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Decomposition of Differences between Household Income Distributions in Poland in Years 2002 and 2012

Abstract: In this study we present the decomposition of income inequalities between household income distributions in Poland in 2002 and 2012. The difference between two distributions may be decomposed using the counterfactual distribution, which can be constructed in various ways. Techniques such as the residual imputation approach and *RIF*-regression method (recentered influence function) were considered. The application of these methods made it possible to show the aggregate detailed decompositions in different quantile points along the income distribution. The influence of several person's characteristics on the differences in income distributions was examined. By decomposing the inequalities into the explained and unexplained components it was possible to receive additional information about their causes.

Keywords: decomposition of income inequalities, differences in distributions

JEL: J31, D31

1. Objective of the study

Objective of the studyNowadays, a variety of techniques for income inequalities decomposition are becoming more and more popular. Many procedures go far beyond simple comparison of average values proposed by Oaxaca (1973) and Blinder (1973). They allow to decompose e.g. the variance, the Gini coefficient or the differences along the whole distribution. These techniques are useful in studying differences of income distributions for various groups of people.

Past studies in Poland were mostly focused on the decomposition of average values for incomes by using the Oaxaca-Blinder method (e.g. Słoczyński, 2012; Śliwicki, Ryczkowski, 2014). Only a few studies go beyond the mean-decomposition (e.g. Newell, Socha, 2005; Rokicka, Ruzik, 2010; Landmesser, Karpio, Łukasiewicz, 2015; Landmesser, 2016). The aim of this work is to study differences between income distributions in Poland in 2002 and 2012. The empirical data used have been collected within the Household Budget Survey for Poland.

Decomposing differences between two distributions, one utilizes the so-called counterfactual distribution. This is a mixture of a conditional distribution of the dependent variable and a distribution of the explanatory variables. Such counterfactual distribution can be constructed in various ways (e.g. DiNardo, Fortin, Lemieux, 1996; Donald, Green, Paarsch, 2000; Machado, Mata, 2005; Fortin, Lemieux, Firpo, 2010: 50–82). We investigate the differences in the whole range of income values by the use of the residual imputation approach (*JMP*-approach) proposed by Juhn, Murphy, Pierce (1993). It is also examined how the people's characteristics (the explanatory variables in estimated models) influence various ranges of income distributions, using the *RIF*-regression method (recentered influence function) proposed by Firpo, Fortin, Lemieux (2009).

2. Methods of the analysis

Let y_i be the outcome variable in year i (e.g. the household disposable income in 2002 or 2012) and X_i the vector of individual characteristics of the household's head or the household in year i (e.g. gender, age, education level, number of children, place of residence). The expected value of y conditional on X is a linear function $y_i = X_i\beta_i + v_i$, $i = T_1, T_2$, where coefficients β_i are the returns to the characteristics. The Oaxaca-Blinder decomposition for the average income inequality between two years at the aggregate level is as follows:

$$\hat{\Delta}^{\mu} = \bar{y}_{T_2} - \bar{y}_{T_1} = \bar{X}_{T_2}\hat{\beta}_{T_2} - \bar{X}_{T_1}\hat{\beta}_{T_1} = \underbrace{(\bar{X}_{T_2} - \bar{X}_{T_1})\hat{\beta}_{T_2}}_{\hat{\Delta}^{\mu}_{\text{explained}}} + \underbrace{\bar{X}_{T_1}(\hat{\beta}_{T_2} - \hat{\beta}_{T_1})}_{\hat{\Delta}^{\mu}_{\text{unexplained}}}. \quad (1)$$

The first term, on the right hand side of the equation, gives the effect of characteristics and expresses the difference of the potentials of households in two years (the so-called explained effect). The second term, called unexplained effect, is the result of differences in the regression coefficients (differences in the returns to observables). The detailed decomposition may be calculated from equation (2):

$$\hat{\Delta}^{\mu} = \sum_{j=1}^{k} (\overline{X}_{jT_2} - \overline{X}_{jT_1})\hat{\beta}_{jT_2} + (\hat{\beta}_{0T_2} - \hat{\beta}_{0T_1}) + \sum_{j=1}^{k} \overline{X}_{jT_1}(\hat{\beta}_{jT_2} - \hat{\beta}_{jT_1}). \quad (2)$$

The important drawback of the Oaxaca-Blinder decomposition is that it focuses only on average effects, and this may lead to a misleading assessment if the effects of covariates vary across the income distribution.

Let $f^{i}(y)$ be the density function for the variable y in year i. One can express it using the conditional distribution $g^{i}(y|X)$ of y and the joint distribution $h^{i}(X)$ of all elements of X:

$$f^{i}(y) = \int_{C(X)} \dots \int g^{i}(y|X)h^{i}(X)dX. \quad (3)$$

The mean decomposition analysis may be extended to the case of differences between the two distributions using the counterfactual distribution $f^{C}(y)$:

$$f^{T_2}(y) - f^{T_1}(y) = [f^{T_2}(y) - f^{C}(y)] + [f^{C}(y) - f^{T_1}(y)]. \quad (4)$$

The counterfactual distribution can be constructed in various ways. One can apply the residual imputation approach (Juhn, Murphy, Pierce, 1993). In this method we have to estimate the equations $y_{T_1 i} = X_{T_1 i}\beta_{T_1} + v_{T_1 i}$ and $y_{T_2 i} = X_{T_2 i}\beta_{T_2} + v_{T_2 i}$, $i = 1, \dots, n$. Then, the income y_{T_2} from the year T_2 is replaced by a counterfactual income $y_{T_1}^{C}$, where both the returns to observables and residuals are set to be as in year T_1. The implementation of the residual imputation procedure is divided into two steps. In the first step, the residuals are replaced by counterfactual residuals under the assumption of the rank preservation:

$$y_{T_1 i}^{C,1} = X_{T_2 i}\beta_{T_2} + v_{T_1 i}^{C,1}, i = 1, \dots, n, \text{ where } v_{T_1 i}^{C,1} = F_{v_{T_1}|X}^{-1}(\tau_{T_2 i}(X_{T_2 i}), X_{T_2 i}) \quad (5)$$

and $\tau_{T_2 i}(X_{T_2 i})$ is the conditional rank of $v_{T_2 i}$ in the distribution of residuals for year T_2.

In the second step the counterfactual returns to observables are also imputed:

$$y_{T_1 i}^{C,2} = X_{T_2 i}\beta_{T_1} + v_{T_1 i}^{C,1}, i = 1, \dots, n. \quad (6)$$

The assumption of the rank preservation is strong since it means that someone with the same unobserved skills would be in exactly the same position, conditional on X, in either year 2012 or 2002. Another limitation of this procedure is that there is no natural way of extending it to the case of the detailed decomposition for the explained effect.

A *RIF*-regression method (Firpo, Fortin, Lemieux, 2009) provides a way of performing detailed decomposition. The *RIF*-regression is similar to a linear regression, except that the variable y is replaced by the recentered influence function of the statistic of interest. Let $IF(y,Q_\tau)=\frac{\tau-\mathrm{I}\{y\le Q_\tau\}}{f_Y(Q_\tau)}$ be the influence function corresponding to an income y for the quantile Q_τ of distribution F_Y. The recentered influence function is defined as:

$$RIF(y,Q_\tau)=Q_\tau+IF(y,Q_\tau)=Q_\tau+\frac{\tau-\mathrm{I}\{y\le Q_\tau\}}{f_Y(Q_\tau)}. \tag{7}$$

The *RIF* is simply an indicator variable $\mathrm{I}\{y \le Q_\tau\}$ for whether the income y is smaller or equal to the quantile Q_τ. The approach assumes that the conditional expectation of $RIF(y, Q_\tau)$ can be modeled as a linear function of the explanatory variables $E[RIF(y, Q_\tau|X)] = X\beta_\tau + \varepsilon$, where parameters β_τ can be estimated by OLS. The linear probability models explain the determinants of the proportion of households with income less than Q_τ. The estimates of models for proportions are locally inverted back into the space of quantiles. This provides a way of decomposing quantiles using regression models for proportions (we get a decomposition model for quantiles by dividing a model for proportions by density, as in (7)).[1] The aggregated and detailed decomposition for any unconditional quantile is then:

$$\hat{\Delta}^\tau=(\bar{X}_{T_2}-\bar{X}_{T_1})\hat{\beta}_{T_1,\tau}+\bar{X}_{T_2}(\hat{\beta}_{T_2,\tau}-\hat{\beta}_{T_1,\tau})=\sum_{j=1}^{k}(\bar{X}_{jT_2}-\bar{X}_{jT_1})\hat{\beta}_{jT_1,\tau}+\bar{X}_{T_2}(\hat{\beta}_{T_2,\tau}-\hat{\beta}_{T_1,\tau}). \tag{8}$$

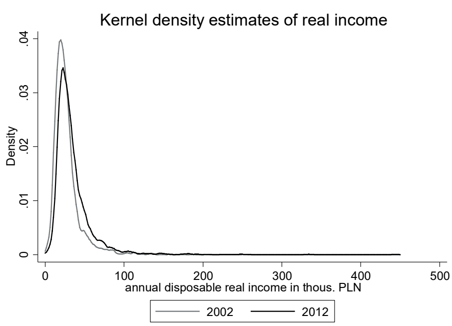
The straightforward inversion of proportions performed locally (we don't need to worry about monotonicity of the distribution) is an advantage of the *RIF*-regression approach. Additionally, the resulting decomposition is path independent.

3. Data basis

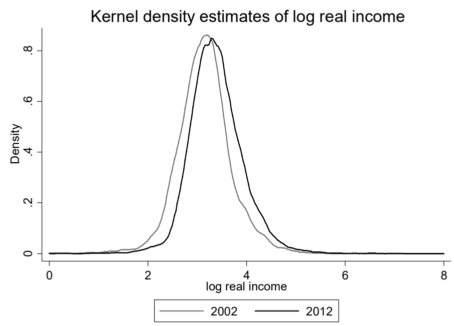
The empirical investigation is based on data from the Household Budget Survey project for 2002 and 2012. For reasons of comparison, the data regards households run by only one person whose main source of income comes from work as an employee. The sample consists of 3178 and 4146 people in 2002 and 2012

[1] In the approach, we first compute the sample quantile $\hat{Q}_\tau$ and estimate the density $\hat{f}_Y(\hat{Q}_\tau)$ using kernel methods. Then, we calculate the *RIF* of each observation according to the equation (7) and run regressions of the *RIF* on the vector X.

respectively (in 2002: 2076 men, 1102 women; in 2012: 2602 men, 1544 women). Each head of household is described by the following characteristics: *sex* (0 – woman, 1 – man), *age* (in years), *education* (education level, 1 – primary, …, 9 – tertiary), *children* (number of children younger than 14 years of age), *residence* (place of residence, 1 – village, …, 6 – town larger than 500 thousand of inhabitants), *position* (0 – manual labor position, 1 – non-manual labor position). The annual disposable incomes in 2012 were compared with those obtained in 2002. The incomes in thousands of zlotys ("PLN") were expressed in prices in 2012 and for subsequent calculations we took the logarithms of real income. Figure 1 shows the kernel density estimates of household real income (a) and log real income (b) for both years. Some descriptive statistics for household real incomes in 2002 and 2012 are shown in Table 1.



(a)



(b)

Figure 1. Densities of household disposable incomes in 2002 and 2012

Source: own research using Stata

Table 1. Descriptive statistics for real household disposable incomes in 2002 and 2012

	Pooled sample	Men	Women
Mean 2002	27.104	28.063	25.296
Mean 2012	34.921	37.177	31.120
1st quartile 2002	16.930	17.464	15.679
1st quartile 2012	21.120	22.128	19.560
Median 2002	23.268	23.994	21.578
Median 2012	28.800	30.000	26.400
3rd quartile 2002	31.361	31.828	30.091
3rd quartile 2012	39.600	42.000	36.423
Standard deviation 2002	19.449	21.145	15.615
Standard deviation 2012	32.681	38.663	18.060
Coefficient of variation 2002	0.718	0.753	0.617
Coefficient of variation 2012	0.936	1.040	0.580
Skewness 2002	6.756	7.453	2.500

	Pooled sample	Men	Women
Skewness 2012	14.317	13.487	2.590
Kurtosis 2002	115.430	123.403	12.130
Kurtosis 2012	371.448	298.659	15.424
Gini coefficient 2002	0.301	0.302	0.294
Gini coefficient 2012	0.313	0.327	0.280

Source: own research

4. Empirical analysis

4.1. Results of Oaxaca-Blinder decomposition technique

Table 2 presents the results of the aggregate Oaxaca-Blinder decomposition of inequalities between log incomes in 2012 and 2002 for the pooled sample as well as for men and women, separately.

The mean predicted log income for 2002 equals 3.142, and for 2012 equals 3.385. There is a positive difference between the mean values of log incomes in 2012 and 2002 not only for the whole sample, but also for men or women separately. For the whole sample, the mean log income differential is 0.243, whereas it is 0.258 for men and only 0.226 for women. The explained effect is very low, but the unexplained is substantial. The inequalities examined should be assigned in the majority to the coefficients of estimated models (rather than to the differentiation of individual characteristics).

Table 2. The aggregate Oaxaca-Blinder decomposition of the average log income differences

	Pooled sample		Men		Women	
Mean log income 2012	3.385		3.430		3.310	
Mean log income 2002	3.142		3.172		3.084	
Raw differential	0.243		0.258		0.226	
Components	explained	unexplained	explained	unexplained	explained	unexplained
	–0.002	0.245	–0.003	0.26	0.01	0.216
	(–0.82%)	(100.82%)	(–1.17%)	(101.17%)	(4.42%)	(95.58%)

Source: own research

In the next step, we tried to explain the differences observed. Using the detailed decomposition method, we evaluated the strength of the influence of the factors analyzed onto the average log incomes (Table 3). The *age* and *education* variables were positively correlated with the change of the average value of log incomes. However the biggest influence was exhibited by the *education* attribute. The increase of the average log incomes can be mostly explained by the big increase of the education level from 2002 to 2012. On the other hand, the *children* variable exhibits negative correlation with the change of the average log income.

Table 3. The detailed Oaxaca-Blinder decomposition of the average log income differences

Variable	Pooled sample		Men		Women	
	explained	unexplained	explained	unexplained	explained	unexplained
sex	–0.006	–0.009	–	–	–	–
age	0.005	0.006	0.005	0.015	0.006	0.008
education	0.034	0.057	0.033	0.045	0.029	0.084
children	–0.037	0.046	–0.038	0.053	–0.028	0.028
residence	–0.008	–0.003	–0.010	–0.030	–0.006	0.055
position	0.010	–0.034	0.009	–0.021	0.008	–0.056
const	0.000	0.182	0.000	0.198	0.000	0.097
Total	–0.002	0.245	–0.003	0.260	0.010	0.216

Source: own research

4.2. Results of decomposition using JMP-approach

Since the Oaxaca-Blinder technique focuses only on average effects, next, we present the decomposition of inequalities along the distribution between log incomes in 2012 and 2002 using the *JMP*-approach. The results of this decomposition are shown in Table 4.

Table 4. The results of decomposition using the *JMP*-approach

Percentile	Pooled sample				
	total difference	explained		unexplained	
p5	0.283	0.051	(18.07%)	0.232	(81.93%)
p10	0.268	0.029	(10.66%)	0.240	(89.34%)
p25	0.221	–0.026	(–11.82%)	0.247	(111.82%)
p50	0.213	–0.032	(–15.07%)	0.245	(115.07%)
p75	0.233	–0.017	(–7.24%)	0.250	(107.24%)
p90	0.252	0.010	(4.17%)	0.241	(95.83%)
p95	0.247	0.009	(3.76%)	0.237	(96.24%)

Source: own research

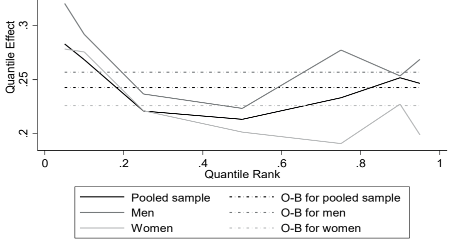
There are positive differences between the values of log incomes in 2012 and 2002 along the whole log income distribution. The differences are expressed as the sum of the explained and unexplained components. The total effect is U-shaped (Figure 2a). The explained effect is lower and the unexplained is higher (Figure 2b), which indicates the importance of the "labor market value" of the households' attributes. We can see that the effect of coefficients is larger in the middle of the income distribution. The effect of characteristics is positive at the bottom and at the top of the income distribution. Positive values mean that the rising values of characteristics of the poorest and the richest increased the income inequalities over time. In the middle of the distribution the growing characteristics decreased the inequalities. The percentages are calculated as (explained part)/(total difference) × 100% (or (unexplained part)/(total difference) × 100%, respectively). The negative percentages indicate that changes in characteristics of households decreased the income inequalities over time (the corresponding percentage values exceeding 100% suggest that changes in "prices" of households' attributes increased conversely to the inequalities examined).

Table 5 and Figure 2 (c, d) present the results of the decomposition of inequalities along the distribution between log incomes in 2012 and 2002 for men and women separately.

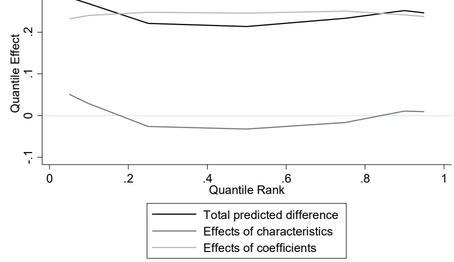
Table 5. The results of the *JMP*-approach for men and women separately

Percentile	Men			Women		
	total difference	explained	unexplained	total difference	explained	unexplained
p5	0.320	20.76%	79.24%	0.278	28.29%	71.71%
p10	0.292	5.44%	94.56%	0.276	25.60%	74.40%
p25	0.237	–13.80%	113.80%	0.221	6.99%	93.01%
p50	0.223	–18.51%	118.51%	0.202	–1.97%	101.97%
p75	0.277	1.13%	98.87%	0.191	–13.47%	113.47%
p90	0.254	7.66%	92.34%	0.227	6.06%	93.94%
p95	0.269	5.68%	94.32%	0.199	–10.06%	110.06%

Source: own research



(a)



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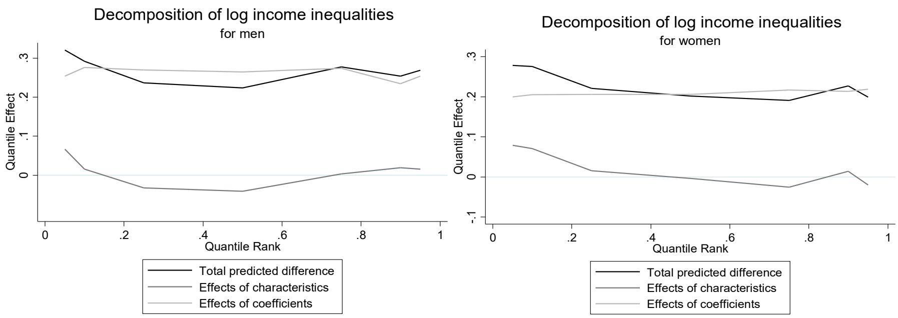

(c) (d)

Figure 2. The Results of decomposition using the *JMP*-approach

Source: own research using Stata

There are positive differences between the values of log incomes in 2012 and 2002, also for men or women along the income distributions. The total effect seems more U-shaped for men than for women. In both cases, the explained effect is low, but the unexplained is substantial. The explained differential for women shrinks as we move toward the top of the income distribution. The important drawback of the *JMP*-approach is the fact, that there is no natural way of extending it to the case of the detailed decomposition. Therefore, we changed the method of the analysis to the *RIF*-regression approach.

4.3. Results of decomposition using RIF-regression approach

Table 6 shows one of many results obtained of the detailed decomposition of inequalities along log income distributions. These are the results for 30th percentile for men. In total, $3 \times 9 = 27$ detailed decompositions for each decile were carried out: 9 for the pooled sample, 9 for men and 9 for women.

Table 6. The example results of the *RIF*-regression approach – for men's 30th percentile only

Men's 30th log income percentile				
Raw differential	**value**	**p-value**		
	0.21635	**0.000**		
Variable	**explained**	**p-value**	**unexplained**	**p-value**
age	–0.00324	0.164	–0.20245	0.003
education	0.02428	0.000	0.00441	0.947
children	–0.03305	0.000	0.02297	0.201
residence	–0.00729	0.002	–0.08590	0.006
position	0.00421	0.058	–0.02173	0.090
const			0.51414	0.000
Total	–0.01509	0.052	0.23144	0.000

Source: own research

The explained and unexplained effects for most variables are statistically significant (the errors have been evaluated using the bootstrap method). In Figure 3 we drew the values of explained effects for each variable and for each decile, for the pooled sample and for men and women separately.

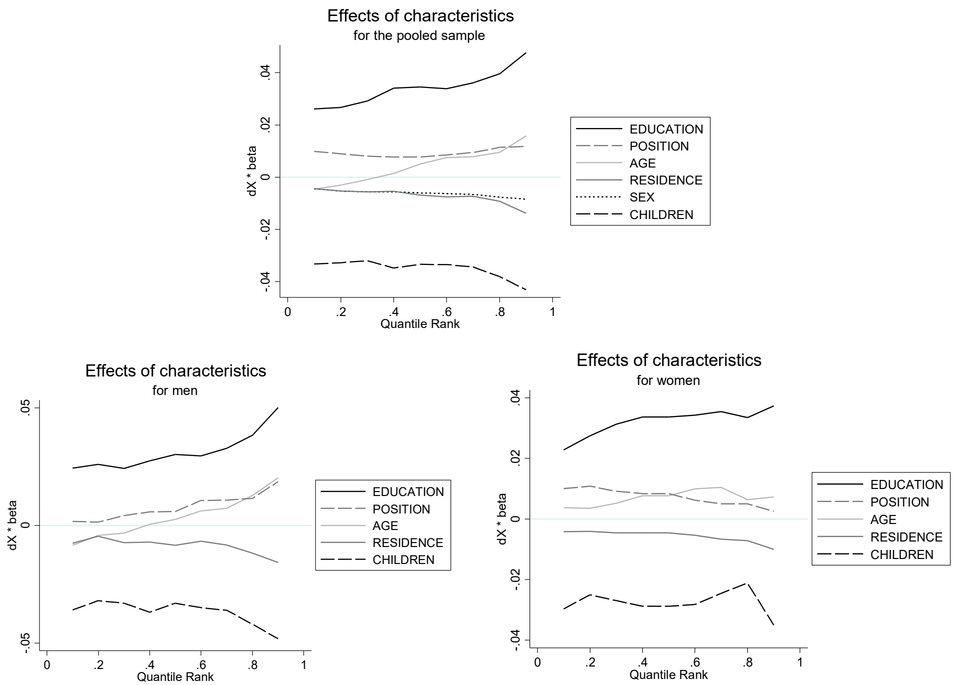

Figure 3. The results of the RIF-regression approach – effects of characteristics

Source: own research using Stata

The most important are the effects related to the variables *education* and *children*. The *education* variable has the greatest positive influence on the differences between the log income distributions in 2012 and 2002. For the variable *children* we observe the influence, which reduces log income differences. It means that having children decreased the income inequalities between 2012 and 2002. It could be interpreted that families with children did not increase their incomes in the analyzed period as much as childless families did, becoming relatively poorer. The importance of both characteristics – *education* and *children* – increases with the size of income (Newell and Socha also found that many of the factors influencing incomes have a stronger impact in higher quantiles of income distribution – cf. Newell, Socha, 2005). Less important are *position* and *residence* variables. The *residence* variable has an increasing negative impact on the differences observed, which indicates a "shift of big incomes towards smaller towns" (cf. Landmesser, Karpio, Łukasiewicz, 2015: 51). The influence of *age* is insignificant for the middle ranges of income.

The calculated values of unexplained effects (effects of coefficients) for each variable and for each decile are presented in Figure 4. The changes in the returns to the attributes have, unfortunately, partly insignificant effects for the pooled sample, for men, and mainly insignificant effects for women. Therefore, they will not be interpreted.

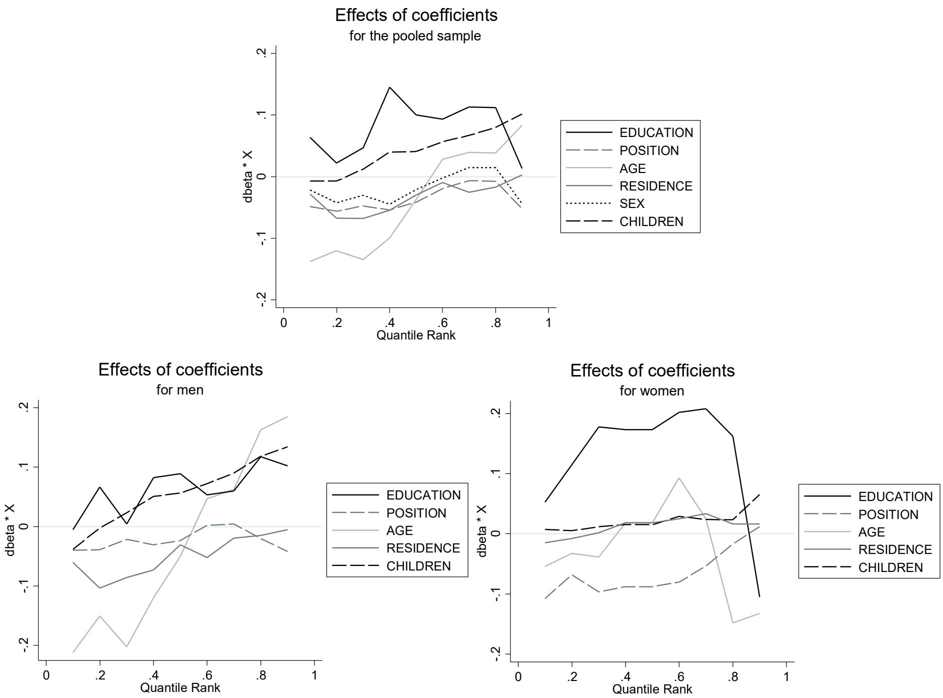

Figure 4. The results of the RIF-regression approach – effects of coefficients

Source: own research using Stata

5. Conclusions

The goal of this paper was to present the decomposition of inequalities between log incomes in 2012 and 2002 for Polish households. For reasons of comparison, the data concerned households run by only one person. We started with the decomposition of the average values for log incomes, by using the Oaxaca-Blinder method. There was a positive difference between the mean values of log incomes. The explained effect was low, but the unexplained was substantial. Then, we decomposed the inequalities between log incomes along the whole distribution, using the residual imputation approach. The total effect was U-shaped and bigger for men than women. The explained effect was low, but the changes in characteristics of the poorest and the richest increased the income inequalities over time. The method of *RIF*-regression provided a way of showing the detailed decomposition of log income inequalities. The explained effects are statistically significant for most variables. The importance of all characteristics increases with income. The *education* has the greatest positive influence on the differences between the income distributions in 2012 and 2002.

From a technical point of view, one should be aware of the problems that arise when working with decomposition methods (e.g. the omitted group problem or the linearity assumption for the Oaxaca-Blinder method). Many decomposition methods for distributional statistics, other than the mean, allow only for the aggregate decomposition (like residual imputation approach) or for the detailed decomposition which is path dependent (e.g. the Machado-Mata method). Although the *RIF*-regression method is path independent, it only provides the local approximation for the effect of changes in a covariate on the distributional parameter of interest. However, even if that approach was useful for quantifying the contribution of factors to the differences in outcomes, it may not necessarily deepen our understanding of the mechanism underlying the analyzed process.

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Dekompozycja różnic między rozkładami dochodów gospodarstw domowych w Polsce w roku 2002 oraz 2012

Streszczenie: W artykule zaprezentowano dekompozycję nierówności między rozkładami dochodów gospodarstw domowych w Polsce w roku 2002 oraz 2012. Różnica między dwoma rozkładami może zostać zdekomponowana przy wykorzystaniu rozkładu kontrfaktycznego, który można skonstruować na różne sposoby. Rozważono następujące techniki: podejście oparte na imputacji reszt oraz metodę *RIF*-regresji (zdecentrowanej funkcji wpływu). Zastosowanie tych metod pozwoliło na przeprowadzenie zagregowanej i szczegółowej dekompozycji dla wybranych kwantyli rozkładów dochodów. Oceniono wpływ indywidualnych cech osób na różnice w rozkładach. Dekomponując nierówności na część wyjaśnioną i niewyjaśnioną, uzyskano dodatkową informację na temat ich przyczyn.

Słowa kluczowe: dekompozycja nierówności dochodowych, różnice między rozkładami

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