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Polish inequality statistics reconsidered: are the poor really that poor?

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ABSTRACT

In the present study income inequality in Poland is evaluated using corrected income data to provide more reliable estimates. According to most empirical studies based on household surveys and considering the European standards, the recent income inequality in Poland is moderate and decreased significantly after reaching its peaks during the first decade of the 21st century. These findings were challenged by Brzeziński et al. (2022), who placed Polish income inequality among the highest in Europe. Such a conclusion was possible when combining the household survey data with information on personal income tax. In the present study the above-mentioned findings are further explored using 2014 and 2015 data and employing additional corrections to the household survey incomes. Incomes of the poorest people are replaced by their predictions made on a large set of well-being correlates, using the hierarchical correlation reconstruction. Applying this method together with the corrections based on Brzeziński's et al. results reduces the 2014 and 2015 revised Gini indices, still keeping them above the values obtained with the use of the survey data only. It seems that the hierarchical correlation reconstruction offers more accurate proxies to the actual low incomes, while matching tax data provides better proxies to the top incomes.

Key words: inequality indices, household income imputation, income correlates.

1. Introduction

According to most of the empirical studies based on household surveys, recent income inequality in Poland is moderate, considering the European standards, and decreased significantly after peaks reached during the first decade of the 21st century (time series for the official Gini indices covering 1995–2015 period may be found in Brzeziński et al., 2022). However, a prevailing part of those studies ignore the problem of the data quality and representativity, although there are reasons to assume that nominally low declared incomes are frequently underestimated, especially in tails

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of the distributions. This affects also official inequality measures in Poland, which may be substantially underestimated, as demonstrated by Brzeziński et al. (2022) on the basis of combined survey and tax return data for 1995–2015 period. Further consequences of prospective underestimation of the official inequality are of political nature, as concluded by those authors: underrating by the previous governments importance of the (real) inequality and degree of the redistribution might be one of the reasons for reaching the parliament majority by Law and Justice (*Prawo i Sprawiedliwość*) party in 2015 election. Although this hypothesis is hardly testable empirically, it seems to be obvious that the social rhetoric represented by this party was widely accepted by the voters. On the other hand, according to Bussolo et al. (2021) the demand for redistribution in Poland between 1992 and 2009 was at a moderate level, as compared to several European countries included into that study. Moreover, other results presented by Bussolo et al. do not claim correlation between the demand for redistribution and the (in)equality perception. Nevertheless, calculation of more accurate inequality indices definitely may shed more light on the abovementioned issues in Poland, especially on discrepancy between the official indicators and the inequality perception. In this study some estimates obtained by Brzeziński et al. (2022) are utilised to correct incomes in the upper tails of the distributions for 2014 and 2015 years. Corrections of the household survey incomes are also performed at the bottom tails, which is an added value of the present research. Incomes of the poorest people are replaced by their predictions estimated on a large set of well-being correlates, using the so-called hierarchical correlation reconstruction (Duda, 2018, Szulc and Duda, 2018). This should yield more accurate inequality measures, as compared to the official ones and to those based solely on the top incomes corrections.

Several sources of non-random errors leading to underestimation of household survey incomes may be pronounced: i/ allocating too large portion of the revenues to production when completing the questionnaires (this applies to self-employed incomes, including farmers), ii/ incorrect tax adjustment, iii/ intentional misreporting, and iv/ seasonality of the revenues. For a comprehensive discussion of household survey measurement errors see Moore et al. (2000) and Kasprzyk (2005), while non-response issues are discussed in Lepkowski (2005). A discussion of the Polish household survey data quality may be found in Kośny (2019). Generally, two approaches to handling the data errors in research on inequality and poverty may be observed in the literature. In the first one additional datasets, usually tax registers, are utilised. Household survey data are combined with administrative records to provide more reliable income statistics at the upper tails of the distribution (Jenkins, 2017, Bartels and Metzing, 2018, Blanchet, 2018, Medeiros et al., 2018, Davern et al., 2019, Brzeziński et al., 2022). The literature on "decontamination" of low declared incomes is rather narrow. Nicoletti et al. (2011) proposed the so-called partial identification approach, taking into account the whole range of the distribution. This allows calculation of bounds for the poverty rates instead of the point estimates. Pudney and Francavilla (2006) employed a data "decontamination" procedure based on observing discrepancies between income and other well-being indicators (like consumption or household durables) ranks for Albania. This procedure, utilising non-parametric regression, is supposed to produce more reliable poverty rates. In this research the so-called hierarchical correlation reconstruction method (hereafter: HCREC) proposed by Duda (2018) is utilised. This methods yields estimates of the income distribution function, conditional on the household attributes correlated with well-being. As they are mainly nonmonetary and/or relatively stable in time, it may be assumed that they are more reliable and therefore can provide more accurate proxies to the household well-being and then to the actual incomes. Moreover, better reliability of the declared incomes in the middle range of the distribution than in the extreme ones is assumed. In this approach no additional information but survey data is required (this applies also to the methods proposed by Nicoletti et al., 2011, and Pudney and Francavilla, 2006).

The remaining part of the paper is organised as follows. In Section 2 the database is described. In Section 3 the main principles of two methods of data imputation are presented. Section 4 reports results of the empirical inequality comparisons. Section 5 concludes.

2. The data issues

The individual data employed in this research come from 2014 and 2015 household budget surveys being carried by Statistics Poland (Główny Urząd Statystyczny). It encompasses, inter alia, information on the households' disposable income and its components, expenditures, assets, durables, dwelling conditions, demographic and socio-economic attributes, and answers to subjective income questions. The samples covered more than 37,000 households and 101,000 persons per year. The reference period of observation is one month. More methodological details on Polish HBS may be found in Główny Urząd Statystyczny – Statistics Poland (2015). For a brief description of the tax data in Poland applicable to this study see Kośny (2019).

Except the disposable income numerous household variables are used in the present research in order to provide estimates of the corrected declared incomes. They may be of financial type and then continuous (remaining equivalent cash at the end of the month, shares of expenditures on the luxury goods and on the food) but most of them are nonmonetary and discrete (demographic attributes, dwelling and neighbourhood characteristics, possession of durables, main income source, subjective evaluations). For the full list of the variables employed in the imputations based on HCREC method see Duda and Szulc (2020). All calculations are performed for equivalent units, using the total household incomes and assuming equal distribution between the household members.

As mentioned in the Introduction, misestimation of the incomes affects mainly tails of the distribution. Since the disposable income is calculated as a difference between the household net revenues and spending on production, allocating too large portion of the revenues to a latter component affects mainly producers' (including farmers) households. Overestimation of the cost of production is quite frequent and leads to underestimation of disposable incomes, making them, in some cases, negative. Although negative disposable incomes constitute only about 0.9% of the whole 2015 sample, there is no reason to believe that the positive ones are free of such a bias. A meta study of the problem may be found in Hlasny et al. (2022). Errors caused by seasonality and by intentional misreporting of incomes may affect most of types of the households. It seems to be rational to suppose that the majority of well-being correlates, like household conditions or possession of durables, are much more stable in time and less likely to be intentionally misreported than the disposable incomes. Assuming moreover that the income data in the middle of the distribution are relatively reliable and the relations between income and welfare correlates are stable for the whole range of the distribution, it is possible to reduce impact of the abovementioned data errors applying imputations based on the HCREC method. However, this technique seems to be rather unproductive at the high ranges of the distribution, due to very low share of the extreme incomes which would result in a serious downward bias of the estimates. As mentioned above, it is possible to handle underestimation of highest incomes by matching survey data with tax registers. In the present research this method is embedded by replacing top 1% or top 5% incomes by estimates of the Pareto distribution obtained by Brzeziński et al. (2022) after matching the tax and the household survey data.

Underestimation of low incomes in the Polish household surveys becomes evident when they are confronted with a simple multidimensional household well-being indicator. The one employed in the present study covers equivalent income, dwelling conditions (esp. dwelling size and quality, presence of various appliances, neighbourhood), household equipment with durables and subjective evaluations of own material position. Each of those components was transformed into [0, 1] interval. Hence, at each dimension of well-being the households or people may be compared directly. For the non-binary, continuous or ordinal variables the multidimensional poverty indicator for each household is calculated as weighted mean of the following components:

$$f_i = f(y) = \frac{Y_{max} - y_i}{Y_{max} - Y_{min}}$$

where y_i stands for *i-th* well-being individual component, e.g. equivalent income, dwelling size per capita or subjective income evaluation. This concept represents a more general method referred to as fuzzy set approach to poverty measurement (for more details see Panek, 2006). In order to relax impact of the outliers, for the continuous, non-limited variables the minimum and maximum values in the above equation were replaced by percentiles of rank 0.05 and 0.95, respectively, with due censoring of y_i values beyond these limits. The highest weight, 0.4, is attached (arbitrarily) to the monetary dimension (equivalent income), the remaining three equal 0.2.

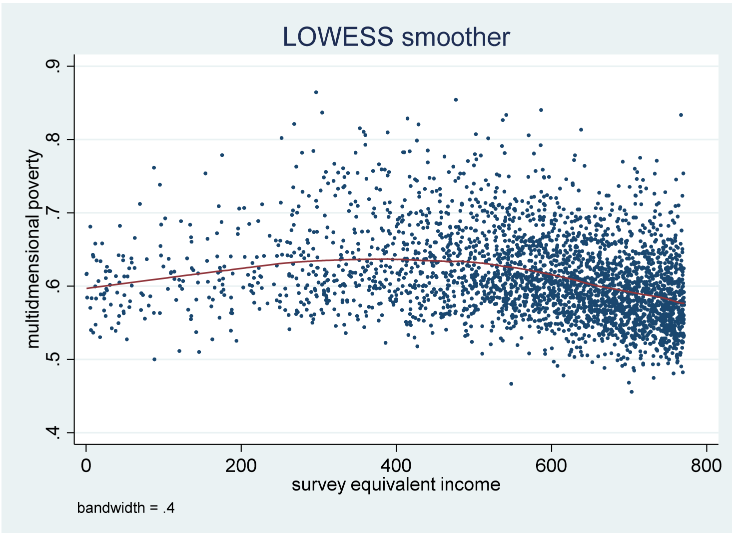

Figure 1a. Nonparametric estimation of multidimensional poverty on survey incomes (PLN per month), below the first decile.

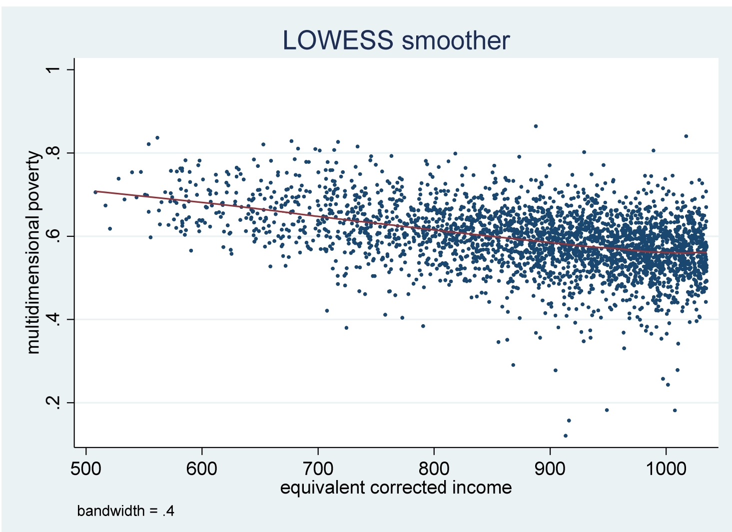

Figure 1b. Nonparametric estimation of multidimensional poverty on imputed incomes (PLN per month), below the first decile.

Figures 1a and 1b display the results of nonparametric LOWESS estimation (for the econometric details see Cleveland, 1979) of the abovementioned multidimensional poverty indicator on the equivalent income declared by the households and on income corrected by means of HCREC, respectively. In the first case, a nonsensical, positive correlation between both variables may be observed for the lowest incomes. The results obtained for the corrected incomes appear to be much more acceptable (see Figure 1b). A positive correlation between the declared income and poverty resulted also in reporting a counterproductive effect of the social transfers on the multidimensional poverty (although the respective indicator included also equivalent incomes). This nonsensical result did not appear when low incomes were replaced by their predictions estimated by means of HCREC (see Duda and Szulc, 2020 for details). Naturally, the components of the multidimensional poverty index and the set of income correlated yielding HCREC estimates do not intersect, as it would result in upper bias in the correlation measures.

3. Income imputations

3.1. Low incomes

The method of imputation applied in the present study, referred to as HCREC, allows to predict conditional probability distribution of an exogenous variable (here: household equivalent income) based on values of endogenous variables (here: income correlates). First, the marginal distribution of the predicted variable is normalized to uniform distribution on [0, 1] using empirical distribution function ($x = EDF(y) \in [0, 1\,]$). Then a density of its conditional distribution is predicted as a linear combination of orthonormal polynomials using coefficients modelled as linear combinations of the remaining variables. Once the conditional density function is estimated, selected declared incomes (here: those below first quintile) may be replaced by the respective theoretical estimates. HCREC offers two advantages, as compared to a standard regression. First, due to employing high order polynomials instead of assuming a priori a functional form, it can fit virtually all types of distribution. Second, except conditional expected values, it is possible to estimate the entire probability distribution as well as a large set of the moments. For more technical details see Duda (2018), and Duda and Szulc (2018). For an empirical application in the measurement of social transfers impact on poverty see Duda and Szulc (2020).

3.2. High incomes

This type of correction utilises findings by Brzeziński et al. (2022), who estimated Pareto I distribution function using the tax data and then replaced top 1% or 5% of equivalent incomes by the predictions. Pareto I cumulative distribution function for income x is defined as follows:

$$x' = x_m \sqrt[\alpha]{1 - F'(x)}$$

where F'(x) represents a cumulative distribution function estimated using a whole sample of the survey data.

3.3. Comparing the survey and the corrected income distributions

In the present study correction of the low incomes utilising HCREC is principally applied to bottom 20%. The impact of corrections applied to alternative low ranges of the distribution (bottom 5%, 10%, 15% and 25%) is also investigated further and the results are reported in Table 4. Figure 2 displays differences in the density functions using the declared (survey) and the bottom corrected incomes. To make the plot more readable, the highest incomes are not included in the subsample. Similar comparisons, using cumulative distribution functions, made for top 1% and 5% corrected incomes are presented in Figures 3 and 4 for the survey equivalent incomes exceeding, approximately, 95th and 90th centiles.

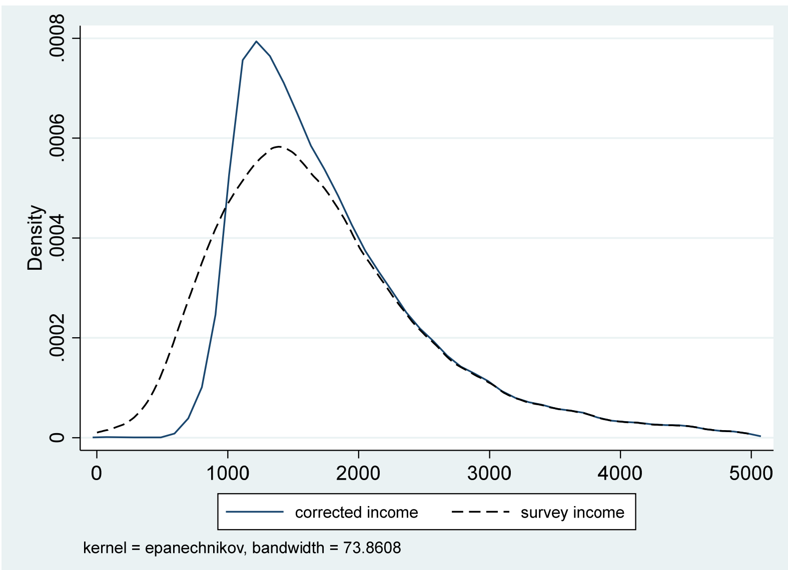

Figure 2. Kernel density functions for the survey and the corrected monthly equivalent incomes below 5000 PLN, 2015 data.

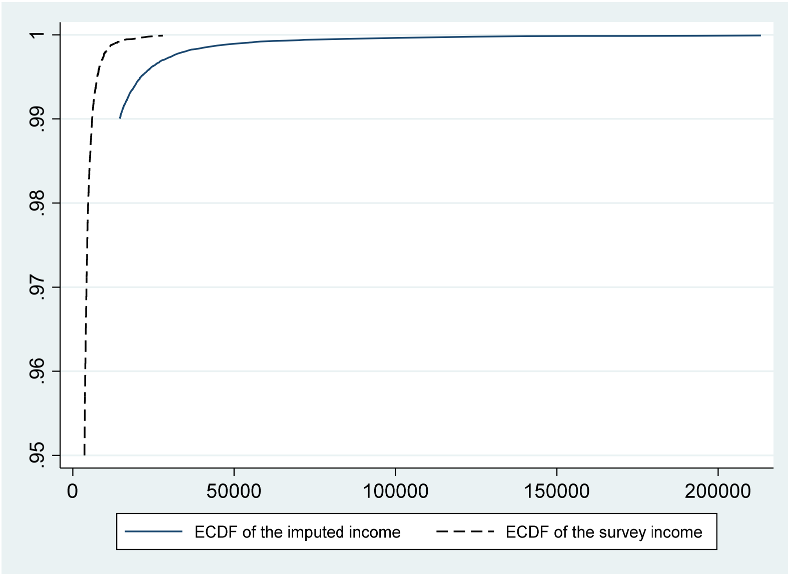

Figure 3. Empirical cumulative distribution function for the survey and the imputed (top 1%) monthly equivalent income, 2015 data.

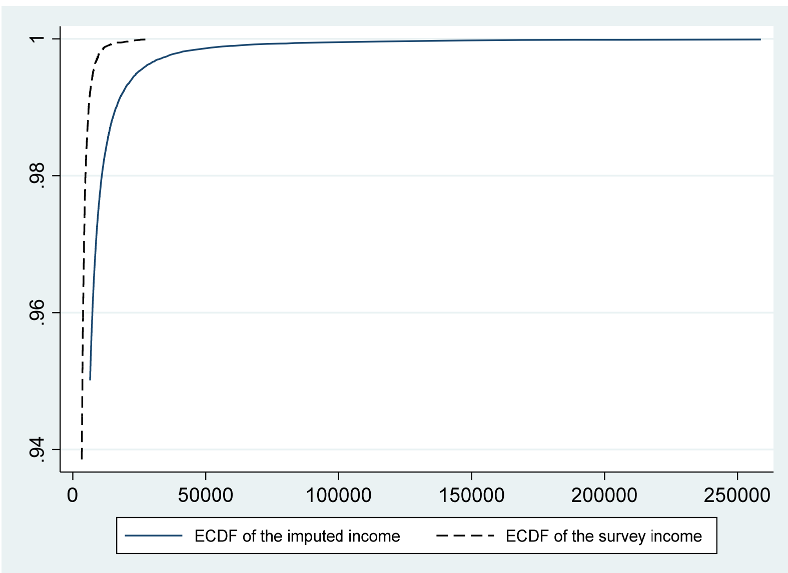

Figure 4. Empirical cumulative distribution function for the survey and the imputed (top 5%) monthly equivalent income, 2015 data.

Table 1 displays mean values of the survey and the corrected incomes in low and top ranges of the distribution for 2014 and 2015, in 2015 prices. Applied corrections raised enormously top 1% and 5% incomes, as compared to the declared ones: in 2014 by 233%/79% and by 248%/85% in 2015. Increases among the poorest 20% were less massive: by 65% in 2014 and by 63% in 2015. Nevertheless, since much larger share of the nominally poor people this growth mitigated significantly the income inequality growth caused by rising the highest incomes. The final results of changes in the inequality are reported in the succeeding section.

Table 1. Changes in mean equivalent incomes due to bottom 20%, top 1% and top 5% corrections, 2015 prices, PLN per month.

Range	Type of income			
	Raw survey	Top 1% corrected	Top 5% corrected	Bottom 20% corrected
			2014	
Bottom 20%	696	-	-	1148 *(+65%)*
Top 1%	9054	30139 *(+233%)*	36895 *(+307%)*	-
Top 5%	5299	9510 *(+79%)*	15002 *(+183%)*	-
			2015	
Bottom 20%	728	-	-	1189 *(+63%)*
Top 1%	9261	32198 *(+248%)*	37519 *(+305%)*	-
Top 5%	5379	9964 *(+85%)*	15067 *(180%)*	-

Legend: in parentheses growth rates, as compared to the survey incomes

Source: own calculation based on the household budget survey.

4. Inequality in Poland after income imputations

The final results on changes in the inequality indices are summarised in Table 2 (top 1%) and Table 3 (top 5%). Similarly to comparisons made in the previous section, inequality indices (Gini, Theil, and 90/10 and 75/25 percentile ratios) are calculated using the raw survey incomes and those corrected at low and high ranges, separately and altogether. It should be noted that corrections of the top incomes are not exactly the same as those proposed by Brzeziński et al. (2022). This is due to the various weighting systems employed in both studies. The one applied in the present study uses the survey weights (the only available), while that of Brzeziński et al. utilises the tax information for that purpose.

Table 2. Inequality indices for the survey and the corrected incomes: top 1% and bottom 20%.

	Raw survey income	Area of income correction		
		Top 1%	Bottom 20%	Both
2014		Gini		
	0.308	0.382	0.263	0.339
		90/10		
	3.89	3.89	2.85	2.85
		75/25		
	1.98	1.98	1.77	1.77
		Theil		
	0.175	0.455	0.135	0.403
2015		Gini		
	0.303	0.382	0.258	0.338
		90/10		
	3.79	3.79	2.78	2.78
		75/25		
	1.95	1.95	1.75	1.75
		Theil		
	0.171	0.470	0.132	0.416

Source: own calculation based on the household budget survey.

As might be expected, applying income correction to the bottom 20% (see Figure 2 for detailed changes in the income distribution) reduces inequality, as compared to that calculated using the survey data only. Gini indices drop by, approximately, 15%. On the other hand, modifying top incomes increases Gini indices, up to 0.38 or by 25% (when top 1% incomes are corrected) and up to 0.45 or by 47-48% (top 5% incomes corrected). Applying both corrections simultaneously places Gini indices between both extremes but still well above, by 10-34%, those calculated with the use of the survey data only. Although the bottom corrections were applied to a larger portion of the sample, the top corrections resulted in much higher increases in the extreme incomes (see Figures 2-4). In a similar way changes in the incomes revised also the Theil index, however with a much higher magnitude. Final estimates raised as much as by 220%, which confirms empirically high sensitivity of this formula to extremes values (proved theoretically by Cowell and Flachaire, 2007). It is worth mentioning that the modifications of top 1% and even top 5% incomes left inequality measures based on the percentile ratios (75/25 and 90/10) unchanged. This is because 75th and 90th centiles derived from the survey data are still below the values derived from the modified incomes. Correcting bottom incomes reduces inequality measures of that type and the amount of this reduction is greater for the 90/10 ratios. In Table 4, the impact of the area of the bottom incomes corrections on inequality is examined by comparing Gini index for the following ranges of the distribution: 10%, 15%, 20%, and 25%, calculated together with top 1% and top 5% corrections. As might be expected, the wider range of the bottom correction, the stronger the reducing effect, however the differences in the size of the changes are rather moderate: from 0.020 to 0.022.

Table 3. Inequality indices for the survey and the imputed incomes: corrections to top 5% and bottom 20%.

	Raw survey income	Area of income correction		
		Top 5%	Bottom 20%	Both
2014		Gini		
	0.308	0.454	0.263	0.413
		90/10		
	3.89	3.89	2.85	2.85
		75/25		
	1.98	1.98	1.77	1.78
		Theil		
	0.175	0.619	0.135	0.561
2015		Gini		
	0.303	0.447	0.258	0.405
		90/10		
	3.79	3.79	2.78	2.78
		75/25		
	1.95	1.95	1.75	1.75
		Theil		
	0.171	0.604	0.132	0.546

Source: own calculation based on the household budget survey.

Additionally, Theil indices are decomposed into between-group and within-group inequality. The following subgroups, created on the basis of the main source of the household income, are observed:

- blue collar employees,
- white collar employees,
- farmers,
- self-employed and those living on a property income,
- retirement pensioners,
- invalid pensioners,
- living on social transfers.

Table 4. Gini index sensitivity to the area of income correction.

Survey income	Area of income correction							
	Top 1% and bottom:				Top 5% and bottom:			
	10%	15%	20%	25%	10%	15%	20%	25%
	2014							
0.308	0.355	0.346	0.339	0.333	0.428	0.420	0.413	0.407
	2015							
0.303	0.354	0.345	0.338	0.332	0.420	0.412	0.405	0.400

Source: own calculation based on the household budget survey.

A question about within- and between-group components of the overall inequality may be, less formally, translated into the question: which gap is, on average, larger – between a rich and a poor employee (say) or between an employee and a pensioner (say)? Probably in all similar calculations based on household incomes performed for a large variety of the countries, the within-group inequality is substantially higher than the between-group one. The present results[2] definitely confirm this rule: depending on the type of income the within-group component ranges from 85% to 89% of the overall inequality. Lower values are obtained when the survey incomes and the incomes with corrections for bottom 20% only are used. When top 1% or top 5% corrections are applied, the within-group component rises to around 89%, irrespective of whether bottom 20% correction is applied or not. Rising highest incomes results in huge rises in the within-group inequality for all groups, however at certainly different paces. The largest increases may be observed for the farmers and the self-employed, which hardly can surprise. Not much smaller inequality increases in within-group inequality were experienced by the white collars households. Changing a type of the income left inequality rankings between groups nearly unaffected.

5. Conclusions and further studies

The results of the present study only partly confirm findings by Brzeziński et al. (2022) on the serious underestimation of the Polish inequality indices. Corrections of the 2014 and 2015 survey income data applied to both tails of the distribution also results in inequality growth, however not so high and not for all types of inequality measures. Possible overestimation of the income inequality by Brzeziński et al. stems from restricting the survey income corrections to the highest ranges of the distribution

[2] Since similarity of the outcomes for 2014 and 2015 only results for the latter year are reported. Detailed results are available upon request.

(top 1% and top 5%). Applying corrections also to the bottom tail of the distribution, which may be informally called making the "fake poor" non poor, leads to lower and probably more reliable estimates of the income inequality in Poland. Nevertheless, the final indices are still well above those calculated solely by means of the survey data (Gini index is higher by at least 10%) but also well below those calculated after correcting highest incomes only (Gini index is lower by at least 9%).

Assuming better reliability of the corrected incomes than of the raw survey data, there is bad and good news. Potentially bad news is a rise in the inequality in Poland, as compared to that based on the survey data. Good news is that the rise in the inequality measures is due to an upward correction of the high incomes ("making the rich more rich"), not due to a downward correction of the low incomes ("making the poor more poor"). One more good news is a reduction of the poverty incidence and depth estimates, due to income corrections applied to the bottom ranges of the distribution (see Duda and Szulc, 2020). Less sizable growth in income disparities put partly in question Brzeziński's et al. (2022) hypothesis on impact of inequality perception by the voters on the results of 2015 election in Poland. Moreover, applying income corrections to both tails of the distribution even decreased inequality measures defined as extreme percentile ratios (75/25 and 90/10). The question which measures of inequality, the latter ones or Gini indices, are better proxies to inequality perception is another issue worth further research. One more argument against the hypothesis under consideration may be pronounced referring to 2015 election campaign. The winner's (Law and Justice) rhetoric was rather pro-poor than anti-rich (with two exceptions: they announced increased taxation for banks and foreign hypermarkets, see Prawo i Sprawiedliwość, 2015). Informally speaking, the future government promised to be Santa Claus rather than Robin Hood.

Another point worth consideration is the source of income growths estimated for some rich people. As pointed out by Brzeziński et al. (2022), it followed a substantial reduction of the personal income tax progressivity. Without deciding whether this growth itself was advantageous or not, the recent changes in the tax system in Poland, referred to as Polish Deal ("Polski Ład"), started in 1st January 2022 make room for further studies in this field. The declared features of those changes are, inter alia: a minor increase in a tax burden for the richest people and an enlargement of tax exemptions for (at least) the less privileged groups. Another relevant reform introduced by the government after 2015 is a reconstruction of the system of social cash transfers. In April 2016 the family support program, referred to as "Family 500+", was launched. Its principal details may be found in Brzeziński and Najsztub (2017) and in Michoń (2021). It ensures monthly unconditional support of tax-free 500 PLN (26% of mean equivalent income in 2016) per each child in families with two or more children and means tested support of same amount for families with one child. The transfers to families with children resulted, inter alia, in reduction of Gini index for equivalent incomes between 2015 and 2017 by 9%, using survey data only. It seems, however, that Family 500+ cash transfers had no impact on underreporting incomes in the household surveys[3].

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