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THE USE OF HAZARD MODELS FOR THE ANALYSIS OF INCOME INEQUALITIES IN POLAND

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Abstract

The aim of the paper is to examine the income inequalities of men and women in Poland. We estimate conditional cumulative distribution functions for incomes in both groups of people using a flexible hazard-function based estimator in the presence of covariates. The conditional piecewise-constant exponential hazard models are applied. Then, we decompose the estimated income differences along the whole income distribution. For this purpose, we construct the counterfactual distribution, which is the distribution of incomes that would prevail for women if they had the distribution of men's characteristics. The method allowed to investigate the structure of inequalities in the entire range of income values for the two analyzed groups of people. The empirical investigation is based on the data collected within the EU-SILC project.

Keywords: gender wage gap, hazard function, decomposition of income inequalities

JEL classification: D31, J31

Introduction

The pay gap between men and women for the same work has existed in the Polish labor market for years. According to the CSO data, in 2014, an average gross monthly salary for male employees amounted to 4,481.75 PLN and for females – 3,717.57 PLN (the median levels were 3,486 PLN and 3,100 PLN respectively) (GUS, 2015). Although women are better educated than men, their labor market situation is worse than that of men. There exists the horizontal segregation (the division into men's and women's occupations) as well as the vertical one (which results in the 'glass ceiling' and 'sticky floor' phenomena). The gender-based income differences favor men in almost all profession groups. The biggest disproportion concerns specialists, government representatives, senior state officials, and managers (Czapiński, Panek, 2014). It happens despite the existence of legal guarantees of gender equality in the sphere of work.

The goal of the paper is to examine differences between the income distributions for men and women in Poland. Recently, the techniques of income inequalities decomposition are becoming more popular. The pioneering works in that field are papers of Oaxaca (1973) and Blinder (1973). Nowadays, many procedures go far beyond the comparison of average values (e.g. Juhn, Murphy and Pierce, 1993; DiNardo, Fortin and Lemieux, 1996; Machado and Mata, 2005; Firpo, Fortin, Lemieux, 2009).

The past studies in Poland were mostly focused on the comparison of average income values by using the Oaxaca-Blinder method (e.g. Zajkowska, 2013; Śliwicki, Ryczkowski, 2014; Cukrowska-Torzewska, Lovasz, 2016). Based on the same method, Mysíková (2012) analyzed the structure of the gender wage gap in Visegrad states – the Czech Republic, Hungary, Poland, and Slovakia. In the world, economic literature techniques for decomposing income inequalities for quantiles are becoming more and more popular. The use of the quantile regression has been presented in, among others, Albrecht, Bjorklund, and Vroman (2003) for Sweden; De la Rica, Dolado, and Llorens (2005) for Spain; Albrecht, Van Vuuren, and Vroman (2009) for the Netherlands; Arulampalam, Booth, and Bryan (2007); or Christofides, Polycarpou, and Vrachimis (2013) across several European countries; and the application of the recentered influence function (the RIF-regression) in Khanna, Goel, and Morissette (2016) for India. For the Poland's labor market, only a few studies go beyond the simple mean comparison. For example, the study of Newell and Socha (2005) showed that many factors influence only high wages, localized in the high quatiles on the wages distribution. Similarly, Rokicka and Ruzik (2010) showed that differences between wages of men and women are the biggest in the right part of the distributions. Other studies in this field are: Magda and Szydłowski (2008), Matysiak, Baranowska, and Słoczyński (2010), Słoczyński (2012), Landmesser, Karpio, and Łukasiewicz (2015), and Landmesser (2016).

We decompose the differences between two distributions using the 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. In this paper, the income differences are investigated applying the hazard function approach (Donald, Green, Paarsch, 2000). We use a flexible hazard-function based estimator in the presence of covariates to construct conditional density and cumulative distribution functions.

1. Method of the analysis

Let Y_g be the personal income in group g, $g = M, W$, and X_g be the vector of individual characteristics of the person in group g. The two linear equations are estimated using a regression technique: $y_g = X_g \beta_g + v_g,\ g = M, W$. The Oaxaca-Blinder decomposition equation is:

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

The unexplained effect is the result of differences in the 'prices' of individual characteristics. It can be interpreted as the labor market discrimination. The explained part gives the effect of characteristics and expresses the difference of the potentials of people in two groups.

We can extend the mean decomposition analysis to the case of differences between the two distributions. Let $F_{Yg}(y)$ be the distribution function for the variable Y in group g, which can be expressed using the conditional distribution $F_{Y_g|X_g}(y|X)$ of Y and the joint distribution $F_{X_g}(X)$ of all elements of X in group g:

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

The counterfactual distribution, which is the distribution of incomes that would prevail for women if they had the distribution of men's characteristics, may be estimated by integrating the conditional distribution for people in group W over the distribution of X in group M:

$$F_{Y_W^C}(y) = \int F_{Y_W|X_W}(y|X) \cdot dF_{X_M}(X) \tag{3}$$

Then, the decomposition of income inequalities along the whole distribution can be written as:

$$F_{Y_M}(y) - F_{Y_W}(y) = \underbrace{[F_{Y_M}(y) - F_{Y_W^C}(y)]}_{\text{unexplained}} + \underbrace{[F_{Y_W^C}(y) - F_{Y_W}(y)]}_{\text{explained}} \tag{4}$$

Following Donald, Green, and Paarsch (2000), we apply a parametric hazard model for non-negative random variable (in our case the income variable Y) and estimate the conditional income distribution. The (conditional) hazard function is defined as $h(y \mid X) = f(y \mid X) / S(y \mid X)$, where $S(y|X) = Pr[Y \geq y|X] = 1 - F(y|X)$ is the survivor function. The survival function gives the probability that incomes are at least as large as y. The hazard function gives the probability that the income equals y conditional on the wage being at least as large as y.

A typical approach in the duration literature is to adopt a proportional hazard model with a flexible specification of the baseline hazard. We divide the income distribution into P segments and construct the conditional piecewise-constant hazard model (exponential hazard with the hazard piece dummies, $0 = c_0 < c_1 < \ldots < c_P = \infty$):

$$h(y|X) = h_{0k}(y)\exp(X\beta) \quad \text{for} \quad y \in (c_{k1}, c_k),\ k = 1, \ldots, P \tag{5}$$

where baseline hazards $h_{0k}(y)$ are allowed to vary for different values (segments) of y.

The survival function then becomes:

$$S(y|X) = \exp\left[-\sum_{j=1}^{k-1} (c_j - c_{j-1}) h_{0j}(y) \exp(X\beta) - (y - c_{k-1}) h_{0k}(y) \exp(X\beta) \right] \quad \text{for} \quad y \in (c_{k1}, c_k) \tag{6}$$

and the conditional distribution function is

$$F(y \mid X) = 1 - S(y \mid X) \tag{7}$$

Therefore, the conditional distribution $\hat{F}(y \mid X)$ of the income variable is easily recovered from the estimates of the hazard model.

Once the counterfactual distribution has been estimated, counterfactual quantiles can be obtained by inverting the estimated distribution functions: $\hat{Q}_{g,\tau} = \hat{F}_{Y_g}^{-1}(\tau)$, $\hat{Q}_{W,\tau}^{C} = \hat{F}_{Y_W^C}^{-1}(\tau)$.

2. Database

The empirical investigation is based on the data collected within the European Union Statistics on Income and Living Conditions project for Poland in 2014.[1] Our data consist of a sample of 5,177 men and 4,727 women containing information on the annual net employee incomes, expressed in k€ (the outcome variable *Y*). Each person is characterized by attributes such as gender, education level (*educlevel* – ordinal variable with values from 1 (lowest) to 5 (highest)), years of work (count variable *yearswork*), information if it is part time or full time job (*parttime* binary variable, 1 – part-time, 0 full-time), and position at work (*manager* – binary variable, 1 – supervisory managerial position, 0 – non-supervisory position). The features of the variables have been collected in Table 1.

Since the condition of using a potential variable in the model was its statistical significance, the following variables were excluded from the initial set of candidates: the type of employment contract and the number of employees in the company. Unfortunately, the database did not contain information about the collective pay agreement. Due to too many variants, the sectoral or occupational dummies were not taken into account.

Table 1. The mean values and the share of categories for selected variables

Variable		Men	Women
		mean value	
Yearswork		20.09	18.46
	category	share (%)	
Educlevel	1	4.91	3.89
	2	1.45	0.55
	3	68.57	47.32
	4	2.55	7.91
	5	22.52	40.32
Parttime	0	95.69	89.91
	1	4.31	10.09
Manager	0	81.32	84.26
	1	18.68	15.74

Source: author's own calculations.

[1] The database was obtained under Eurostat project number 234/2016-EU-SILC.

3. Empirical results

3.1. Results of Oaxaca-Blinder decomposition technique

In the first step of the analysis, the Oaxaca-Blinder decomposition has been applied for the average values. The results are listed in Table 2.

There is a positive difference between average values of the men's and women's incomes. The explained effect is very low, but the unexplained is huge. The inequalities examined should be assigned in the majority to the coefficients of estimated models (rather than to the differentiation of individual characteristics). The negative value of the explained effect means that the difference of the average incomes between men and women is reduced by the women's better characteristics (the different properties possessed by both people's groups decrease the income inequalities). Similar results for Poland were received by Mysíková (2012), Zajkowska (2013), Śliwicki and Ryczkowski (2014), or Christofides, Polycarpou, and Vrachimis (2013).

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

Average income in the men's group			7,165.94
Average income in the women's group			5,900.21
Raw gap			1,265.73
Aggregate decomposition			
Unexplained effect			1,552.13
Explained effect			–286.398
% unexplained			122.63
% explained			–22.63
Detailed decomposition			
Unexplained component		Explained component	
Educlevel	824.87	educlevel	–690.13
Yearswork	–356.02	yearswork	105.16
Parttime	–107.65	parttime	195.95
Manager	219.08	manager	102.62
Cons	971.85	cons	0.00
Total	1,552.13	Total	–286.34

Source: author's own calculations.

Using the Oaxaca-Blinder decomposition method, we evaluated the strength of the influence of the analyzed factors onto the average incomes. The biggest influence exhibited the *educlevel* attribute. The difference in the average men's and women's incomes is reduced by the higher level of education of women.

3.2. Results of the conditional piecewise-constant hazard models estimation

In the next step of the analysis, the conditional piecewise-constant hazard models have been estimated separately for men and women (see Table 2 for details). We used 20 baseline segments with dividing points at the 20-quantiles of the unconditional pooled income distribution.

Also, plots of hazard were made (not presented due to the lack of space). The higher located graph of hazard for women indicates greater exposure of women to the loss of earnings than in the case of men.

Table 3. The estimates of the conditional piecewise-constant hazard models

Variable	Men		Women	
	beta	exp(beta)	beta	exp(beta)
tp1	–9.315	0.0001 ***	–8.168	0.0003 ***
tp2	–8.470	0.0002 ***	–7.437	0.0006 ***
tp3	–8.020	0.0003 ***	–7.120	0.0008 ***
tp4	–6.925	0.0010 ***	–5.855	0.0029 ***
tp5	–6.851	0.0011 ***	–5.729	0.0032 ***
tp6	–7.276	0.0007 ***	–6.086	0.0023 ***
tp7	–6.750	0.0012 ***	–5.714	0.0033 ***
tp8	–6.918	0.0010 ***	–5.846	0.0029 ***
tp9	–6.823	0.0011 ***	–5.836	0.0029 ***
tp10	–6.675	0.0013 ***	–5.653	0.0035 ***
tp11	–6.458	0.0016 ***	–5.416	0.0044 ***
tp12	–6.889	0.0010 ***	–5.802	0.0030 ***
tp13	–6.548	0.0014 ***	–5.594	0.0037 ***
tp14	–6.169	0.0021 ***	–5.201	0.0055 ***
tp15	–6.658	0.0013 ***	–5.518	0.0040 ***
tp16	–6.425	0.0016 ***	–5.346	0.0048 ***
tp17	–6.590	0.0014 ***	–5.426	0.0044 ***
tp18	–6.584	0.0014 ***	–5.380	0.0046 ***
tp19	–6.492	0.0015 ***	–5.312	0.0049 ***
tp20	–6.963	0.0009 ***	–5.792	0.0031 ***
Educlevel	**–0.344**	0.7090 ***	**–0.459**	0.6319 ***
Yearswork	**–0.017**	0.9829 ***	**–0.027**	0.9732 ***
Parttime	**1.259**	3.5221 ***	**0.951**	2.5893 ***
Manager	**–0.598**	0.5499 ***	**–0.520**	0.5946 ***
No. of obs.	5,177		4,727	
lnL	–4,222.57		–3,484.62	

Source: author's own calculations.

The estimates of the hazard function for income are difficult to interpret. The negative values of parameters by the variables *educlevel*, *yearswork*, and *manager* mean that with the increase in the value of these variables, there is a decrease in the risk of not earning the amount *y*.

For example, the higher the level of education, the lower the risk of loss of incomes, while for women this effect is stronger. The positive parameter values by the variable *parttime* mean that the income loss is more risky in the case of a part time job than in the case of a full time job (the effect is stronger for men).

3.3. Construction of the cumulative distribution functions

Now we treat the hazard function as a flexible functional form that allows us to generate the estimates of the CDFs. On the basis of formulas (6) and (7), the two distributions were determined: $\hat{F}_{Y_M|X_M}(y|X)$ and $\hat{F}_{Y_W|X_W}(y|X)$. Each of them gives the probability that incomes will take values lower than a certain level *y* (for fixed *X* and parameters β). Figure 1 shows the course of $\hat{F}_{Y_M|X_M}(y|X)$ calculated for the 'average' man (the curve labeled F_M_(y)) and the course of $\hat{F}_{Y_W|X_W}(y|X)$ calculated for the 'average' woman (F_W_(y)). Since $\hat{F}_{Y_W|X_W}(y|X) > \hat{F}_{Y_M|X_M}(y|X)$ for all *y*, then for the 'average' woman, the probability of not exceeding the income level *y* is higher than for the 'average' male (i.e. the average female earns less than the average male).

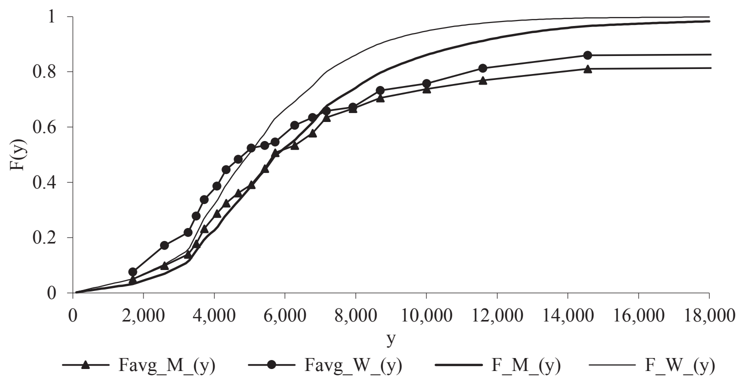

Figure 1. The cumulative distribution functions for men's and women's incomes

Source: author's own calculations.

However, to illustrate the variability of both income levels and people's characteristics along the income distribution, the results for each individual were averaged over the intervals (c_{k-1}, c_k), *k* = 1, ..., 20. The functions $F_{Y_g|X_g}(y|X)$ averaged in this way are presented in the form of points connected by straight lines in Figure 1 (broken lines Favg_M_(y) and Favg_W_(y)).

The counterfactual distribution $\hat{F}_{Y_K^C}(y)$ was determined by setting, first, the distribution of incomes that would prevail for women if they had the distribution of men's characteristics (in the formula (3) parameters β_K were taken from the hazard model for women and the values of explanatory variables X_M for men). Then, the results were averaged over the intervals (c_{k-1}, c_k), k = 1, ..., 20, gaining the curve Favg_C_(y) in Figure 2.

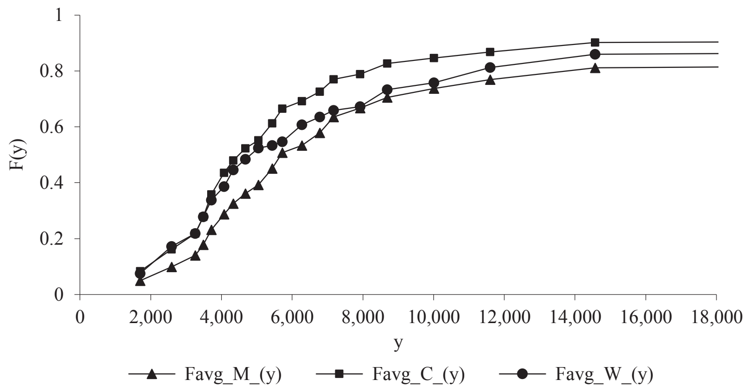

Figure 2. The averaged cumulative distribution functions for incomes

Source: author's own calculations.

3.4. Decomposition of differences in income distributions

Finally, the quantiles for distributions of men's and women's income and the counterfactual distribution are determined by inverting the estimated distribution functions. The precise values of $\hat{Q}_{g,\tau} = \hat{F}_{Y_g}^{-1}(\tau)$ and $\hat{Q}_{W,\tau}^{C} = \hat{F}_{Y_W^C}^{-1}(\tau)$ were computed using linear interpolations. This allowed to decompose the income gap for quantiles. The approach also made it possible to determine the explained and unexplained components of the difference in terms of quantiles. The results are presented in Table 4.

The results indicate positive differences between male and female incomes at each level of income. These differences are non-monotonous. They are initially decreasing (among the poorest), for quantiles of the order 0.4–0.6 are higher again, then lower again, and, on the right end of the income distribution, they grow stronger (among the richest).

Table 4. Decomposition of difference in income distributions in terms of quantiles

τ	$\hat{Q}_{M,\tau}$	$\hat{Q}_{W,\tau}$	$\hat{Q}^{C}_{W,\tau}$	Total difference $\hat{Q}_{M,\tau}-\hat{Q}_{W,\tau}$	Unexplained part $\hat{Q}_{M,\tau}-\hat{Q}^{C}_{W,\tau}$	Explained part $\hat{Q}^{C}_{W,\tau}-\hat{Q}_{W,\tau}$	Unexplained part (%)	Explained part (%)
0.1	2,615.9	1,924.9	1,885.3	691.1	730.7	–39.6	105.7	–5.7
0.2	3,581.2	2,998.4	3,047.8	582.8	533.5	49.4	91.5	8.5
0.3	4,161.2	3,572.4	3,551.1	588.8	610.1	–21.3	103.6	–3.6
0.4	5,099.0	4,133.5	3,912.1	965.5	1,186.9	–221.4	122.9	–22.9
0.5	5,680.9	4,826.6	4,495.2	854.2	1,185.6	–331.4	138.8	–38.8
0.6	6,926.3	6,211.0	5,351.4	715.3	1,574.9	–859.6	220.2	–120.2
0.7	8,587.5	8,272.1	6,394.3	315.4	2,193.3	–1,877.8	695.4	–595.4
0.8	13,799.2	11,233.9	8,161.7	2,565.4	5,637.6	–3,072.2	219.8	–119.8
0.9	85,765.0	69,868.3	14,433.1	15,896.7	71,331.9	–55,435.2	448.7	–348.7

Source: author's own calculations.

The unexplained component of the income gap (associated with the 'valuation' of the people's characteristics by the market) increases with the amount of income. Its share is at a high level from 92% to 695% of the total gap. This demonstrates that the discrimination is more evident for higher values of incomes. Another interesting result is the negative values of the explained component of the income difference, especially large in the groups of the best earning people (similar results as in Rokicka and Ruzik (2010) or Christofides, Polycarpou, and Vrachimis (2013)). This reflects the reduction of wage inequality, probably due to 'better' characteristics of women than men. Such a favorable reduction in the gap for women deepens as the higher income groups are considered (maybe women in the richest group should earn much more than men).

Conclusions

The aim of the study was to analyze the differences between the income distributions of men and women in Poland. We started with the decomposition of the average values for incomes by using the Oaxaca-Blinder method. There was a positive difference between the mean values of incomes. The explained effect was low and negative, but the unexplained was huge and positive.

Then, we estimated two conditional piecewise-constant hazard models for men and women, separately. The distribution of incomes can be estimated using a hazard model, as this model is typically used to describe the distribution of non-negative random variables. In the study, the role of such variable takes a non-negative income variable. We also constructed the counterfactual distribution.

The use of the models estimated made it possible to decompose the inequalities between men's and women's incomes along the whole distribution. The decomposition of differences in distributions allowed to consider the income inequalities more accurately than using the Oaxaca-Blinder method. The total effect increased with income, whereas the explained effect was lower and negative.

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. Consequently, all countries should implement the principle of equal pay for equal work in their national legislations. Also, the transparency is an important tool for closing the gender wage gap in the future (e.g. big companies should report their financial remuneration data for male and female employees).

However, even if the approach applied was useful for measuring and decomposing the income differences, it may not necessarily deepen our understanding of the mechanism underlying the analyzed process. One has to consider the other components of the wage gap – length of the work day or factors such as occupation and sector. The key employment indicator that might explain the gender wage gap is the lower women's labor force participation. Women often leave the labor market due to lacking flexible and affordable childcare facilities. It is worth considering whether the housework and childcare done by women should be compensated as paid wage labor. On the other hand, sometimes women are themselves guilty of the gap. They are afraid to ask for a higher salary when beginning a job, and are less successful in negotiating the salary increase.

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