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THE COMPARISON OF INCOME DISTRIBUTIONS FOR WOMEN AND MEN IN POLAND USING SEMIPARAMETRIC REWEIGHTING APPROACH

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ABSTRACT

In this paper, we compare the income distributions for women and men in Poland. The gender wage gap can only be partially explained by different 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 for the pay gap along the whole income distribution. To describe differences between two distributions of incomes we use a semiparametric reweighting approach (DiNardo, Fortin, Lemieux, 1996). The reweighting factor is computed for each observation by estimating a logit model for probabilities of belonging to men's or women's group. Then, we estimate probability density functions, including the counterfactual density function, using kernel density methods. This allows us to decompose the inequalities into the explained and unexplained components. The analysis is based on the EU-SILC data for Poland in 2014.

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

1. Introduction

There is now a growing number of papers analysing the differences in income distributions for women and men. The past studies in Poland were mostly focused on a simple comparison of average values for incomes by using the Oaxaca-Blinder method. The findings of these studies show that males earn substantially higher wages than females (e.g. Słoczyński, 2012; Śliwicki, Ryczkowski, 2014). Differences in income distributions have been studied by Newell, Socha (2005), Rokicka, Ruzik (2010), Landmesser, Karpio, Łukasiewicz (2015), Landmesser (2016). They utilized such a decomposition method as a quantile regression method (Machado, Mata, 2005). The obtained results showed that differences between wages of men and women are the biggest in the right part of the distribution. Also, the other methodological approaches have been suggested in the economic decomposition literature: the residual imputation approach (Juhn, Murphy, Pierce, 1993), hazard model approach (Donald, Green, Paarsch, 2000),

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RIF-regression (recentered influence function) method (Firpo, Fortin, Lemieux, 2009).

The objective of this study is to extend the income gap analysis to the whole distribution and to decompose the income inequalities between women and men in Poland into the explained and unexplained components. In our paper, we suggest to describe differences between two distributions using a semiparametric reweighting approach proposed by DiNardo, Fortin, Lemieux (1996). In this method the counterfactual density function is estimated employing the reweighting factor. The analysis will be based on the EU-SILC data for Poland in 2014.

2. Analysis method

This section outlines the applied methodology. First, the Oaxaca-Blinder decomposition of mean wages differences is presented. Then, we explain the idea of the reweighting approach to the decomposition that allows analysing the differences along the whole distribution.

2.1. Oaxaca-Blinder Decomposition of Mean Wages Differences

The Oaxaca-Blinder decomposition method may be applied whenever there is a need to explain the differences between the expected values of dependent variable in two comparison groups (Oaxaca, 1973; Blinder, 1973).

Let two groups A and B , an outcome variable y and a set of predictors X be given. In this case the variable y may present log wages and predictors X may concern such individual characteristics of people as age, education level or work experience. The expected value of y conditionally on X is a linear function of X :

$$y_g = X_g \beta_g + v_g, \quad g = A, B, \quad (1)$$

where X_g are the characteristics of people in group g and β_g are the coefficients related to these characteristics. The estimated expected value of income \hat{y} in each group is:

$$\hat{y}_g = X_g \hat{\beta}_g, \quad g = A, B \quad (2)$$

The idea of the Oaxaca-Blinder decomposition of the difference between expected values of incomes in each of groups \hat{y}_A and \hat{y}_B is as follows:

$$\hat{\Delta}^\mu = \bar{X}_A \hat{\beta}_A - \bar{X}_B \hat{\beta}_B = \underbrace{(\bar{X}_A - \bar{X}_B) \hat{\beta}_A}_{\hat{\Delta}_{\text{explained}}^\mu} + \underbrace{\bar{X}_B (\hat{\beta}_A - \hat{\beta}_B)}_{\hat{\Delta}_{\text{unexplained}}^\mu} \quad (3)$$

The above equation is based on one group's characteristics and the estimated coefficients of another group's equation. The first term on the right-hand side of the equation gives the effect of characteristics and expresses the

difference of the potentials of both groups (the so-called explained, endowments or composition effect). The second term represents the effect of differences in the estimated parameters (unexplained by characteristics of groups). This is typically interpreted as discrimination.

One important disadvantage of the Oaxaca-Blinder decomposition method is that it focuses only on average effects, and this may lead to a misleading assessment if the effects of covariates vary along the entire distribution (Salardi, 2012).

2.2. Decomposition Along the Entire Distribution

The idea to avoid the drawback of the Oaxaca-Blinder decomposition method may be to extend the mean decomposition to the case of differences between distributions or density functions of income. This approach is the basis of most decomposition methods. It requires the counterfactual distribution to be considered. In general, the counterfactual distribution is interpreted as a distribution for people from group B if they were described by characteristics of people from group A (in our case this is the distribution of income for women with characteristics of men).

In terms of density functions the difference can be expressed as follows:

$$\hat{\Delta}^f = \hat{f}_M(y) - \hat{f}_W(y) = \underbrace{[\hat{f}_M(y) - \hat{f}_C(y)]}_{\hat{\Delta}^{\mu}_{\text{explained}} \text{ (structure effect)}} + \underbrace{[\hat{f}_C(y) - \hat{f}_W(y)]}_{\hat{\Delta}^{\mu}_{\text{unexplained}} \text{ (composition effect)}} \tag{4}$$

where $f_M(y)$ is the density function of income for men, $f_W(y)$ and $f_C(y)$ are the density functions for women and counterfactual distribution respectively.

In turn, the application of the cumulative distribution function of incomes allows writing the difference between the men and women density function of income $\hat{F}_M(y) - \hat{F}_W(y)$ with the counterfactual distribution $\hat{F}_C(y)$ in the following form:

$$\hat{\Delta}^F = \hat{F}_M(y) - \hat{F}_W(y) = \underbrace{[\hat{F}_M(y) - \hat{F}_C(y)]}_{\hat{\Delta}^{\mu}_{\text{explained}} \text{ (structure effect)}} + \underbrace{[\hat{F}_C(y) - \hat{F}_W(y)]}_{\hat{\Delta}^{\mu}_{\text{unexplained}} \text{ (composition effect)}} \tag{5}$$

2.3. Semiparametric Reweighting Approach

The semiparametric reweighting approach to the decomposition of distribution differences was introduced by DiNardo, Fortin and Lemieux in 1996 (DiNardo, Fortin, Lemieux, 1996). The method allows performing the decomposition of differences along the entire distributions in terms of density function (according to expression (4)).

The method requires the estimation of probability density functions for groups and for the counterfactual distribution. For this purpose, the kernel density

estimation methods are applied. The kernel estimator of the density function for each group (in the case $g = W$ for women and $g = M$ for men) is as follows:

$$\hat{f}_g(y) = \frac{1}{h \cdot N_g} \sum_{i \in g} K\left(\frac{Y_i - y}{h}\right) \quad (6)$$

where K is the kernel function, N is the number of people in the group and h is a smoothing parameter called bandwidth. The value of h is chosen to minimize the mean squared error. In this method the counterfactual density function is also estimated employing the kernel density estimation but, additionally, the reweighting factor $\hat{\Psi}(X)$ is required. Then, the kernel density estimator for the counterfactual density is:

$$\hat{f}_c(y) = \frac{1}{h \cdot N_w} \sum_{i \in W} \hat{\Psi}(X_i) K\left(\frac{Y_i - y}{h}\right) \quad (7)$$

The counterfactual distribution interpretation in the reweighting approach is different than in most decomposition methods. In this case, the counterfactual distribution is the distribution for women that consists of the influence of the whole sample characteristics.

The impact of the characteristics of the whole sample is ensured by the construction of the reweighting factor $\hat{\Psi}(X)$, which is defined as (Fortin, Lemieux, Firpo, 2010):

$$\hat{\Psi}(X) = \frac{d\hat{F}_{x_m}(X)}{d\hat{F}_{x_w}(X)} = \frac{\hat{P}(X|D_M = 1)}{\hat{P}(X|D_M = 0)} \quad (8)$$

where $D_M = 1$ means that the person is a man and $D_M = 0$ is a woman.

By applying Bayes' rule the reweighting factor can be written as:

$$\hat{\Psi}(X) = \frac{\hat{P}(D_M = 1|X) / \hat{P}(D_M = 1)}{\hat{P}(D_M = 0|X) / \hat{P}(D_M = 0)} \quad (9)$$

The reweighting factor value $\hat{\Psi}(X)$ can be computed for each observation by estimating a logit or probit model for conditional probabilities of belonging to groups M and W ($\hat{P}(D_M = 1|X)$ and $\hat{P}(D_M = 0|X) = 1 - \hat{P}(D_M = 1|X)$) and from the classical definition of probability using the sample proportions in both groups ($\hat{P}(D_M = 1)$ and $\hat{P}(D_M = 0)$).

The advantages of the reweighting approach are the opportunity to compare the differences along the whole distribution as well as simplicity and efficiency. On the other hand, a limitation of this method is that it is impossible to extend this approach to the case of the detailed decomposition due to the estimation of the logit (or probit) model.

3. Results of Empirical Analysis

This section is devoted to introduce the results of the empirical analysis. First, the data used for analysis are presented. Then, we provide estimated density functions for women and men as well as the construction of the counterfactual distribution. Finally, the results of the decomposition of the difference in incomes in both groups are discussed.

3.1. Database

We employ data from the European Union Statistics on Income and Living Conditions (EU-SILC) for Poland in 2014³. It is the source of microdata on income, poverty, social exclusion and living conditions. The EU-SILC belongs to the European Statistical System (ESS).

Our data consist of a sample of 4727 women and 5177 men containing information on annual income, natural logarithm annual income as well as on persons' attributes such as age, gender, marital status, education level, information if it is full-time or part-time job and other describing the type of contract. The applied variables with description and possible values are presented in the table below.

Table 1. Description of the variables

Variable	Description and possible values
<i>age</i>	age in years
<i>men</i>	sex, 1 – man, 0 – woman
<i>married</i>	marital status, 1 – married, 0 – unmarried
<i>educlevel</i>	educational level, 1 – primary, ..., 5 - tertiary
<i>parttime</i>	1 – person working part-time, 0 – person working full-time
<i>big</i>	number of persons working at the local unit, 1 – more than 10 persons, 0 – less than 11 persons
<i>permanent</i>	type of contract, 1 – permanent job/work contract of unlimited duration, 0 – temporary contract of limited duration
<i>manager</i>	managerial position, 1 – supervisory, 0 – non-supervisory
<i>yearswork</i>	number of years spent in paid work
<i>income</i>	gross annual income in € (including benefits)
<i>ln_income</i>	natural logarithm gross annual income in €

3.2. Density functions of income for men and women

We apply the kernel estimation method to obtain the density function of income for women and men. In our analysis the logarithm of the annual income is the outcome variable. Two kernel functions – Epanechnikov and Gaussian – are

³ This database was obtained under Eurostat project number 234/2016-EU-SILC.

applied. We prefer Epanechnikov kernel for the reason it is optimal in a mean square error sense (Epanechnikov, 1969). The kernel function is as follows:

$$K = \begin{cases} \frac{3}{4}(1-x^2) & x \in [-1, 1] \\ 0 & x \notin [-1, 1] \end{cases} \quad (10)$$

The estimated density functions of income for men and women are compared in Figure 1a. The income distribution for men is shifted to the higher values of the logarithm of income related to the distribution for women. This fact may be interpreted as meaning that men earn more than women.

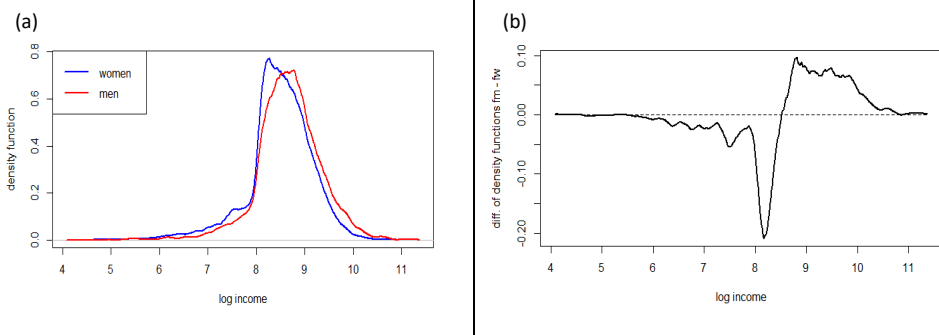


Figure 1. The estimated density functions of the logarithm of income for women and men (a) and the difference between the density function of men and women (b)

The difference between the density function for men and women $\hat{\Delta}^f = \hat{f}_M(y) - \hat{f}_W(y)$ is presented in Figure 1b. We can see a greater participation of women in the case of lower wages. On the other hand, there are more men for higher values of income. This is also the evidence that men earn more.

3.3. Reweighting Factor Computation

For the aim of the estimation of the counterfactual density function, the reweighting factor $\hat{\Psi}(X)$ is required. It may be written as in formula (9):

$$\hat{\Psi}(X) = \frac{\hat{P}(D_M = 1|X) / \hat{P}(D_M = 1)}{\hat{P}(D_M = 0|X) / \hat{P}(D_M = 0)}$$

The probabilities $\hat{P}(D_M=1)$ and $\hat{P}(D_M=0)=1-\hat{P}(D_M=1)$ are computed from the classical definition of probability using the groups and sample size as follows: $\hat{P}(D_M=1)=\frac{5177}{9904}\approx 0,5227$ and $\hat{P}(D_M=0)=1-\frac{5177}{9904}\approx 0,4773$.

To determine the conditional probability $\hat{P}(D_M=1|X)$, the logit model is estimated. The logarithm of the maximum likelihood function is -6359.066, AIC = 12736. In the Likelihood ratio test the hypothesis that model coefficients are equal to 0 was rejected (p -value $< 2.2 \cdot 10^{-16}$). The estimated parameters for each of variables are presented in Table 2.

Table 2. Results of logit model estimation

Variable	Parameter	p-value
<i>age</i>	-0.089004	$< 2e-16^{***}$
<i>educlevel</i>	-0.422461	$< 2e-16^{***}$
<i>married</i>	0.095614	0.05466 .
<i>yearswork</i>	0.085015	$< 2e-16^{***}$
<i>permanent</i>	-0.143589	0.00505 **
<i>parttime</i>	-0.861151	$< 2e-16^{***}$
<i>manager</i>	0.488480	$< 2e-16^{***}$
<i>big</i>	0.162550	0.00378 **
<i>constance</i>	3.593760	$< 2e-16^{***}$

where significance levels codes are as follows: *** 0,001; ** 0,01; * 0,05; . 0,1.

Based on the above results, it can be easily seen that all the variables in the model are statistically significant. The positive values of parameters indicate that an increase in the value of the corresponding variable increases the probability that the person is a man with the fixed values of the other variables. The interpretation of negative parameter values is analogical.

In this way the conditional probability $\hat{P}(D_M=1|X)$ is estimated by the logit model. Using probability values, obtained as described above, the reweighting factor is computed separately for each person from the sample.

3.4. Counterfactual Distribution and Decomposition for Density Functions

In the next step, using the reweighting factor obtained earlier for each person in the sample, we estimate the counterfactual distribution. It is worth emphasizing that the interpretation of the counterfactual distribution is different in comparison with typical decomposition methods. In most approaches the counterfactual distribution mixes the distribution of outcome variable Y for women and explanatory variables X for men. In this case the counterfactual distribution may be understood as the distribution for women reweighted by the effect of characteristics of both groups, which is contained in the reweighting factor.

We also apply the kernel estimation method with Epanechnikov kernel to obtain the density function for the counterfactual distribution. The estimated density functions of logarithm of income for women, men and counterfactual distribution are presented in Figure 2.

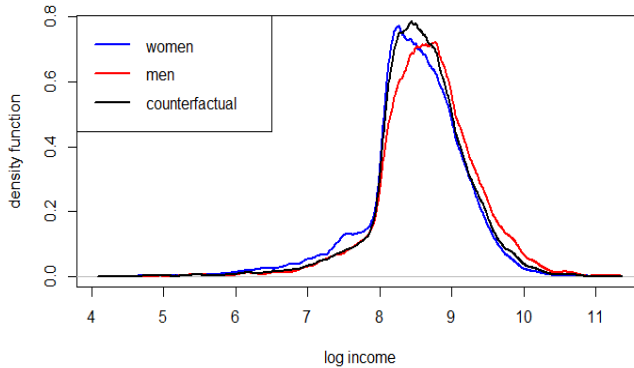


Figure 2. The estimated density function of the counterfactual distribution in comparison with the density functions of the logarithm of income for women and men

Subsequently, we decompose the inequalities of income in men's and women's group into the explained and unexplained components. This procedure is performed in terms of probability density functions, which allows for the analysis along the entire distribution. The results illustrating the formula (4) are presented in Figure 3.

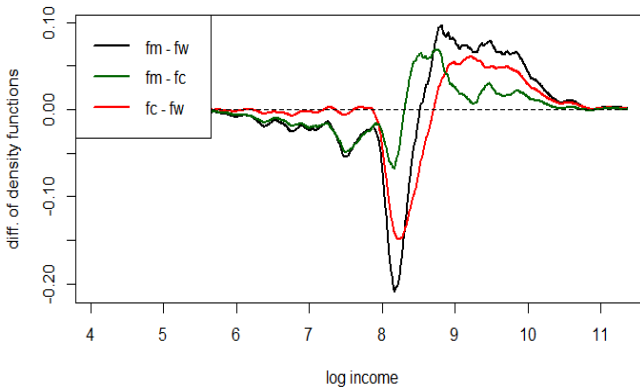


Figure 3. The results of the decomposition of income inequalities for men and women. The explained and unexplained components are indicated respectively by green and red line

Analyzing the results of the decomposition, it is easy to notice that the dominance of women in the group with lower incomes is explained. This may be related to the fact that women are much more likely to work part-time than men. On the other hand, the dominance of men in the group of the higher income is mainly due to the discrimination. It is worth taking into account that the significant dominance of men is explained only for the values of the logarithm of wages from 8 to 9, which corresponds to the income of 3000 to 8000 €. Moreover, the occurrence of the unexplained part leads to the shift of the distribution for men into higher incomes. However, it should be noticed that the fact of including benefits in the gross annual income increases the gender pay gap in the upper quantiles of the distributions. In general, the better-paid men receive higher bonuses.

3.5. Distribution Function and Decomposition for Quantiles

It is worth considering that the comparison of distributions in terms of probability density functions gives only a partial insight into the analysis of the wage gap. The decomposition of differences in distributions using quantiles allows considering the income inequalities completely.

Using the estimated density functions, the cumulative distribution functions (CDFs) may be determined by the trapezoidal numerical integration method. Figure 4 presents the cumulative distribution functions. The cumulative distribution function curve for women’s income is above this for the men’s one. From this fact, and on the basis of CDF definition, we can conclude that women earn less.

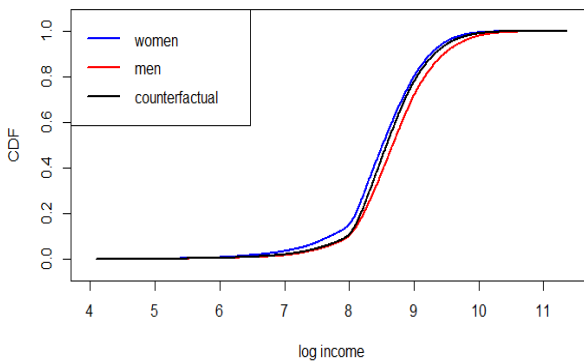


Figure 4. The distribution functions for women’s and men’s income as well as the counterfactual distribution

In the next step, the quantiles for distributions of men’s, women’s income and counterfactual distribution are determined. The precise values of quantiles $\hat{Q}_{g,\tau} = \hat{F}_Y^{-1}(\tau)$ are computed by linear interpolation. This allows decomposing the wage gap for quantiles. The results are presented in Table 3.

Table 3. Decomposition of difference in income distributions in terms of quantiles

τ	\hat{Q}_W	\hat{Q}_M	\hat{Q}_C	$\hat{Q}_M - \hat{Q}_W$	$\hat{Q}_M - \hat{Q}_C$	$\hat{Q}_C - \hat{Q}_W$
0.1	7.7009	7.9848	7.9629	0.2839	0.0219	0.2620
0.2	8.1009	8.2205	8.1775	0.1196	0.0430	0.0766
0.3	8.2415	8.3843	8.3154	0.1428	0.0689	0.0739
0.4	8.3745	8.5297	8.4458	0.1552	0.0840	0.0713
0.5	8.5127	8.6704	8.5756	0.1577	0.0948	0.0629
0.6	8.6574	8.8102	8.7119	0.1528	0.0984	0.0544
0.7	8.8140	8.9642	8.8588	0.1502	0.1054	0.0448
0.8	8.9952	9.1635	9.0403	0.1683	0.1232	0.0451
0.9	9.2563	9.4603	9.3180	0.2040	0.1423	0.0616
1	10.7675	11.1478	10.7270	0.3803	0.4208	-0.0405

This approach also allows determining the explained and unexplained components of the difference in terms of quantiles (see Table 4). For an easier analysis, the logarithmic values are converted to income in euro.

We can see that for a quantile of the order of 0.1 the difference is high. This is also accompanied by a large share of the explained part in the wage gap. This may be due to the much greater share of women working part-time than men. Starting with the quantile of the order of 0.2 the wage gap grows with the order of the quantile as well as with the amount of income.

Table 4. Wage gap for women's and men's group and share of explained and unexplained part of difference

τ	\hat{Q}_W [€]	\hat{Q}_M [€]	$\hat{Q}_M - \hat{Q}_W$ [€]	unexplained part [%]	explained part [%]
0.1	2210.32	2935.94	725.62	7.72%	92.28%
0.2	3297.41	3716.50	419.09	35.94%	64.06%
0.3	3795.28	4377.97	582.69	48.24%	51.76%
0.4	4335.02	5063.03	728.02	54.08%	45.92%
0.5	4977.52	5827.94	850.42	60.13%	39.87%
0.6	5752.78	6702.53	949.75	64.37%	35.63%
0.7	6727.68	7817.99	1090.31	70.15%	29.85%
0.8	8064.33	9542.33	1478.00	73.21%	26.79%
0.9	10470.53	12839.69	2369.16	69.78%	30.22%
1	47453.68	69411.97	21958.30	110.65%	-10.65%

It is also worth noticing that the unexplained component of the wage gap increases with the amount of income. This demonstrates that the discrimination is

more evident for higher values of wages. The interesting result is the negative value of the explained component of the income difference in the group of the best earning people. It may be associated with the fact that women in this group should earn more than men. However, it is worth mentioning that there is far fewer people in this group in comparison with the others (for the reason there are more people having incomes about mean level than in the tail of income distribution), which causes that the result may be misleading.

4. Conclusions

The aim of this study was to perform a decomposition of income inequalities between women and men. It was achieved by using the semiparametric reweighting DFL method (DiNardo, Fortin, Lemieux, 1996). It allows extending the income gap analysis to the whole distribution rather than just the average level of wages as in the case of the Oaxaca-Blinder decomposition method. Furthermore, the chosen approach leads to more accurate results than the Oaxaca-Blinder decomposition method for the average value because the DFL decomposition method is not based on the linear regression.

The major drawback of the applied method is that it is not suitable for the detailed (taking into account the individual explanatory variables) decomposition of inequalities between distributions. This is because all of these variables are included during the estimation of the logit model.

In this work the decomposition of the wage gap between women and men was performed in terms of the density function. Moreover, the explained and unexplained (associated with discrimination) components of the difference were determined. Furthermore, for the aim of the more accurate analysis of the inequalities in women's and men's incomes, the cumulative distribution functions and quantiles were calculated. This allowed decomposing the wage gap in terms of quantiles and the "horizontal analysis" of differences between distributions.

In the light of the results obtained, we found that the share of the unexplained part of inequalities is higher than the explained one and it tends to increase with the rising values of income. This is the evidence that the discrimination in wages is significant. However, it should be noticed that this study was based only on factors from EU-SILC database. The inclusion in the model of the additional explanatory variables, describing in more detail the job position or the employment environment, could influence the results and lead to reduction of the unexplained component. In addition, we should be aware of the effect of the increase in the wage gap in the upper part of earnings distribution by including higher bonuses in annual income.

The obtained results are consistent with those for Poland reported in the literature. Other researchers also notice the higher level of incomes for men (Kompa, Witkowska, 2013; Matuszewska-Janica, 2014; Witkowska, 2014). A significant unexplained part of the wage gap and the larger inequality at the top of distribution are observed (Śliwicki, Ryczkowski, 2014; Rokicka, Ruzik, 2010).

It is worth considering performing an analogous analysis of the difference in income distributions for women and men according to the individual levels of education. The expected result is to obtain information about the relation between the level of employees' education level and the occurrence of discrimination.

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