries of Eastern Europe and Central Asia may be associated with more distrust in governments and increased propensity to vote for radical political parties.

Finally, our analysis suggest also that survey-based estimates of income inequality may be underestimated to a much larger extent in transition countries or emerging economies compared to the statistics computed for advanced economies. Yet such estimates are frequently used in international comparisons exploiting inequality data from such cross-national sources as the World Income Inequality Database (WIID) or Luxembourg Income Study (LIS). If those figures are distorted by underreporting of top incomes to a different extent in different groups of countries, the studies examining cross-country determinants or consequences of income inequality may be seriously biased.

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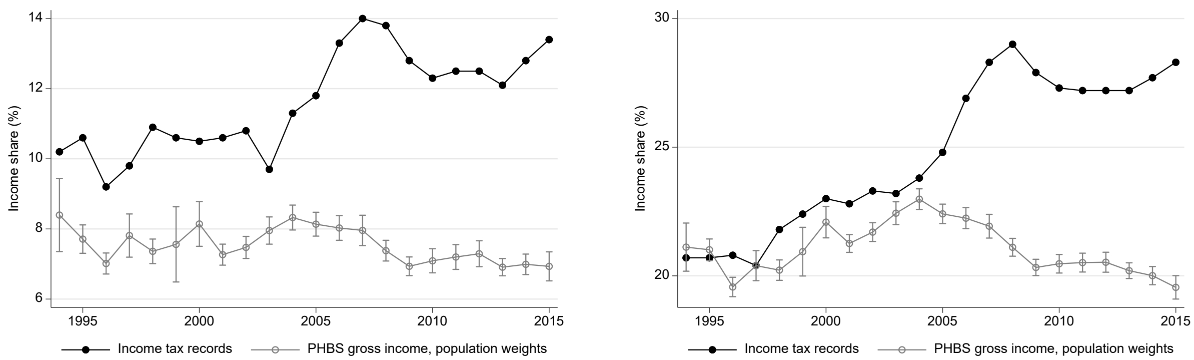
Figures

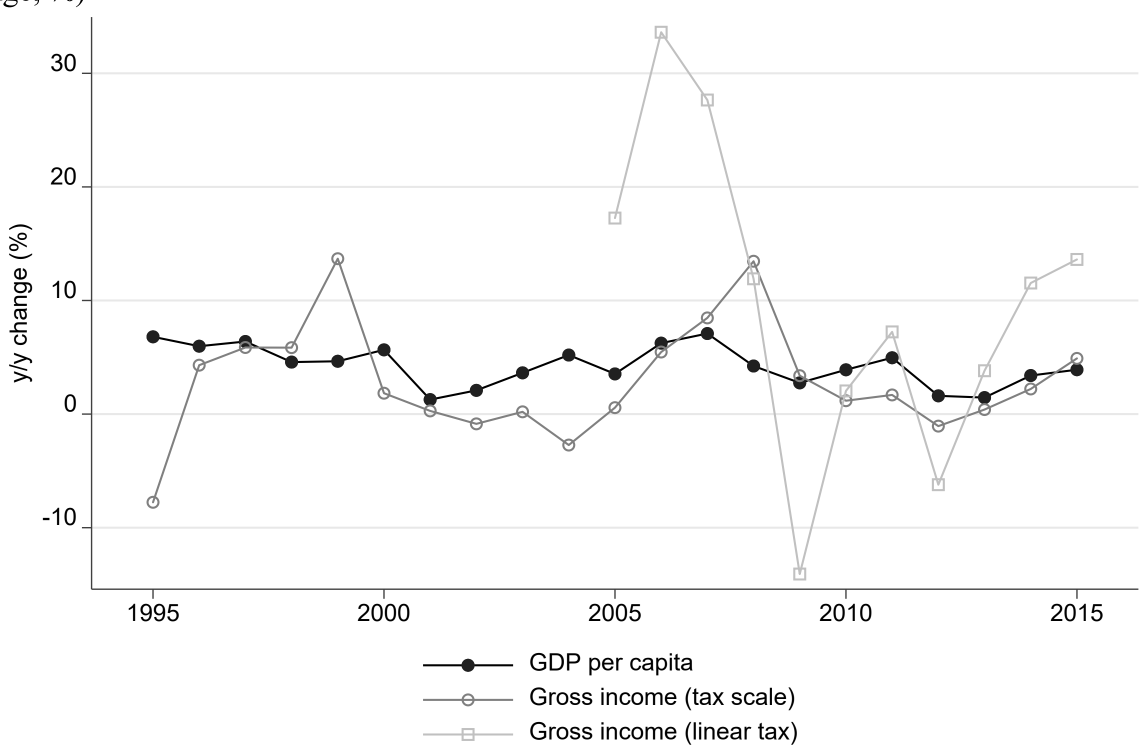
Figure 1. Top income shares in income tax data and unadjusted household survey data for Poland, 1994-2015

a) Top 1% b) Top 5%



Note: Vertical lines show 95% confidence intervals obtained using bootstrap. For both tax and survey data, income refers to gross income and unit of observation is tax unit.
Source: Own calculations using PHBS data and Bukowski and Novokmet (2017).

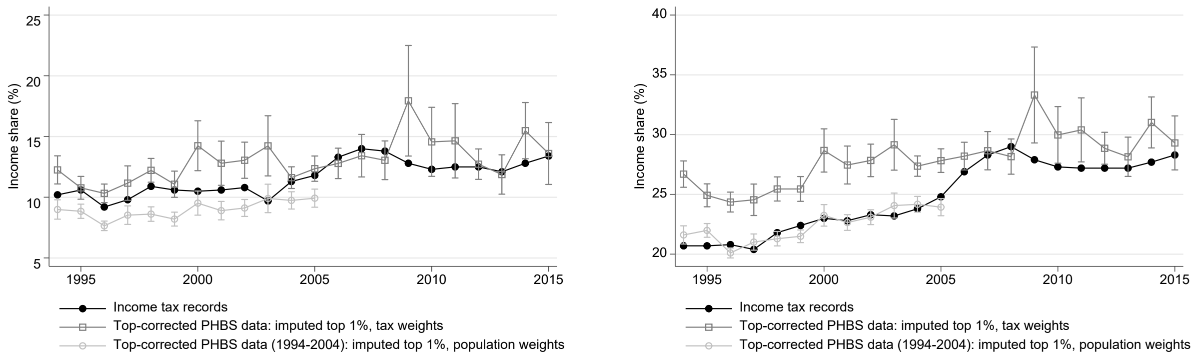
Figure 2. Reported real gross income versus real GDP per capita for Poland, 1995-2015 (y/y change, %)



Source: World Development Indicators and Poland's Ministry of Finance data.

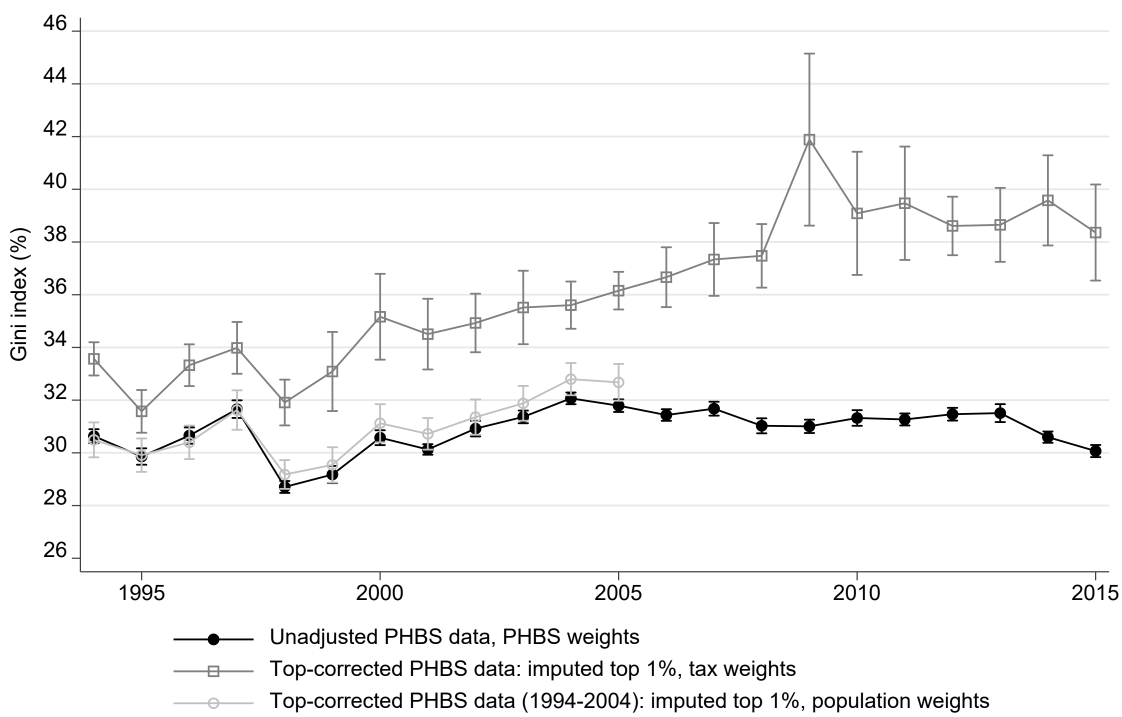
Figure 3. Top income shares in income tax data and top-corrected household survey data for Poland, 1994-2015

a) Top 1% b) Top 5%



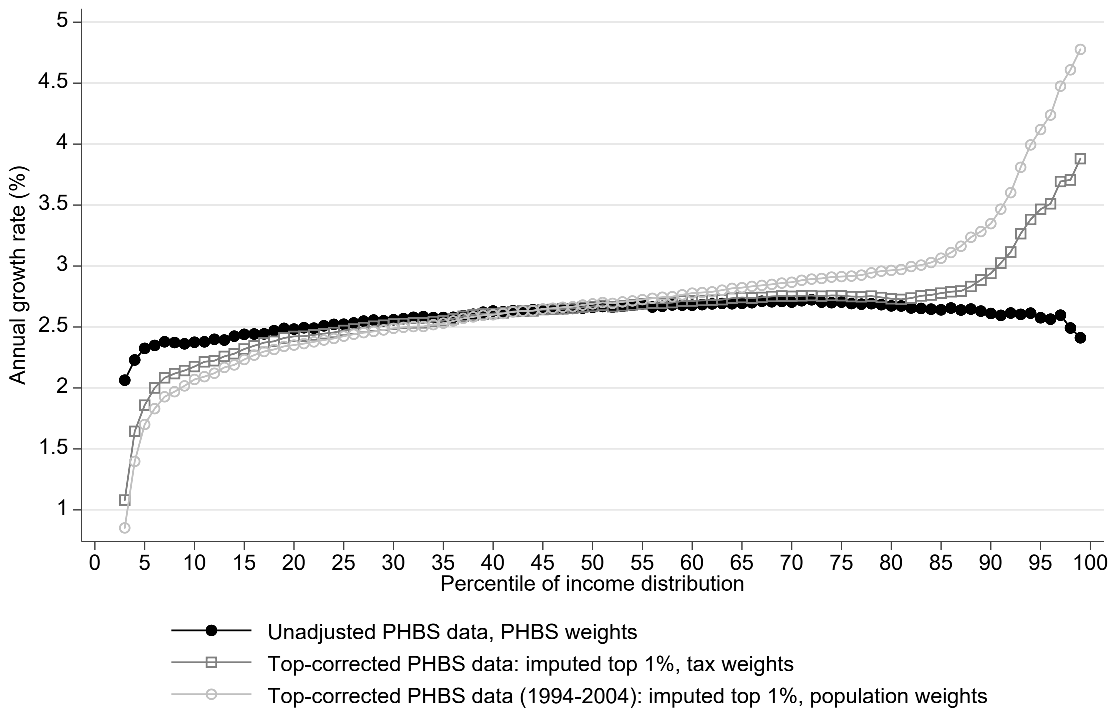
Note: Vertical lines show 95% confidence intervals obtained using bootstrap. For both tax and survey data, income refers to gross income and unit of observation is tax unit. See main text for the details of the top-correction procedures.
Source: Own calculations using PHBS data and Bukowski and Novokmet (2017).

Figure 4. The Gini index for Poland, 1994-2015: unadjusted vs top-corrected estimates



Note: Vertical lines show 95% confidence intervals obtained using bootstrap. See main text for the details of the top-correction procedures.
Source: Own calculations using PHBS data.

Figure 5. Annual real income growth rates by percentile in Poland, 1994-2015

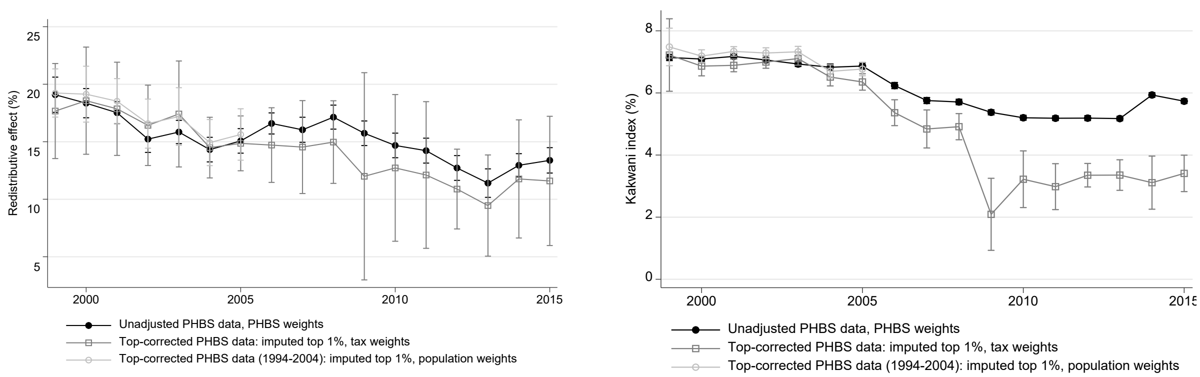


Note: For clarity we do not show confidence intervals.
Source: Own calculations using PHBS data.

Figure 6. Redistributive effect and Kakwani's progressivity index for SICs and PIT in Poland, 1999-2015

a) Redistributive effect of SICs and PIT

b) Kakwani's progressivity index for PIT and SICs



Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data.

Appendix A. Methodology for reconciling Polish survey and tax data, imputing top incomes and survey reweighting

1. Converting the PHBS net incomes to gross incomes

Our data from the PHBS spans from 1993 until 2015. We harmonised income and other variables throughout this period obtaining a homogenous data set for the microsimulation analysis. The microsimulation is based on individual net incomes as basic input variables. We drop data for 1994 as until this year income data in the PHBS were reported only on the household level. For 1994, there is information on individual incomes coming from employment, pensions and unemployment benefits. Complementing this with information on individual sources of income we can assign detailed income categories to individuals.

The PHBS data contain income values net of taxes. We follow the methodology of Levy and Morawski (2008) to assign gross values to net incomes. In short, the approach simulates net incomes out of a linear space of gross incomes. For each type of income, conditional on joint taxation and year specific SSCs and tax system parameters we simulate the tax withheld depending on month of year resulting in a combination of gross and net incomes. To this end, we have constructed a time series of SSCs and PIT parameters since 1994. Having our gross incomes with simulated net incomes, we match the latter with net incomes in the data and assign based on those matches the source gross incomes. Finally, we generate additional variables needed for simulation input including household and family composition, seasonally corrected farming income, etc.

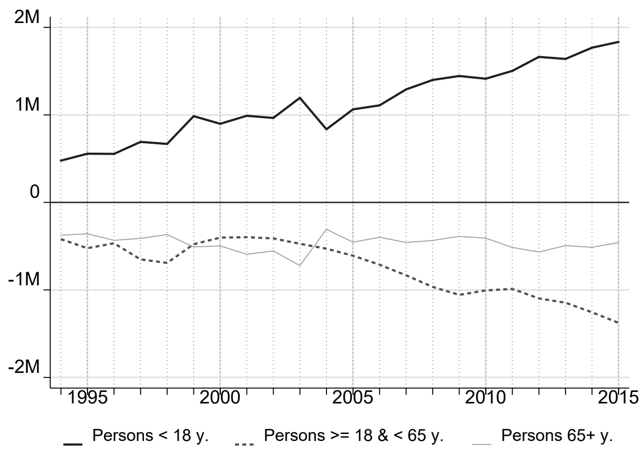
2. Simulating PIT and SSCs using the SIMPL microsimulation model

In order to simulate income taxes, SSCs and social benefits, we use the SIMPL microsimulation model. SIMPL was developed by Bargain et al. (2007) for modelling taxes and benefits using the PHBS data. As such, it allows to take advantage of the level of detail in income and expenditure available in the PHBS data. The SIMPL includes not only procedures for calculating taxes and benefits, but also tax and benefit system parameters since 1993. The parameters of the system did not change much over 1994-2015, with exception of addition and removal of tax credits, changing tax brackets and rates. A major reform took place in 1999 with the introduction of a new pension system in Poland. Before that SSCs employees were insured in a pay-as-you-go system, where current employees were financing current pensioners. SSCs were paid wholly by the employer as a percentage of the whole lump labour fund. The contributions started at 25% and reached 45% before the reform. In effect employees were receiving wages net only of income taxes, thus SSCs were not a part of gross income. In 1999, a new contributory pensions system was introduced in which both employers and employees contributed to individual retirement accounts. In addition, a new health insurance system was introduced with contributions based on the gross wage. Since 1999, the gross wage is defined as net wage plus income tax, health insurance contributions and employee SSCs. The amount of SSCs was divided between employers and employees, each paying their share taking gross wages as contribution base. It is noteworthy that as an effect of the reform, wages were artificially grossed-up. We take into account all these reforms in simulating income taxes, SSCs and health insurance contributions.

3. Reweighting according to population composition and PIT thresholds

Statistics Poland provides sampling weights for the PHBS. These weights are based on the probability of a household being selected using clustered stratified sampling procedure. The weights are corrected to match the number of households by sizes, urban/rural division and total number of people by regions coming from the latest censuses. Unfortunately, this procedure does not reflect the fact that different households can have different response rates. For this reason, the sampling weights supplied by Statistics Poland do not allow for achieving full representatives of the PHBS samples. Some of those differences can be explained by excluding some households from the survey (institutions like dormitories, hospitals, prisons). Figure A1 shows the differences in size of age groups between the official data coming from the registers and that data calculated using raw PHBS weights. The overestimation of children by nearly 2 million in 2015 is alarming and calls for corrections to be made in our distributional analysis.

Figure A1. Differences between size of population groups according to register data and the PHBS weights



Source: own computation using the PHBS and register population data.

To correct for this problem, we employ weight calibration technique of Deville and Särndal (1992). Following this method, we adjust raw PHBS weights to corrected weights that represent the Polish population in a best possible way using a "minimum-distance" criterion minimizing the sum of differences between original and corrected weights. We obtain two main sets of adjusted weights. First, we adjust the raw PHBS weights by calibrating them to match the census-based number of males and females in several age groups. Second, we adjust the weights for the number of PIT contributors obtained from simulating grossed up incomes in each of tax bracket. In addition, since 2004 we adjust to the number of linear tax payers. In calibrating weights using tax information, we use the modified Chi-squared distance function due to large differences between weights and totals coming from official Ministry of Finance documents.

Table A1 presents the reweighting tax targets ("MF" columns) with raw PIT amounts calculated using raw PHBS weights ("SIM" columns). Clearly, the number of top-income receivers is underestimated. Moreover, the number of linear tax payers in the PHBS data is much lower than in the official MF documents. We also observe a sharp drop in the number of linear tax payers in the PHBS data after 2008 when two tax brackets were introduced reducing the number of possible linear tax beneficiaries in the survey data. The SIMPL simulations are design to calculate income taxes both according to PIT scale and using the linear rate. The joint taxation of couples is assumed when this alternative is optimal to a household compared to individual taxation. Since in practice individuals do not optimize perfectly, there are probably cases when we might incorrectly choose type of taxation.

Table A1. Number of PIT payers by tax brackets and linear tax payers in the official statistics (MF) and simulated using raw PHBS weights (SIM)

Year	All taxpayers		2nd bracket		3rd bracket		Linear tax	
	MF	SIM	MF	SIM	MF	SIM	MF	SIM
1994	22 130 002	103.1%	1 509 582	54.8%	344 327	40.0%	-	-
1995	22 874 054	92.6%	1 380 661	53.0%	288 529	39.1%	-	-
1996	23 428 131	99.7%	1 286 354	52.1%	275 042	31.5%	-	-
1997	23 485 729	100.2%	1 038 069	64.7%	237 206	42.8%	-	-
1998	23 798 083	99.7%	897 174	72.0%	284 171	30.6%	-	-
1999	22 968 087	102.3%	896 075	55.7%	217 214	33.0%	-	-
2000	24 014 848	97.7%	951 752	58.7%	307 208	28.3%	-	-
2001	23 785 180	98.0%	882 094	47.7%	227 315	20.9%	-	-
2002	23 776 800	97.5%	870 388	53.5%	260 695	22.7%	-	-
2003	24 004 756	96.3%	956 744	57.0%	270 639	28.3%	-	-
2004	23 801 484	99.4%	1 033 313	51.5%	201 188	38.7%	200 168	87.0%
2005	23 938 623	100.6%	1 102 502	50.4%	208 327	41.2%	260 999	72.9%
2006	24 063 759	101.5%	1 319 557	56.6%	266 467	36.0%	328 047	69.1%
2007	24 454 995	101.6%	1 083 448	53.7%	208 272	35.3%	393 780	55.9%
2008	24 747 173	101.6%	1 575 511	53.1%	342 230	32.7%	463 115	48.2%
2009	24 740 297	101.6%	387 295	34.9%	-	-	391 784	10.8%
2010	24 907 974	101.7%	463 567	36.4%	-	-	395 039	13.5%
2011	24 654 420	102.8%	521 600	40.2%	-	-	410 813	13.2%
2012	24 324 790	103.5%	554 382	45.5%	-	-	429 096	14.6%
2013	24 694 043	101.5%	601 621	39.2%	-	-	446 485	14.6%
2014	24 764 126	101.9%	657 764	40.3%	-	-	473 954	13.9%
2015	24 944 845	101.9%	710 471	35.4%	-	-	502 648	15.3%

Source: Ministry of Finance data and own calculations.

4. Pareto imputation for the top 5% and 1% of gross income distribution

We add up individual gross incomes simulated using the SIMPL to the total gross income of tax unit that is subject to income taxation. To be consistent with Bukowski and Novokmet's (2017) approach, we define the population eligible for income taxation as persons aged 18 and older excluding farmers. Using individual income data, we identify farmers as persons aged 18 and more not receiving any taxable income and receiving farming revenue greater than median of farming income. We use corrected PHBS weights to obtain the 95th and 99th percentile of individual gross income distribution, which together with top income shares from Bukowski and Novokmet (2017) serve as input parameters for estimating the Pareto distribution parameters (Bartels and Metzing 2018). Table A2 presents the values of Pareto distribution parameters that we use. Finally, we impute gross incomes by taking random draws from the Pareto distribution with parameters taken from Table A2. We assign new gross incomes keeping the ordering of the initial distribution. By doing so we impose rank conservation between new and old incomes. We include the possibility of weights being correlated with income (rank).

Table A2. Parameters of the Pareto distribution, Poland, 1994-2015

Year	95th percentile			99th percentile		
	Income, PLN	Pareto tail index (α)	Lower bound on Pareto behaviour (x_m)	Income, PLN	Pareto tail index (α)	Lower bound on Pareto behaviour (x_m)
1994	945	2.109	228.261	2215	1.983	217.157
1995	1200	2.109	289.855	2665	1.951	251.415
1996	1520	2.102	365.385	3420	2.075	371.739
1997	1805	2.131	442.402	3835	2.018	391.327
1998	2065	2.034	473.624	4660	1.928	427.512
1999	2720	1.998	607.143	5630	1.951	531.132
2000	2960	1.963	643.478	6705	1.959	638.571
2001	3190	1.974	699.561	6745	1.951	636.321
2002	3208	1.947	688.387	7000	1.935	648.148
2003	3314	1.952	714.161	7270	2.027	749.485
2004	3625	1.920	761.555	7485	1.899	662.389
2005	3765	1.871	759.073	7815	1.866	662.288
2006	4210	1.780	782.528	8680	1.780	652.632
2007	4590	1.728	810.954	9740	1.745	695.714
2008	5610	1.704	967.241	11040	1.755	800.000
2009	5645	1.743	1011.649	14255	1.806	1113.672
2010	6000	1.765	1098.901	13475	1.835	1095.528
2011	6360	1.769	1169.118	14230	1.823	1138.400
2012	6375	1.769	1171.875	14975	1.823	1198.000
2013	6845	1.769	1258.272	14925	1.847	1233.471
2014	7080	1.750	1277.978	15000	1.806	1171.875
2015	7080	1.728	1250.883	15860	1.774	1183.582

Note: x_m is expressed in real PLN (2015 prices).
Source: own calculations using PBHS and top income shares from Bukowski and Novokmet (2017).

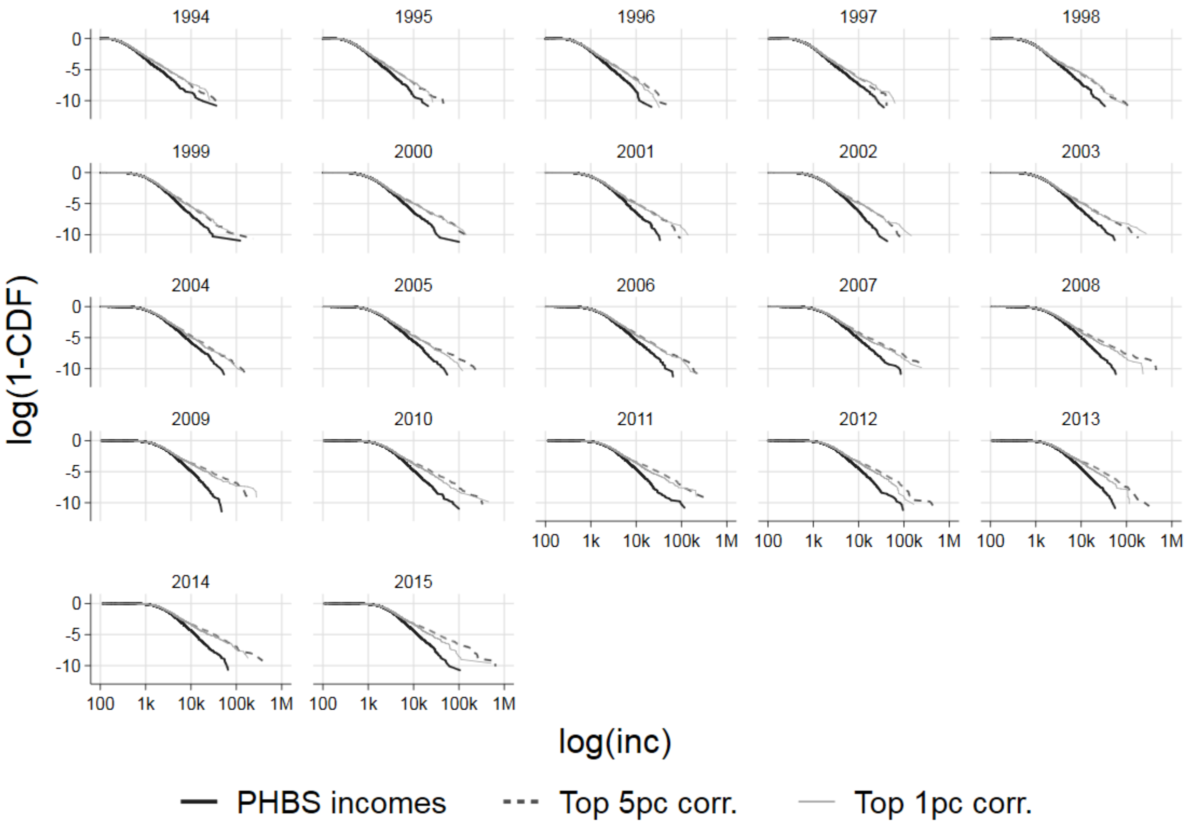
Figure A2 presents fits of Pareto distribution with parameters from Table A2 to the unadjusted PHBS data and to the top-corrected data. For majority of years, the unadjusted survey data do not show Pareto behaviour in the upper tail.

After imputing gross incomes, the number of persons in PIT bracket changes and we need to account for this change in reweighting. For that we once again simulate SSCs and PIT for our new incomes and use this information for reweighting. In effect we have final weights, gross incomes together with PIT and SSCs amounts. Using these values, we can calculate the total income change due to imputation. Our main income variable is household disposable income. We add income change due to imputation to the PHBS disposable income. Finally, we express the resulting variable in real terms and equivalize it using the modified OECD equivalence scale.

Additional references

Levy, H., & Morawski, L. (2008). EUROMOD Country Report – Poland 2005. EUROMOD Country Reports. Available at https://www.euromod.ac.uk/sites/default/files/country-reports/old-country-reports/poland/CR_PL2005_v1.pdf.

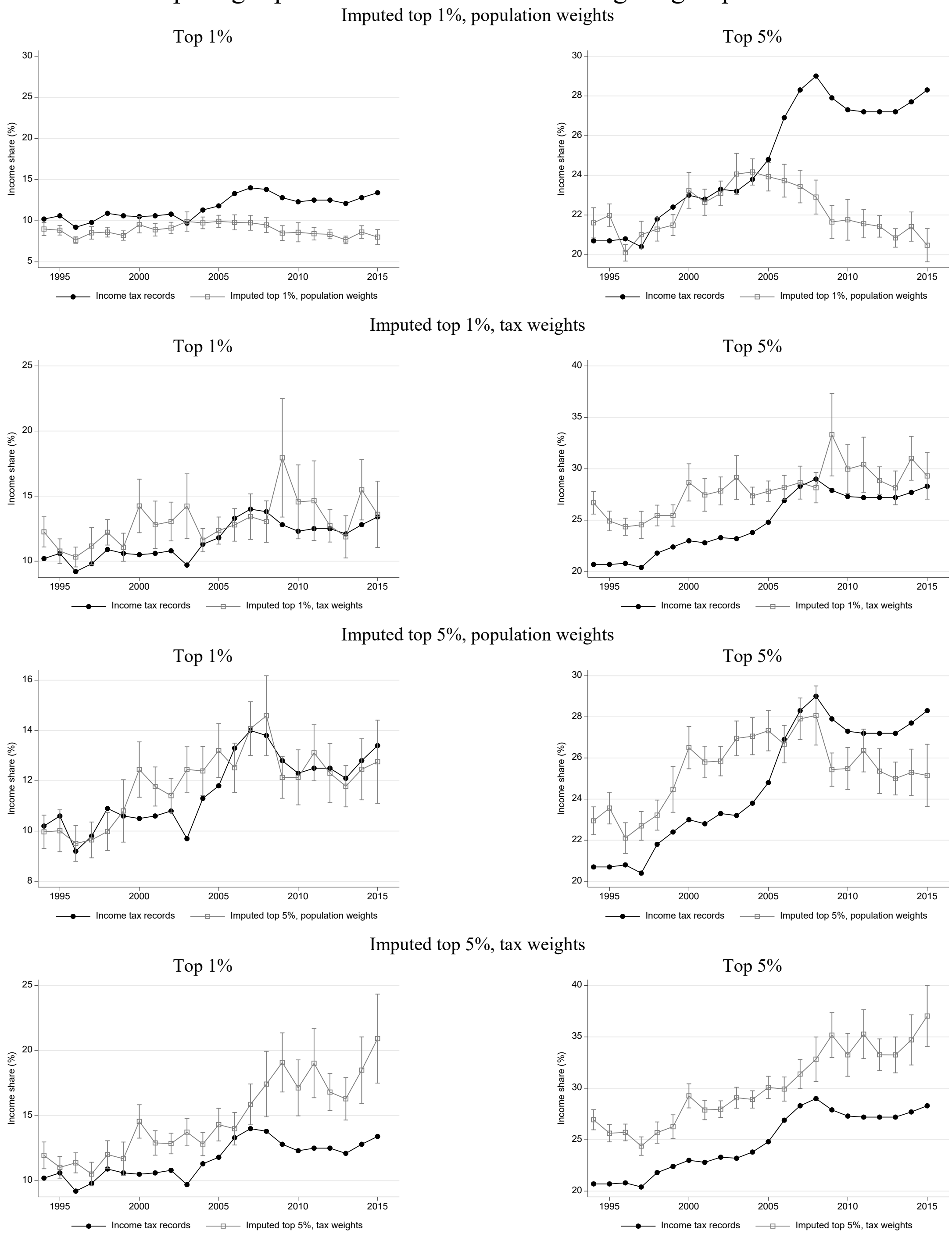
Figure A2. Fit of the Pareto distribution to unadjusted survey data (PHBS) and data top-corrected by imputing top 5% incomes (Top 5pc corr.) or top 1% incomes (Top 1pc corr.), Poland, 1994-2015



Source: Own calculations using PHBS data.

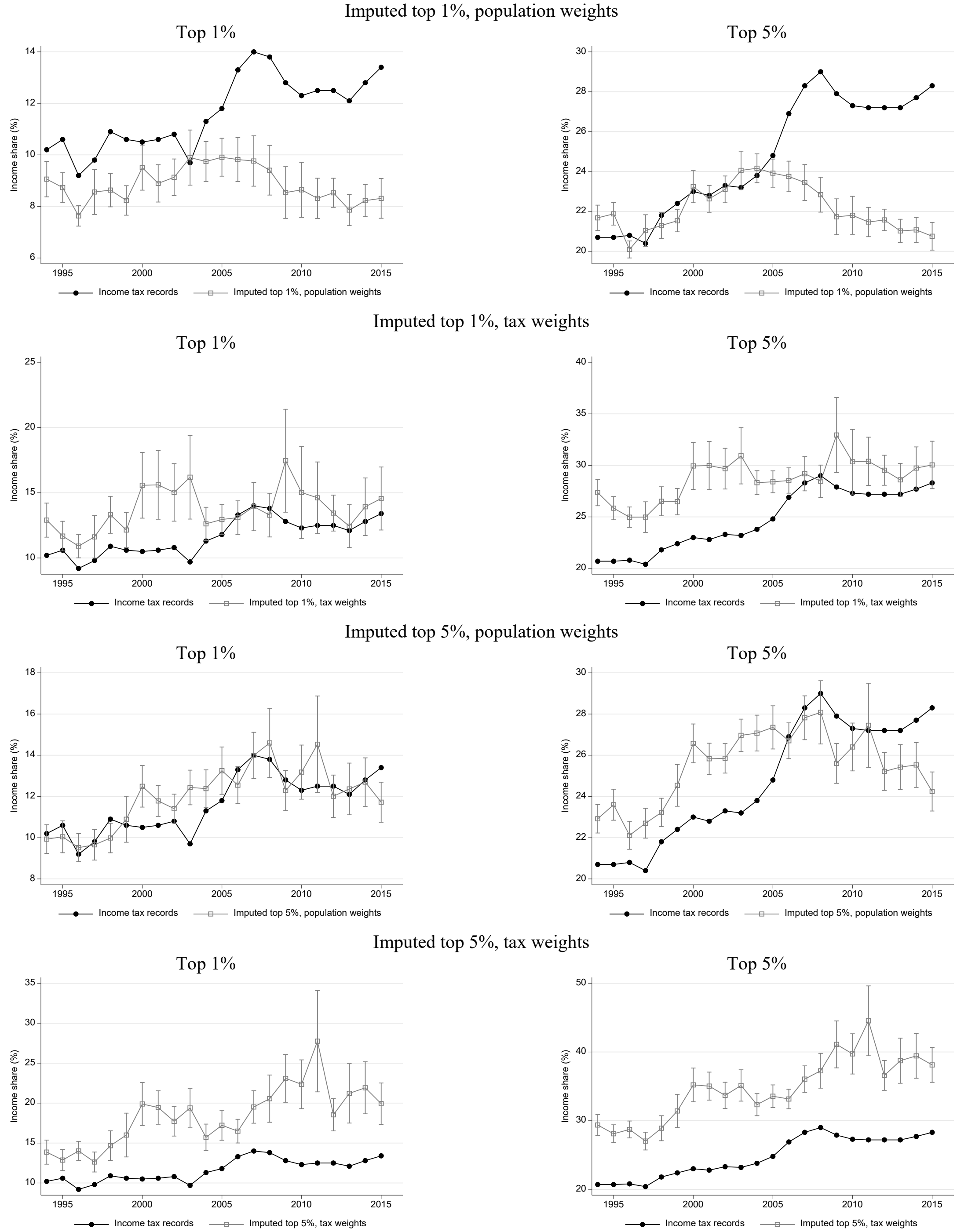
Appendix B. Additional figures

Figure B1. Four methods of top-correcting survey data for Poland, 1994-2015. Results from the approach based on imputing top incomes first and then reweighting imputed data



Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data and Bukowski and Novokmet (2017).

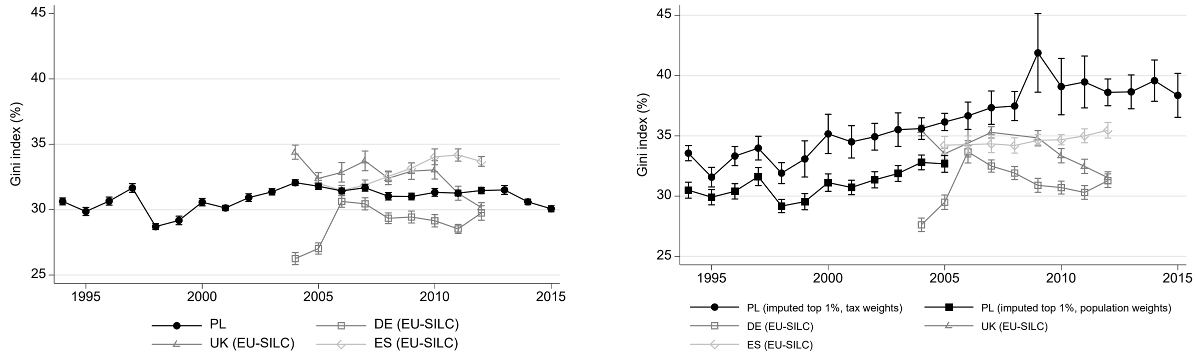
Figure B2. Four methods of top-correcting survey data for Poland, 1994-2015. Results from the approach based on reweighting data first and imputing top incomes to reweighted data



Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data and Bukowski and Novokmet (2017).

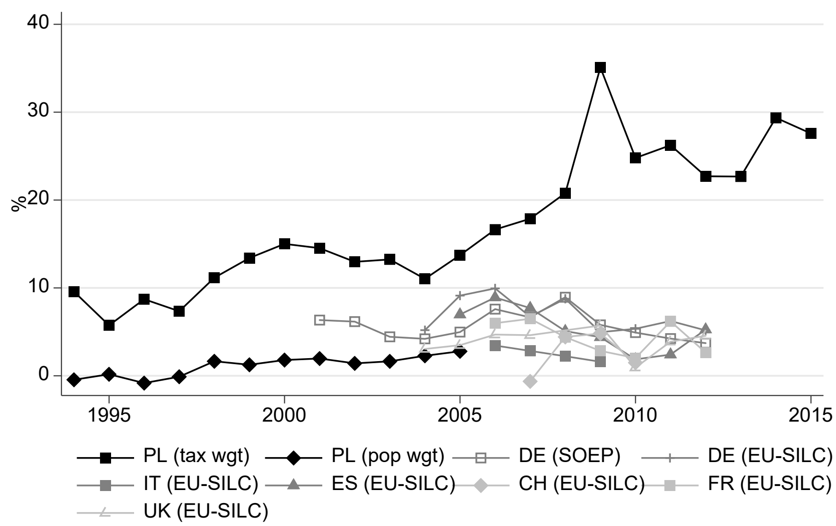
Figure B3. Gini indices for Poland and other countries: unadjusted versus top-corrected estimates

a) Unadjusted estimates b) Top-corrected estimates



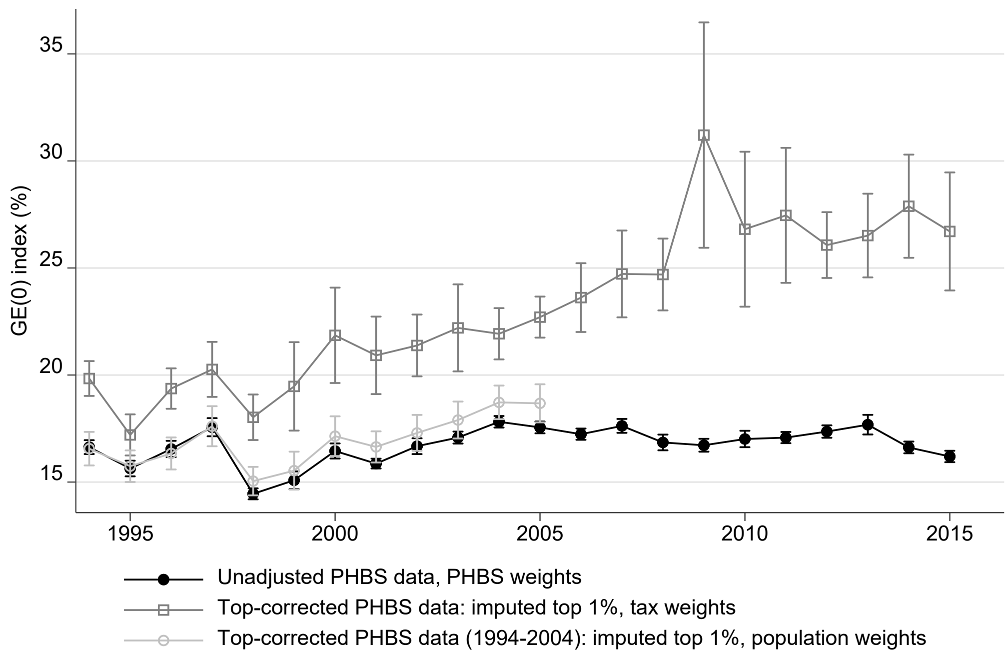
Note: The Gini indices are computed for real equivalent net household income. Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations for Poland, Bartels and Metzing (2018) for other countries.

Figure B4. Percentage increase in the Gini index due to the top-correction: Poland versus other countries



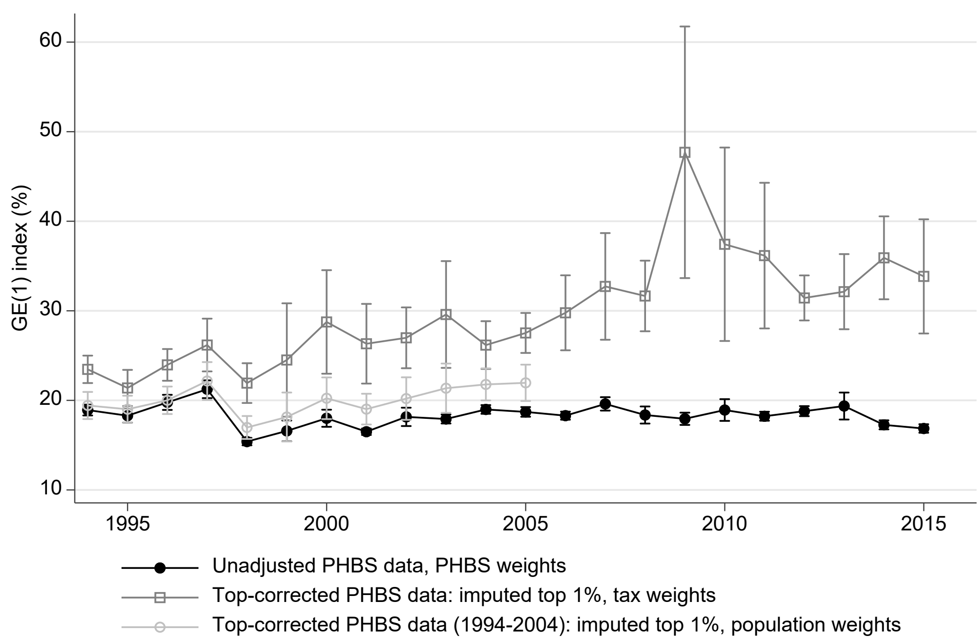
Note: The Gini indices are computed for real equivalent net household income. Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations for Poland, Bartels and Metzing (2018) for other countries.

Figure B5. Generalized entropy, GE(0), index for Poland, 1994-2015: unadjusted vs top-corrected estimates



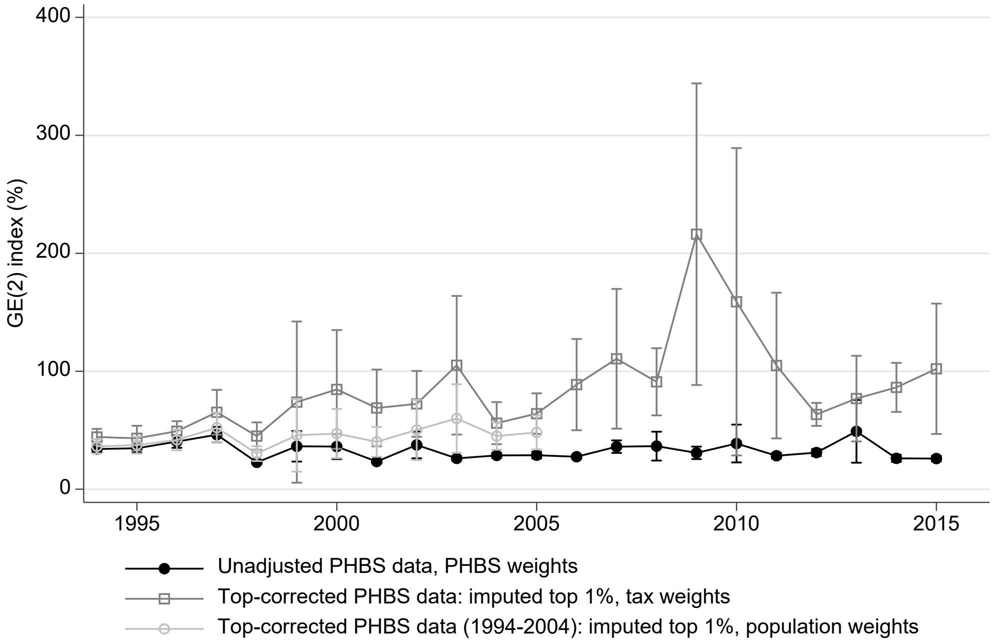
Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data.

Figure B6. Generalized entropy, GE(1), index for Poland, 1994-2015: unadjusted vs top-corrected estimates



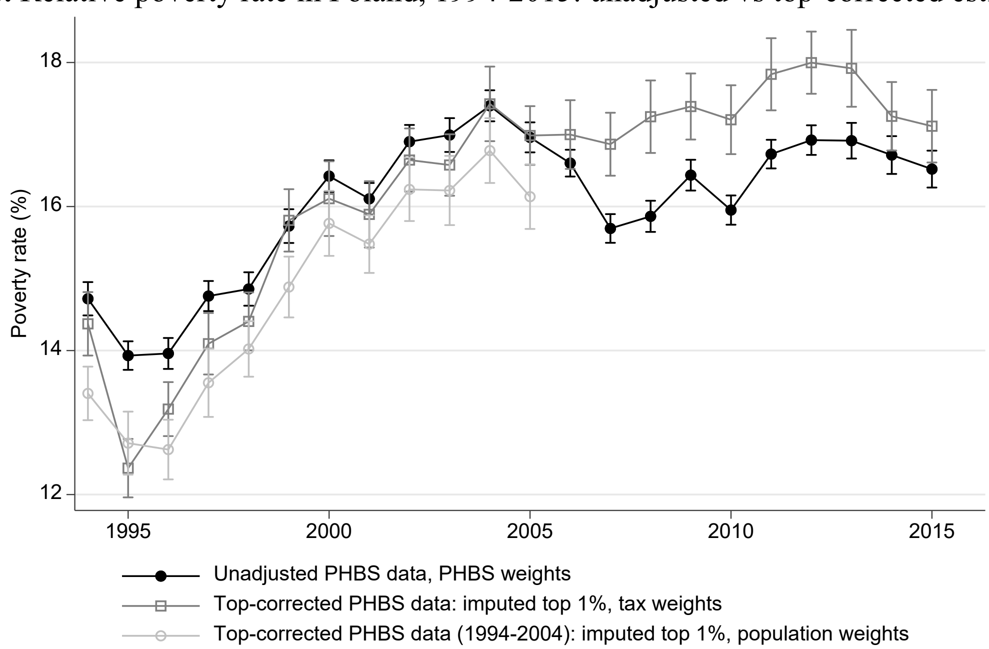
Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data.

Figure B7. Generalized entropy, GE(2), index for Poland, 1994-2015: unadjusted vs top-corrected estimates



Note: Vertical lines show 95% confidence intervals obtained using bootstrap.
Source: Own calculations using PHBS data.

Figure B8. Relative poverty rate in Poland, 1994-2015: unadjusted vs top-corrected estimates



Note: Vertical lines show 95% confidence intervals obtained using bootstrap. Relative poverty rate is proportion of population with income less than 60% of median income.
Source: Own calculations using PHBS data.