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DIFFERENCES IN INCOME DISTRIBUTIONS FOR MEN AND WOMEN IN POLAND – AN ANALYSIS USING DECOMPOSITION TECHNIQUES

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ABSTRACT

In the paper, we compare income distributions in Poland, taking into account gender differences. The gender pay gap can only be partially explained by differences in men's and women's characteristics. The unexplained part of the gap is usually attributed to the wage discrimination. The objective of the study is to extend the Oaxaca-Blinder decomposition procedure to different quantile points along the income distribution. We utilize such decomposition methods as the residual imputation approach, the reweighting approach and the RIF-regression method to describe differences between the incomes of men and women along the two distributions. We evaluate the strength of the influence of personal characteristics onto the various parts of the income distributions. The analysis is based on data from the EU-SILC data for Poland in 2014.

Key words: wage gap, differences in distributions, decomposition methods

INTRODUCTION

Recently there has been an increase in interest in the studies of income (wages) inequalities. Numerous empirical studies tend to focus on the gender wage gaps. The findings of these studies show that males earn substantially higher wages than females. Women are paid only a part of what men with similar characteristics are paid.

A variety of techniques of income inequalities decomposition are becoming more popular. Many procedures go far beyond the simple comparison of average values proposed by Oaxaca [1973] and Blinder [1973]. They allow to decompose the variance or the differences along the whole distributions. These techniques are useful in studying differences of income distributions for various groups of people. The past studies in Poland concentrated mainly on the decomposition of the average values for incomes [Słoczyński 2012, Śliwicki and Ryczkowski 2014]. Only a few analyses go beyond the simple mean-decomposition [Rokicka and Ruzik 2010, Landmesser et al. 2015, Landmesser 2016]. The aim of this work is to study differences between income distributions for men and women in Poland in 2014. The empirical investigation is based on data from the European Union Statistics on Income and Living Conditions project for Poland.

To decompose the differences between two distributions one uses the so-called counterfactual distribution, which is a mixture of a conditional distribution of the dependent variable and a distribution of the explanatory variables. Such a counterfactual distribution can be constructed in various ways [DiNardo et al. 1996, Donald et al. 2000, Machado and Mata 2005, Fortin et al. 2010]. We will examine the differences in the entire range of income values by the use of the residual imputation approach (JMP-approach) [Juhn et al. 1993] and the reweighting approach [DiNardo et al. 1996]. It will also be found how the men's and women's characteristics

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(the explanatory variables in estimated models) influence various ranges of income distributions using the *RIF*-regression method (recentered influence function) [Firpo et al. 2009].

METHODS OF THE ANALYSIS

Let Y_g denote the outcome variable in group g (e.g. the personal income in men's group, $g = M$, or in women's group, $g = W$) and X_g the vector of individual characteristics of the person in group g (e.g. age, education level, number of years spent in paid work). The expected value of y conditionally on X is a linear function $y_g = X_g\beta_g + v_g$, $g = M$, W, where β_g are the returns to the characteristics. The Oaxaca-Blinder decomposition for the average income inequality between two groups at the aggregate level can be expressed as

$$\hat{\Delta}^{\mu} = \bar{Y}_M - \bar{Y}_W = \bar{X}_M\hat{\beta}_M - \bar{X}_W\hat{\beta}_W = \underbrace{\bar{X}_M(\hat{\beta}_M - \hat{\beta}_W)}_{\hat{\Delta}^{\mu}_{\text{unexplained}}} + \underbrace{(\bar{X}_M - \bar{X}_W)\hat{\beta}_W}_{\hat{\Delta}^{\mu}_{\text{explained}}} \tag{1}$$

The first component, on the right side of the equation, called the unexplained effect, is the result of differences in the returns to observables. This is the result of differences in the estimated parameters, and so in the "prices" of individual characteristics of group representatives. It can be interpreted as the labor market discrimination. The second term gives the effect of characteristics and expresses the difference of the potentials of people in two groups (the so-called explained effect). Also the detailed decomposition may be calculated. A drawback of the approach is that it focuses only on average effects which may lead to a misleading assessment if the effects of covariates vary across the wage distribution.

Let $F_{Y_g}(y)$ be the distribution function for the variable Y in group g, which can be expressed using the conditional distribution $F_{Y_g|X,D_g}(y|X = x)$ of Y and the joint distribution $F_{X|D_g}(X)$ of all elements of X ($D_g = 1$ if $g = M$; $D_g = 0$ if $g = W$):

$$F_{Y_g|D_g}(y) = \int F_{Y_g|X,D_g}(y|X = x) \cdot F_{X|D_g}(X)\,dx, \qquad g = M, W \tag{2}$$

Now, we extend the mean decomposition analysis to the case of differences between the two distributions using the counterfactual distribution $F_{Y_W^C}(y) = \int F_{Y_W|X_W}(y|X) \cdot dF_{X_M}(X)$ (distribution of incomes that would prevail for people in group W if they had the distribution of characteristics of group M):

$$F_{Y_M}(y) - F_{Y_W}(y) = \underbrace{[F_{Y_M}(y) - F_{Y_W^C}(y)]}_{\substack{\hat{\Delta}^{\mu}_{\text{unexplained}} \\ \text{(structure effect)}}} + \underbrace{[F_{Y_W^C}(y) - F_{Y_W}(y)]}_{\substack{\hat{\Delta}^{\mu}_{\text{explained}} \\ \text{(composition effect)}}}. \tag{3}$$

The counterfactual distribution can be constructed using the residual imputation approach [Juhn et al. 1993]. In this method, we estimate the two equations: $y_{Wi} = X_{Wi}\beta_W + v_{Wi}$ and $y_{Mi} = X_{Mi}\beta_M + v_{Mi}$, $i = 1, \ldots, n$. Then, the wage y_M form the group M is replaced by a counterfactual wage y_W^C, where both the returns to observables and residuals are set to be as in group W. The implementation of the procedure is as follows:

1. The residuals are replaced by counterfactual residuals under the assumption of the rank preservation: $y_{Wi}^{C,1} = X_{Mi}\beta_M + v_{Wi}^{C,1}$, $i = 1, \ldots, n$, where $v_{Wi}^{C,1} = F^{-1}_{v_W|X}(\tau_{Mi}(X_{Mi}), X_{Mi})$ and $\tau_{Mi}(X_{Mi})$ is the conditional rank of v_{Mi} in the distribution of residuals for M.
2. The counterfactual returns to observables are imputed: $y_{Wi}^{C,2} = X_{Mi}\beta_W + v_{Wi}^{C,1}$, $i = 1, \ldots, n$.

Another way of estimating the counterfactual distribution is to replace the marginal distribution of X for group W with the marginal distribution of X for group M using a reweighting factor $\Psi(X)$. This reweighting approach was introduced by DiNardo, Fortin and Lemieux [1996]. The counterfactual distribution (distribution of incomes that would prevail for women if they had the distribution of men's characteristics) is constructed as

$$F_{Y_W^C}(y) = \int F_{Y_W|X_W}(y|X)\Psi(X)dF_{X_W}(X) \text{ with } \Psi(X) = dF_{X_M}(X)/dF_{X_W}(X) \quad (4)$$

where: $\Psi(X) = \dfrac{dF_{X_M}(X)}{dF_{X_W}(X)} = \dfrac{\Pr(X|D_M = 1)}{\Pr(X|D_M = 0)} = \dfrac{\Pr(D_M = 1|X)/\Pr(D_M = 1)}{\Pr(D_M = 0|X)/\Pr(D_M = 0)}$.

The reweighting factor value $\hat{\Psi}(X)$ can be computed for each observation by estimating a logit or probit model for probabilities of belonging to groups M and W ($\hat{\Pr}(D_M = 1|X)$ and $\hat{\Pr}(D_M = 0|X)$) and using the sample proportions in two groups ($\hat{\Pr}(D_M = 1)$ and $\hat{\Pr}(D_M = 0)$). Then the probability density function can be estimated using kernel density methods.

A limitation of the residual imputation approach and the reweighting approach is the difficult way to extended it to the case of the detailed decomposition. The detailed decomposition can be easy performed by the RIF-regression method [Firpo et al. 2009]. This method is similar to a linear regression, except that the variable y is replaced by the recentered influence function of the statistic of interest. We define the recentered influence function as:

$$RIF(y,Q_\tau) = Q_\tau + IF(y,Q_\tau) = Q_\tau + \frac{\tau - \mathrm{I}\{y \le Q_\tau\}}{f_Y(Q_\tau)} \quad (5)$$

where: $IF(y, Q_\tau)$ – influence function corresponding to an income y for the quantile Q_τ of the distribution $F_{Y;}$
I $\{y \le Q_\tau\}$– indicator variable for whether the income y is smaller or equal to the quantile Q_τ.

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 the parameters β_τ can be estimated by OLS. 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 estimate the linear probability model for the proportion of people with income less than $\hat{Q}_\tau$, calculate the RIF of each observation and run regressions of the RIF on the vector X. The aggregated and detailed decomposition for any unconditional quantile is then:

$$\hat{\Delta}^\tau = \bar{X}_M(\hat{\beta}_{M,\tau} - \hat{\beta}_{W,\tau}) + (\bar{X}_M - \bar{X}_W)\hat{\beta}_{W,\tau} = \sum_{j=1}^{k}(\bar{X}_{jM}(\hat{\beta}_{jM,\tau} - \hat{\beta}_{jW,\tau}) + (\bar{X}_{jM} - \bar{X}_{jW})\hat{\beta}_{jW,\tau}) \quad (6)$$

DATA BASIS

The empirical data used have been collected within the European Union Statistics on Income and Living Conditions project for Poland in 2014 (research proposal 234/2016-EU-SILC). The sample consists of 5,177 men and 4,727 women. Each person is described by the following characteristics: *age* (in years), *educlevel* (education level, 1 – primary, . . ., 5 – tertiary), *married* (marital status, 1 – married, 0 – unmarried), *yearswork* (number of years spent in paid work), *permanent* (type of contract, 1 – permanent job/work contract of unlimited duration, 0 – temporary contract of limited duration), *parttime* (1 – person working part-time, 0 – person working full-time), *manager* (managerial position, 1 – supervisory, 0 – non-supervisory), *big* (number of persons working at the local unit, 1 – more than 10 persons, 0 – less than 11 persons). The sample features presents Table 1.

Table 1. The selected sample features

Characteristic		Men	Women	Characteristic	Men	Women
Number of observators		5 177	4,727	average *age*	42.07	42.36
average *income*		7 165.94	5 900.21	average *yearswork*	20.09	18.46
educlevel	= 1	4.91%	3.89%	*married* = 1	71.53%	69.60%
	= 2	1.45%	0.55%	*permanent* = 1	70.60%	71.63%
	= 3	68.57%	47.32%	*parttime* = 1	4.31%	10.09%
	= 4	2.55%	7.91%	*manager* = 1	18.68%	15.74%
	= 5	22.52%	40.32%	*big* = 1	82.91%	80.18%

Source: Own calculations.

The annual net employee (cash or near cash) incomes of men were compared with those obtained by women. Employee income is defined as the total remuneration payable by an employer to an employee in return for work done by the latter during one year. The net employee income corresponds to the gross employee income (mainly wages and salaries paid for the time worked or work done in the main and any secondary job(s), remuneration for the time not worked, enhanced rates of pay for overtime, payments for fostering children, supplementary payments (e.g. thirteenth month payment)) but the tax at source, the social insurance contributions are deducted. In our empirical decomposition analysis the logarithm of the annual income (*log_income*) constitutes the outcome variable.

EMPIRICAL ANALYSIS

Results of Oaxaca-Blinder decomposition for differences in mean log incomes

Table 2 presents the results of the aggregate and detailed Oaxaca-Blinder decomposition of inequalities between men's and women's log incomes in 2014. The mean predicted log income for men equals 8.670 (annual net income = 5,825.50 Euro), and for women equals 8.483 (annual net income = 4,831.92 Euro). There is a positive difference between the mean values of log incomes for men or women (the mean log income differential is 0.186). The difference between the mean log income values was decomposed into two components: the first one explaining the contribution of the different values of models coefficients (the unexplained part) and the second one explaining the contribution of the attributes differences (the explained part). The unexplained effect is huge and positive (0.212), but the explained is very low and negative (–0.026), which means that the inequalities examined should be assigned in the majority to the coefficients of estimated models (rather than to the differentiation of individual characteristics).

The detailed decomposition, which was also carried out, made it possible to isolate the factors explaining the inequality observed to a different extent. The strong effect of different education levels of men and women can be noticed (Table 2). The negative value of the adequate component (which equals –0.087) means that the difference of the average log incomes between men and women is mostly reduced by the women's

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

Specification	Value	Detailed decomposition		
Mean log income men	8.670	Variable	Unexplained component	Explained component
Mean log income women	8.483	*age*	–0.170	0.000
Raw differential	0.186	*educlevel*	–0.095	–0.087
		married	0.094	0.001
		yearswork	–0.052	0.021
Aggregate decomposition		*permanent*	–0.049	–0.004
Unexplained effect	0.212	*parttime*	–0.006	0.031
Explained effect	–0.026	*manager*	0.015	0.007
% unexplained	113.98	*big*	–0.010	0.004
% explained	–13.98	*cons*	0.486	0.000
		Total	0.212	-0.026

Source: own elaboration using the Stata command 'decompose'

higher education levels. On the other hand, the values of *yearswork* and *parttime* attributes possessed by men and women increase the inequality in the average log incomes (see the positive component values 0.021 and 0.031). A different "evaluation" of personal characteristics (the unexplained component) allow the conclusion that women are discriminated against men (but not because of the education levels).

Results of the aggregate decomposition using the residual imputation approach

Since the Oaxaca-Blinder technique focuses only on average effects, next, we present the decomposition of inequalities along the distribution of log incomes for men and women using the *JMP*-approach. The results of this decomposition are shown in Table 3, where the inequalities are expressed in terms of percentiles. The symbols p5, p10, …, p95 stand for 5th, 10th, …, 95th percentile (e.g. the 5th percentile is the log income value below which 5% of the observations may be found). For each of the seven percentiles the total differences between the values of log incomes for men and women were computed (the 2nd column). Then these differences are expressed as the sum of the unexplained and explained components (the 3th and 4th column).

Table 3. The results of aggregate decomposition using the *JMP*-approach

Percentile	total difference	unexplained		explained	
p5	0.336	0.177	52.56%	0.160	47.44%
p10	0.285	0.196	68.76%	0.089	31.24%
p25	0.132	0.207	157.32%	–0.075	–57.32%
p50	0.140	0.202	143.59%	–0.061	–43.59%
p75	0.166	0.180	108.56%	–0.014	–8.56%
p90	0.212	0.166	78.59%	0.045	21.41%
p95	0.281	0.175	62.29%	0.106	37.71%

Source: Own elaboration using the Stata command 'jmpierce'.

There are positive differences between the values of log incomes for men and women along the whole log income distribution. The unexplained effect (effect of coefficients) is bigger and the explained (effect of characteristics) is lower, which indicates the importance of the "labor market value" of men's and women's attributes. Going across the rows to compare quantile effects shows that gender differences in characteristics increase the income inequalities at the bottom (below the 10th percentile) and at the top (above the 90th percentile) of the log income distribution (the 4th column). We can see that the share of the unexplained part is high (between 53 and 157 percent) and the effect of coefficients is positive in the whole range of the income distribution and is larger in the middle of the distribution (see the 3th column). This is the result of differences in the "market prices" of individual characteristics of men and women (interpreted as the labor market discrimination).

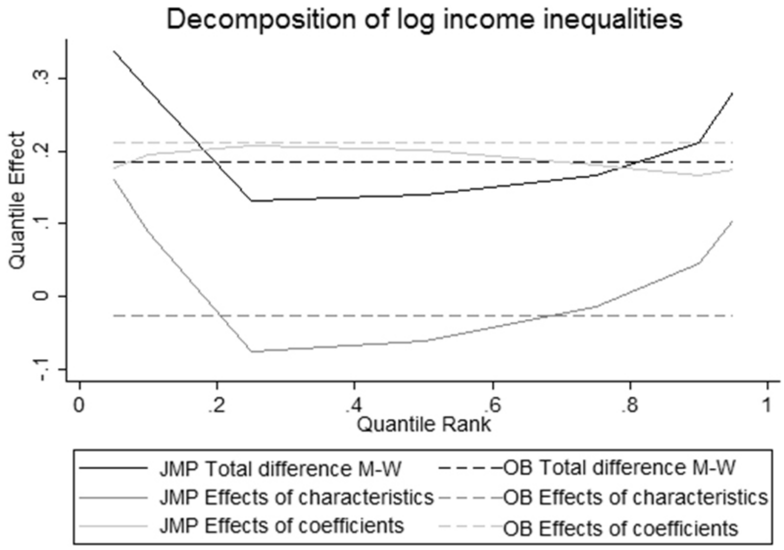

Fig. 1. The differences between the log income distributions for men and women calculated using the JMP-approach

Source: Own elaboration.

Figure 1 contains the differences between the log income distributions for men and women vs. quantile rank. The total effect is U-shaped. The positive values indicate on higher log income values for men than for women. The explained differential, first, is falling and, then, is growing as we move toward the top of the income distribution. We can see, that the effect of characteristics is positive at the bottom and at the top of the income distribution. The positive values observed mean that the different values of characteristics of men and women increase the income inequalities in these income ranges. In the middle of the distribution the effect of characteristics is negative, which means that the properties possessed by both people's groups decrease the inequalities.

Results of the aggregate decomposition using the reweighting approach

Looking at differences between the pairs of densities also provides a broad description of differences in the men's and women's incomes. The results of the decomposition using the reweighting approach are presented in Figure 2. Figure 2a plots the smoothed differences between men's log income density and the counterfactual density (density for incomes that would prevail for women if they had the distribution of men's charactera b c

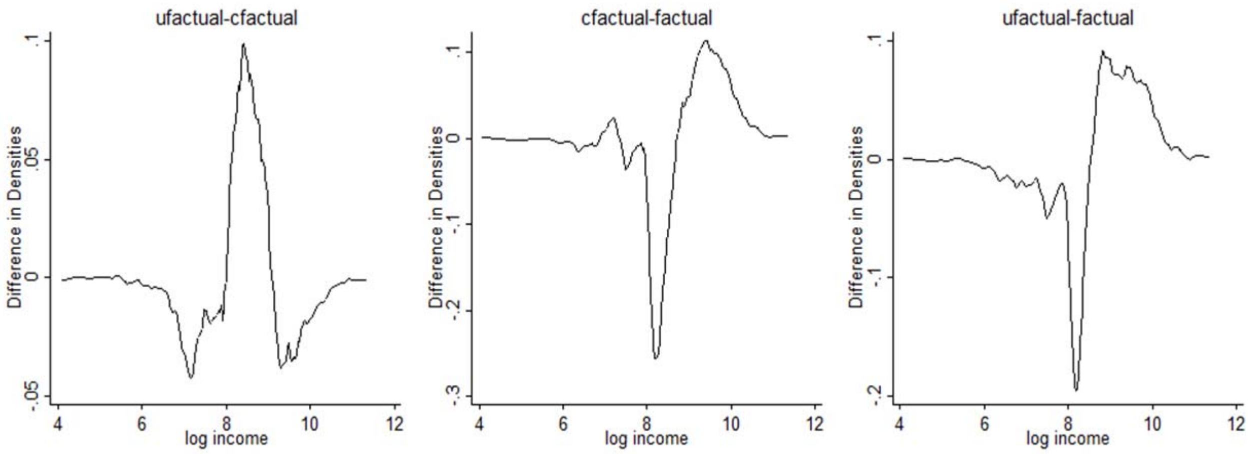

Fig. 2. The results of the decomposition using the reweighting approach

Source: Own elaboration.

istics). Figure 2b plots the smoothed differences between the counterfactual density and women's log income density. Figure 2c illustrates the estimated differences between the men's and women's log income densities (the estimated raw gap using the kernel densities).

We can notice that unexplained (Fig. 2a) and explained (Fig. 2b) effects play a large role in changes in overall wage inequality. One of the most important feature of the difference between the two distributions is the tall "hump" in Figure 2a, which presents the income discrimination on the labor market, which occurs mainly in the middle of the income distribution (the lower and upper tails of the distribution do not indicate discrimination). On the other hand, the deep down for the middle incomes in Figure 2b indicates that the different characteristics of men and women in this income group decrease the inequalities. The course of Figure 2c is compatible with the fact that the mass of men's income density is shifted to the right and the mass of the women's density is shifted to the left.

Results of the detailed decomposition using the RIF-regression approach

Now, for the same sample we change the method of the analysis to the RIF-regression approach. This method enables us to extend our analysis to the case of the detailed decomposition. Table 4 shows one of many results obtained of the detailed decomposition of inequalities along log income distributions.

These are only the results for 50th percentile of log income distributions (for the median log incomes; please do not confuse this with the results of decomposition for average log incomes presented in Table 2). In all, nine detailed decompositions for each decile were carried out (the results for the remaining eight deciles and the bootstrap errors are not presented here due to lack of space).

For better understanding of the results obtained and in order to formulate general conclusions, in Figure 3 we drew the values of explained (a) and unexplained (b) components for each variable and for each decile group (vs. quantile rank), for the log income inequalities observed between men and women. The ordinate axes present: on the panel (a) the values $(\overline{X}_{jM} - \overline{X}_{jW})\hat{\beta}_{jW,\tau}$ (detailed explained effects) and on the panel (b) the values $\overline{X}_{jM}(\hat{\beta}_{jM,\tau} - \hat{\beta}_{jW,\tau})$ (detailed unexplained effects).

Table 4. The example results of the RIF-regression approach – for 50th percentile only

Specification		Detailed decomposition		
		Variable	Unexplained component	Explained component
		age	–0.312	0.002
Raw differential	0.141	*educlevel*	–0.316	–0.077
		married	0.110	0.003
		yearswork	–0.041	0.016
Aggregate decomposition		*permanent*	–0.034	–0.002
		parttime	0.000	0.014
Unexplained effect	0.171	*manager*	0.018	0.009
Explained effect	–0.030	*big*	0.006	0.005
		cons	0.739	–
		Total	0.171	–0.030

Source: Own elaboration using the Stata command 'rifreg'.

a b

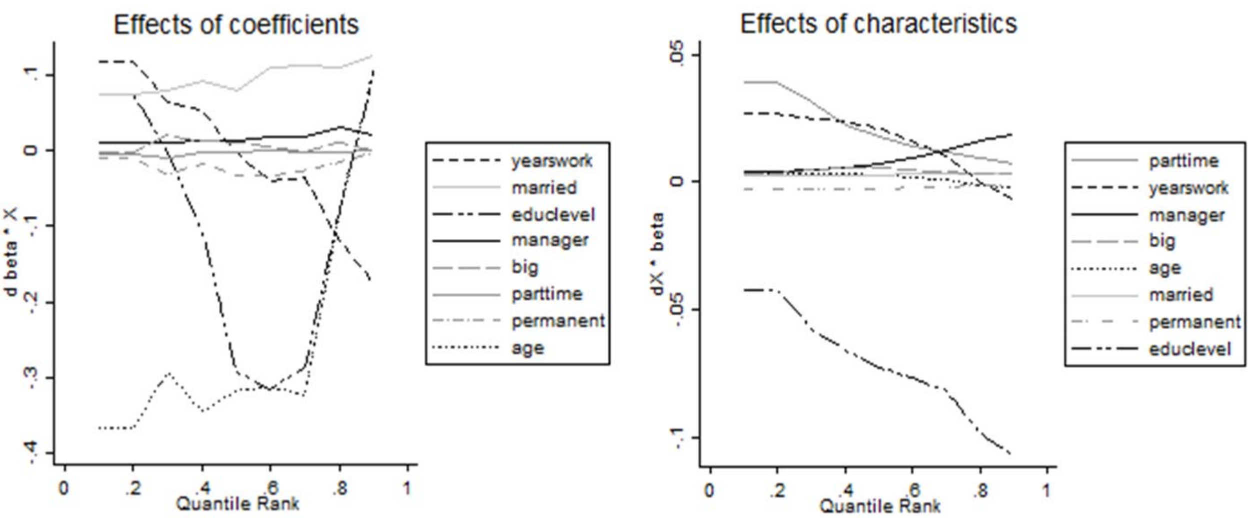

Fig. 3. The results of the RIF-regression approach for the detailed income inequalities decomposition

Source: Own elaboration.

The most important are effects related to the variables *educlevel* , *parttime* and *yearswork*. The *educlevel* has the greatest reduced influence on the differences between the log income distributions for men and women. It means that on average higher level of education among women decrease the income inequalities, especially as we move toward the top of the income distribution. For the variables *parttime* and *yearswork* we observe the influence, which enlarges log income differences but increasingly less as we move toward the top of the income distribution. The importance of both characteristics – *parttime* and *yearswork* – decreases with the size of income. The variable *manager* is less important, which has a stronger impact on higher quantiles of wage distribution. That indicates a shift of big incomes towards men. The influence of other variables is insignificant. The calculated values of unexplained effects for each variable and for each decile are presented in Figure 3b.

The changes in the returns to the attributes often have, unfortunately, insignificant effects. The effects of "prices" of variables: *married* (increasing income inequalities), *age* (decreasing) and *educlevel* (mostly decreasing) are noteworthy (and mostly significant).

CONCLUSIONS

The goal of this paper was to present the decomposition of inequalities between log incomes for men and women in Poland. We started with the decomposition of the average values for log incomes by using the Oaxaca-Blinder method. As has been documented in the previous research, we also found that there is a positive difference between the mean income values for men and women. The unexplained effect was big, but the explained was low. The decomposition showed the influence of the men's and women's attributes on the average log income differences. The most analyzed variables had the positive influence (that means they increased the inequalities observed). The variables with negative impact are *educlevel* and *permanent* what indicates that the difference of mean log incomes between men and women was reduced by women's higher education levels and more frequent permanent job contracts.

Then, we decomposed the inequalities between log incomes along the whole distribution using the JMP-residual imputation approach. The total effect was U-shaped. The explained effect was low again. An additional description of differences in densities of men's and women's incomes provided the reweighting approach, which captured the discrimination effect on the labor market and the effect of uneven mass distribution in both groups.

Many decomposition methods for distributional statistics other than the mean, allow only for the aggregate decomposition (like the JMP-residual imputation approach or the reweighting approach). The RIF-regression method allows the detailed decomposition and provides the approximation for the effect of various factors on changes in the distribution of the outcome variable. In our research the method of RIF-regression provided a way of showing the detailed decomposition of income inequalities and helped to exhibit the influence of the attributes on the whole log income distribution. The explained effects for most variables were statistically significant. The variable *educlevel* exerted the greatest reduced influence on the differences between the income distributions for men and women. Higher average levels of education among women decreased the income inequalities. The importance of *educlevel* characteristic increased with income. The part-time work enlarged the income differences but importance of this characteristic decreased with the size of income. Likewise, higher number of years spent in work increased the inequalities between men's and women's incomes (but the effect was weaker as the income grew). We also observed strong impact of managerial position in higher quantiles of income distribution, which indicates a shift of big incomes towards men.

It is noteworthy to mention that the procedure applied yields not only a presentation of where various factors have their greatest impact in the distribution but also can be used to explain of the processes occurring on the labor market. Our analysis confirmed that the gender wage gap in Poland can be poorly explained by gender differences in observable characteristics of people. The conducted decomposition showed that the discrimination component quantitatively dominates. The gender discrimination may lead to considerable loss in productivity and wealth, therefore inequalities induced in this way pose a serious challenge for politicians and society.

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RÓŻNICE W ROZKŁADACH DOCHODÓW MĘŻCZYZN I KOBIET W POLSCE – ANALIZA WYKORZYSTUJĄCA TECHNIKI DEKOMPOZYCYJNE

STRESZCZENIE

W pracy porównano rozkłady dochodów w Polsce, biorąc pod uwagę różnice zachodzące ze względu na płeć. Luka płacowa może być tylko fragmentarycznie wyjaśniona przez różne charakterystyki mężczyzn i kobiet, a jej niewyjaśniona część wiąże się z tzw. dyskryminacją płacową. Celem badania było rozszerzenie procedury dekompozycji nierówności Oaxaca-Blindera na różne kwantyle wzdłuż całego rozkładu dochodów. Opisu różnic między rozkładami dochodów dokonano wykorzystując takie metody dekompozycyjne jak podejście polegające na imputacji reszt, metodę ważenia oraz metodę zdecentrowanej funkcji wpływu. Oceniono również siłę oddziaływania charakterystyk osób w różnych fragmentach rozkładu dochodów. Wykorzystano dane z badania EU-SILC dla Polski w 2014 roku.

Słowa kluczowe: luka płacowa, różnice w rozkładach, metody dekompozycji