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Gender Wage Gap Convergence and Skills Heterogeneity in Poland (2005–2014) – Quantile Regression Analysis Based on Microdata from EU SILC[4]

Summary

In this article we quantify the magnitude and evolution of gender wage differentials in Poland over the years 2005–2014 using microlevel data from EU-SILC database (Statistics on Income and Living Conditions). It the study gender wage gap is examined through quantile regression analysis. It is shown that the gender wage gap varies along the wage distribution with workers' skills heterogeneity playing a role. Additionally, the decomposition technique reveals that the unexplained wage gap is highest for the top of the distribution. Finally, the results suggest a slow decrease in discriminatory component of the wage gap –only for the bottom of the wage distribution.

Keywords: gender wage gap, wage differentials, EU-SILC, skills heterogeneity, quantile regression

JEL Classification Codes: J16, J31, J7

1. Introduction

According to the recent data from Eurostat (March 2017), in 2015, women's gross hourly earnings were on average 16.3% below those of men in EU28. The gender pay gap[5] varied significantly across EU member states, ranging from 5.5%

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4 This research has been conducted within a project financed by the National Science Centre, Poland (Narodowe Centrum Nauki, NCN) – decision number DEC-2015/19/B/HS4/02884.

5 The unadjusted gender pay gap is defined by Eurostat as „the difference between average gross hourly earnings of male and female employees as % of male gross earnings"

in Italy and Luxembourg to 26.9% in Estonia (7.7% in Poland). It is a persistent phenomenon and unsurprisingly the literature on wage differentials between males and females (gender wage gap) has a long tradition and is among one of the key issues addressed in labor economics (see a survey in Weichselbaumer and Winter-Ebmer, 2005 or Ponthieus and Meurs, 2014 pp.1005–1049).

In this article we analyse gender wage differentials in Poland (2005–2014) using microlevel data from EU-SILC database (Statistics on Income and Living Conditions). However, we go beyond traditional mean analysis and perform the quantile regression through which we show the importance of workers' skill heterogeneity for the gender wage gap. Additionally, based on quantile function decomposition techniques proposed by Melly (2006) and Chernozhukov et al. (2013) we estimate „explained" and „unexplained" wage differentials along wage distribution. Finally, thanks to the use of several waves of EU-SILC data we are able to compare how gender wage gap (and its discriminatory component) evolved over time and hence to verify empirically the hypothesis of gender wage gap convergence.

Our aim is to contribute to the existing literature on the wage gap in Poland studied among others by: Rokicka and Ruzik, 2010; Goraus and Tyrowicz, 2014; Kaszubowski and Wolszczak-Derlacz, 2014; Majchrowska et al., 2015; Majchrowska and Strawiński, 2016.

Additionally, we take into account recent developments in labor economics. Traditionally such characteristics such as gender, age or experience were taken into account in basic wage determination models (see Heckman et al., 2006 for a survey on the evolution of earnings functions a 'la Mincer). However, in line with the recent literature on changing task composition of labor (among others: Acemoglu and Autor, 2011) it is important to capture properly the dynamic changes in the task content of jobs, affecting occupational structure of employment and wages. In a recent study Hardy et al. (2016) document an increase in non-routine cognitive tasks and a decrease in manual tasks in 10 CEE countries (1998–2013), including Poland. The type of occupations matters for gender wage differentials – for instance Majchrowska et al. (2015) find that the highest share of unexplained part of wage gap in Poland is among managers and in groups in which the specific vocational skills are required. We address this issue by using occupational skill level classification of workers based on information on their occupations.

(http://ec.europa.eu/eurostat/statistics-explained/index.php/Gender_pay_gap_statistics [dostęp 7.04.2017].

2. The data

In order to perform empirical analysis of gender wage gap differentials evolution in Poland, we rely on microlevel data from EU-SILC database (The European Union Statistics on Income and Living Conditions)[6]. The EU-SILC provides comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion and living conditions, and is thus suitable for cross-country comparisons.[7] We combine here various waves of EU-SILC cross-sectional data files up to the most recent release available at the time we were writing this paper: EU-SILC 2015 (August 2016). We restrict the sample to polish workers. The data accessible for Poland was collected in the surveys conducted in the years 2005–2014 and this is the time span of our analysis. In our dataset we observe between 8 306 and 9 447 workers (the number of observations depends on the year).

Our crucial variable of interest (gross hourly wage) is obtained for every person on the basis of the information on gross earnings and the time of work provided in EU-SILC datasets.[8] We use HICP from Eurostat to express wages

6 The microdata have been obtained from Eurostat and refer to EU-SILC, 2004–2014 (grant agreement 64/2013-LFS-EU-SILC-SES). The responsibility for all conclusions drawn from the data lies entirely with the authors. Joanna Wolszczak-Derlacz acknowledges co-foundation by the Erasmus+ Programme of the European Union (Jean Monnet Chair in Economics). The European Commission support for the production of this publication does not constitute an endorsement of the contents which reflects the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

7 A complete library containing the documents on EU-SILC, including guidelines for different waves of EU-SILC data (containing a detailed description of the target variables) can be found at: https://circabc.europa.eu/faces/jsp/extension/wai/navigation/container.jsp?FormPrincipal:_idcl=FormPrincipal:left-menu-link-lib-closed&FormPrincipal_SUBMIT=1&id=570fe72e-aa7f-4eff-8f09-3dc140f0359a&javax.faces.ViewState=GnEcDEStvOavdalxMlQXghwqec%2BfBsHRlsx4cNAxkie1QzD3plnFeZZvswA0xbqstLhA7XopLGBGQ1T-1M%2FdR9etdjOhhXfgMwNYdKSFT3SNBnS%2BiPD%2FDpz2mCga2D819ppF8wHH9DP4FlTydgKW8OiuNFbY%3D [dostęp 5.04.2017].

8 In particular, we use the data on gross monthly earnings for employees (variable PY200G) and the number of hours usually worked per week in main job (PL060). We follow the methodology of Schäfer and Gottschall (2015, p.477): „monthly gross earnings are the basis for calculating hourly earnings by multiplying the weekly working hours by 4.2 and dividing the monthly gross earnings by the resulting monthly working hours". Such a strategy is suitable for countries such as Poland with information on income reported for the actual period. Alternatively, hourly wage could be obtained from the information on gross annual earnings, total weekly hours worked in the main job and monthly information on employment status

in real terms (HICP 2015 = 100). For the purpose of our analysis we also employ other microlevel information from EU-SILC important for the determination of wages. The set of individual characteristics includes: sex (PB150, crucial for detecting wage differentials due to gender), age (based on PB140 and the survey year), marital status (PB190), education (PE040: highest ISCED level attained)[9], experience (PL200: number of years spent in paid work). We additionally employ firm/job characteristics: company size (micro, medium and big – based on PL130)[10], type of contract (permanent, temporal: PL140) and managerial position (supervisory type of work: PL150). We also dispose of information on the sector of employment (NACE: PL110 and PL111) and NUTS 1 region (DB040 from the household register).

We keep in our sample only full time workers for whom we have the information on occupation type. We drop from our sample armed forces workers, as well as agricultural, fishery and related laborers as their jobs are characterized by very specific wage determination schemes and regulations.

Occupations of individuals present in EU-SILC follow ISCO (International Standard Classification of Occupations)[11]. ISCO-88 is used till 2011 operations (waves) of EU-SILC data while ISCO-08 is to be used from the 2012 operation onwards. We use the information on occupation to classify workers into categories according to their occupational skill level. We use the mapping of ISCO occupations to skill levels (the mapping based on major ISCO groups is presented in Table 1) based on ILO methodology and presented by Hunter (2013). Skill levels mean here the complexity and range of tasks and duties performed in an occupation.[12] Hence, it differs from the conventional classification obtained with educational data and ignoring the type of tasks actually performed in the job[13].

during the income reference year (for details on wage derivation from EU-SILC data see Engel and Schaffner, 2012).

[9] We reclassify variable PE040 to obtain three educational groups: low (ISCED level 0 and 1), medium (ISCED level 2, 3 and 4) and high education (ISCED level 6, 7 and 8).

[10] We reclassify variable PL130 to obtain three categories of companies: micro (if less than 11 persons working in the local unit), medium (11–49) and big (equal to 50 or more).

[11] http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm [dostęp 05.04.2017].

[12] According to the description provided in Hunter (2014), „it is measured operationally by considering: (i) the nature of the work performed in an occupation (in relation to the characteristic tasks and duties defined for each ISCO-08 skill level) and/or (ii) the level of formal education and (iii) the amount of informal on-the-job training and/or previous experience in a related occupation which is required for competent performance of the tasks and duties".

[13] An alternative skill typology, typically employed in sector-level analysis where information on tasks is missing, is based on educational attainment. It classifies workers into three groups: the low skilled (those with primary education), medium skilled (with secondary

Table 1. Mapping of ISCO-08 groups to skill levels

ISCO-08 major groups	Skill Level
1 – Managers	3 + 4*
2 – Professionals	4
3 – Technicians and associate professionals	3
4 – Clerical support workers 5 – Service and sales workers 6 – Skilled agricultural and fishery workers 7 – Craft and related trades workers 8 – Plant and machine operators, and assemblers	2
9 – Elementary occupations	1
0 – Armed forces occupations	1, 2 + 4

Source: own elaboration based on Hunter (2013)
Note: * in the case of managers, we assign skill level 4. Individuals employed in armed forces occupations, as well as agriculture and fishery workers are dropped from our sample.

In Table 2 we present summary statistics (weighted means) of all the variables by gender, based on our sample of Polish workers. The data reported in the table refers to the last available cohort – 2014. On average males receive higher wage than females (4.28 versus 4.07 euro per hour) and are more experienced in terms of years spent in a paid job. Females are on average educated better: 44% of females and 25% of males have tertiary education. Females and males do not differ significantly with respect to the marriage status, size of the company they are employed in or the type of the job contract. Approximately two-thirds of females and males from our sample in 2014 are married, around half of them are employed in 'big' firms employing more than 49 persons, circa 70% possess a permanent contract and approx. 20% have supervisory responsibilities. There is a noticeable difference in the distribution of females and males across sectors: 77% of females were employed in services (versus 45% of males), 20% in manufacturing, mining, electricity, gas and water supply sector (versus 39% of males) and only 1% in the construction sector (versus 15% of males). There is also noticeable gender heterogeneity in terms of the skill type of performed occupations: bigger percentage of females (35% versus 23 of males) work in the most demanding occupations characterised by the highest required skill level (see Table 1).

education) and high skilled workers (with tertiary education). See Wolszczak-Derlacz and Parteka (2016) for an example of wage analysis using such a skill grouping.

Table 2. Summary statistics (mean values)*, by gender, Poland, 2014

variable	female	male
Wage_hour (gross hourly wage, EUR)	4.07	4.28
Age (age, in years)	40.23	40.22
Exp (experience, in years)	16.60	18.29
Loweduc (low education completed)	0.03	0.04
Mededuc (medium education completed)	0.53	0.71
Hieduc (high education completed)	0.44	0.25
Married (family status)	0.68	0.67
MicroFirm (company size: micro, 1–10)	0.18	0.17
SizeMed (company size: medium, 11–49)	0.31	0.27
SizeBig (company size:big, >=50)	0.50	0.55
Cont_Perm (permanent contract)	0.72	0.72
Cont_Temp (temporary contract)	0.28	0.28
Manag (managerial position)	0.17	0.20
ManufMinWater (employed in manufacturing, mining, energy, gas & water supply)	0.20	0.39
Const (employed in construction)	0.01	0.15
Service (employed in services)	0.77	0.45
Skill1 (occupational skill level 1 – the lowest)	0.11	0.06
Skill2 (occupational skill level 2)	0.41	0.65
Skill3 (occupational skill level 3)	0.13	0.06
Skill4 (occupational skill level 4 – the highest)	0.35	0.23

Source: own elaboration based on EU-SILC 2015, the data refers to 2014. The number of observations (individuals) in the sample = 8 450

Note: * weighted by personal cross-sectional weights.

Table 3. Females and males wages by skill groups, 2014

	Females			Males		
Skill group	1st quartile	2nd quartile	3 rd quartile	1st quartile	2nd quartile	3 rd quartile
1	2.25	2.39	2.82	2.25	2.39	2.93
2	2.37	2.62	3.52	2.39	3.21	4.22
3	3.03	3.94	5.14	3.38	4.65	6.42
4	3.69	4.93	6.87	4.22	5.86	7.89
Total	2.39	3.38	4.93	2.53	3.52	5.07

Source: own elaboration based on EU-SILC 2015

Note: * weighted by personal cross-sectional weights.

Additionally, in Table 3 we present the wages of females and males by skill groups. This time, we report statistics by quartiles. We note the inter-skill group differences in wages with the skill group no 4 being characterised by the highest earnings both for women and men. At the same time we notice that the distribution of wages along quartiles can be important for the gender wage differentials which will be verified in the further empirical analysis.

3. Results of a quantile regression wage model

In order to assess gender wage inequality observed in Poland we estimate the following regression model grounded in a traditional Mincer-type wage equation (Mincer and Polachek, 1974; Heckman et al., 2006):

$$lnw_{it} = \alpha + \sum_{j=1}^{J} \beta_j Ind_{jit} + \sum_{k=1}^{K} \gamma_k Job_{kit} + \theta Skill_{it} + Reg_{nt} + \mu_t + e_{it} \tag{1}$$

The dependent variable, $w_{it,}$ denotes the real gross hourly wage of individual i at time t. Explanatory variables, described in section 2, include: *Ind* – the vector of j individual characteristics (gender, age, age squared, experience, experience squared, the level of education), *Job* – a vector of k job characteristics (company size, type of contract, supervisory position, sector of employment) and occupational skill level (*Skill*) defined in Table 1. Additionally, we control for the regional variation in wages (*Reg*) and we include time dummies. Eq. 1 is estimated with the use of a quantile regression with the algorithm proposed by Frölich and Melly, 2010. Estimations are carried out separately for the 1st, 2nd and 3rd quartile.

The results are presented in Table 4. They indicate that males on average earn more than women while the wage gap is not constant over the wage distribution but increases at the higher quantiles. It is coherent with the „glass ceiling" hypothesis. Furthermore, the results show that older employees, with longer job experience and higher level of completed education, employed in bigger firms, possessing permanent contract and supervising others earn more. It is also confirmed that higher skill levels are positively correlated with wages.

In Columns (1A, 2A and 3A) we augment the model specification with the interaction between the occupational skill level and male/female indicator. For the 1st quantile the interaction term is not statistically significant, while for the

2nd and 3rd it is. This suggests that occupational skill category lowers the gender wage gap as we move along the wage distribution.

Table 4. Estimation results of quantile regression (Poland, 2005–2014)

	1st quartile		2nd quartile		3rd quartile	
	(1)	(1A)	(2)	(2A)	(3)	(3A)
Sex (male=1)	0.098***	0.113***	0.136***	0.189***	0.163***	0.249***
	[0.004]	[0.012]	[0.004]	[0.011]	[0.005]	[0.013]
Age	0.016***	0.017***	0.016***	0.017***	0.021***	0.022***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Age^2	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Experience	0.010***	0.010***	0.013***	0.013***	0.015***	0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Experience^2	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Education (low=1, medium =2, high=3)	0.176***	0.177***	0.197***	0.198***	0.213***	0.211***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Firm size (micro <11 employees, medium 11–49 employees, big >49 employees)	0.087***	0.087***	0.081***	0.081***	0.076***	0.076***
	[0.003]	[0.003]	[0.002]	[0.002]	[0.003]	[0.003]
Contract (permanent=1)	0.132***	0.132***	0.143***	0.141***	0.134***	0.134***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.006]
Manager (supervisory position=1)	0.095***	0.096***	0.126***	0.130***	0.135***	0.139***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
ManufMinWater	0.019***	0.019***	0.024***	0.023***	0.031***	0.030***
	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.005]
Const	–0.038***	–0.038***	–0.020**	–0.023***	0.002	–0.009
	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]
Skill level	0.171***	0.172***	0.193***	0.201***	0.216***	0.230***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Sex × Skill level		–0.006		–0.022***		–0.034***
		[0.005]		[0.004]		[0.005]

Source: own elaboration based on EU-SILC (various waves).

Note: regression weighted by personal cross-sectional weights, time and region (*Reg*) dummies included in all specifications, central region (PL1) and 2005 are the reference variables (omitted), kernel estimate of the VCE as proposed by Powell (1991).

So far, we have found evidence that the gender wage gap in Poland is different at the bottom and at the top of the wage distribution. Now we turn to the decomposition of the observed wage gap into two components: a part explained by differences in characteristics („explained") and a part due to the differences in coefficients („unexplained"). The interpretation is the same as in the standard Oaxaca-Blinder decomposition of mean wage differentials (Oaxaca, 1973; Blinder, 1973). The decomposition makes it possible to answer the question of how much of the gender wage gap can be explained by male-female differences in human capital (education), experience and other specific characteristics. The unexplained part is often interpreted as gender discrimination (residual wage), although other interpretations are possible (unobserved skills, missing covariances etc., Fortin et al. 2011). We follow the quantile function decomposition techniques proposed by Melly (2006) and Chernozhukov et al. (2013). Figure 1 plots the decomposition as a function of quantiles for 2005 (left plot) and 2014 (right plot) based on estimated 100 quantile regressions.

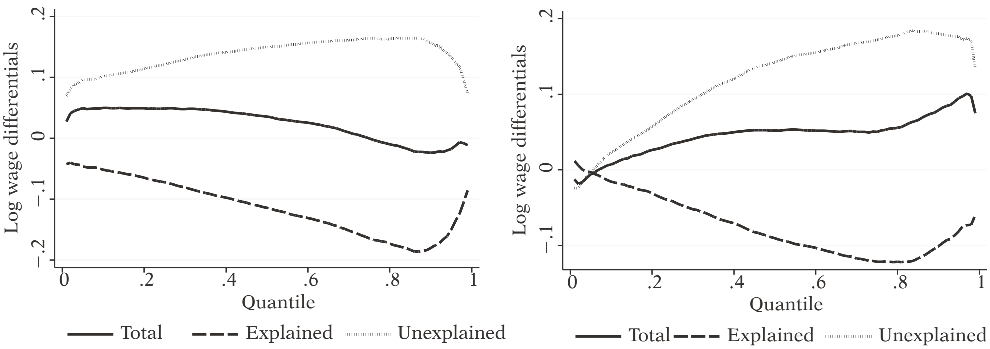

Figure 1. Decomposition of the gender wage gap using quantile regression, Poland (2005 – left plot versus 2014 – right plot)

Source: own elaboration with the use EU-SILC data and the *rqdeco* procedure in Stata14.
Notes: Models correspond to specification (1) as in Table 4.

The estimated total differentials show that the gender wage gap in 2005 was higher at the bottom end of the distribution while in 2014 at the top end of the distribution (the curve is S-shaped). However, after controlling for the effects of all the other characteristics, the distributions of the unexplained part of the differentials in 2005 and 2014 are similar: first increasing but after the 80th percentile – decreasing. The reverse is observed for the explained part of wage gap differentials. The discrimination part is bigger than the total difference. It is a sign that females being better educated, having higher skills should earn more than males so the actual wage difference does not illustrate the discriminatory power.

Finally, in the figure 2 we present the time trend in the unexplained part of differentials by quartile from 2005 to 2014. It can help us to answer the question whether the discriminatory component of the gender wage gap is decreasing. First of all, we see that for the whole period of time the discriminatory component of the wage differential is smaller at the bottom of wage distribution. Additionally, only for the 1st quartile we can confirm the slow level of adjusted wage gap convergence (the decrease in the unexplained part of the differentials by 0.05 log points).[14]

All of these: the unexplained component being more pronounced at the top of the wage distribution and its persistence can be a sign of a glass ceiling in Polish economy. Arulampalam et al. (2007) finding the similar glass ceiling effect for some of the European countries explain it by hierarchical nature of labour markets, promotions and appointments procedures favoring men rather than women and parental leave policy.

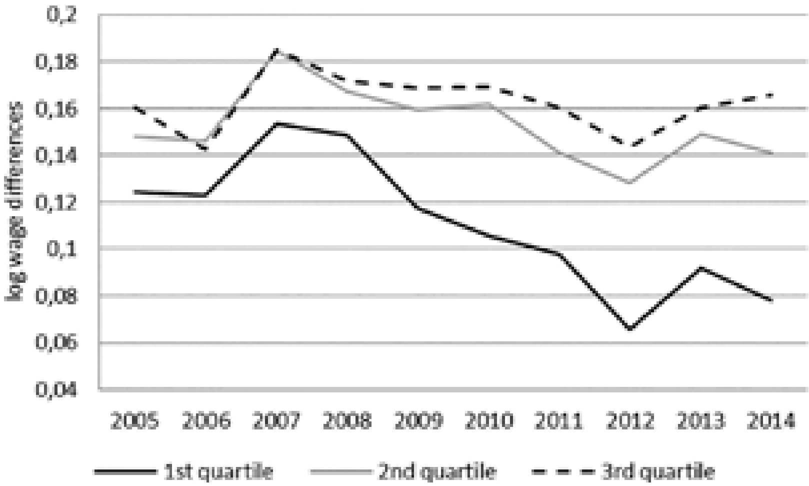

Figure 2. Unexplained differentials in male/female wages by quartiles (2005–2014).
Source: own elaboration with the use EU-SILC data and the *rqdeco* procedure in Stata.

[14] It is also confirmed by the formal regression analysis of beta convergence – not shown here for the clarity, but available from authors upon request.

4. Conclusions and the directions for further research

In this paper we have addressed a several issues of gender wage gap in Poland over the period 2005–2014. In order to evaluate the differences between a man's and a woman's wages we used EU-SILC micro data. A detailed examination has been conducted passing from descriptive statistics, through regression analysis, to decomposition methods.

We showed that a gender wage gap varies along the wage distribution. In the regression analysis it was shown that the variable related to the skill heterogeneity of workers is not only among the important determinants of wages *per se*, but it was shown to be an important determinant of the gender wage gap (especially at the top of the wage distribution). Further, through the decomposition methods we estimated that the unexplained part of the gender wage gap is higher than the raw gap indicating that women as better educated, having higher skills should earn more than males. However, again this discriminatory component of the wage gap is not constant over wage distribution.

The increasing unexplained part of differentials at the high end of the distribution could be a sign of a glass ceiling in Polish economy. Finally, we confirmed the slow level of adjusted wages convergence between men and women, but only at the bottom of distribution, for high end of the distribution the discriminating part was stable.

We argue that our analysis can be the starting point for further research on gender wage gap e.g. the analysis of the impact of offshoring or other forms of production sharing on explained and unexplained wage differentials. However, as proven by the current study, the quantile models are the essentials tools of the analysis of all aspects of changes in wage inequalities.

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Zróżnicowanie wynagrodzeń pomiędzy kobietami i mężczyznami a heterogeniczność umiejętności pracowników w Polsce (2005–2014) – analiza na podstawie regresji kwantylowej z wykorzystaniem mikrodanych z EU-SILC

Streszczenie

W artykule przedstawiono ocenę wielkości i ewolucji różnic płacowych pomiędzy kobietami i mężczyznami w Polsce w latach 2005–2014. W analizie wykorzystano mikrodane z bazy EU-SILC. Zróżnicowanie płac jest badane na podstawie regresji kwantylowej. Wykazano, że luka płacowa nie jest stała wzdłuż rozkładu wynagrodzeń i jest powiązana z umiejętnościami/kwalifikacjami pracowników. Dodatkowo za pomocą dekompozycji pokazano, że czynnik dyskryminacyjny (niewyjaśniona luka płacowa) jest najwyższy w górnych częściach rozkładu. Wyniki wskazują na powolny spadek dyskryminacyjnego składnika luki płacowej w analizowanym okresie, ale tylko w odniesieniu do dolnych części rozkładu płac.

Słowa kluczowe: luka płacowa, zróżnicowanie płac pomiędzy kobietami a mężczyznami, heterogeniczność umiejętności, regresja kwantylowa

Zgodnie z oświadczeniem Autorów, ich udział w przygotowaniu artykułu wyniósł: Aleksandra Parteka – 33%, Sabina Szymczak – 33%, Joanna Wolszczak-Derlacz – 33%.