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GENDER WAGE GAP IN POLAND – CAN IT BE EXPLAINED BY DIFFERENCES IN OBSERVABLE CHARACTERISTICS?

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Gender Wage Gap in Poland – Can It Be Explained by Differences in Observable Characteristics?

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Abstract

The raw gender wage gap over the period 1995-2012 amounts to app. 9% of hourly wage and is fairly stable. However, the raw gap does not account for differences in endowments between genders. In fact, the adjusted wage gap amounts to as much as 20% on average over the analyzed period and shows some cyclical properties. The estimates of adjusted gender wage gap do not seem to exhibit any long-term trends, which suggest that in general neither demographic changes nor the progressing transition underlie the phenomenon of unequal pay for the same work among men and women.

Keywords:

Wage gap, discrimination, decomposition, Oaxaca-Blinder, Nöpo, non-parametric estimation

JEL:

J21, J70

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1 Introduction

Most societies declare preference for equality. Yet, differences in compensation persist across genders, ethnicities and races. On the other hand, individuals' earnings are likely to exhibit considerable heterogeneity due to large differences in the underlying characteristics that are relevant for the labor market (for instance education, occupation, experience, etc.). While causal attribution of these differences to discrimination *per se* relies heavily on the reliability of a particular estimator in a particular context – majority of the statistical procedures used in wage gaps analyzes are able to fairly well isolate the effects of the so-called observables on the differences in earnings. The adequate estimation of the reminder – attributed partly to unobservables and at least partly to discrimination – is at the core of both econometric and labor economics attempts in the field. Thus, the real challenge lies in providing reliable measures of adjusted wage gaps.

The objective of this paper is to inquire the nature of the gender wage gap in Poland using a fairly comprehensive collection of data sets covering the span of 1995-2012, i.e. eighteen years of economic transition from a centrally planned to a market economy. To the best of our knowledge this is a first so comprehensive study, providing a novel, time series perspective on the gender wage gap over this period. The raw gender wage gap in the analyzed period amounts to around 9%, which is low by many standards. On the other hand, Poland is a country with extremely large educational gap between men and women (who tend to be better educated), which suggests that the raw gender wage gap may underestimate the extent to which compensations differ across genders. In fact, as we find, adjusted gender wage gap is twice as high as the raw gender wage gap in that period.

If women are on average better educated, standard parametric approach to estimating the adjusted gender wage gap may yield misleading results due to the so-called common support problem. Namely, there may be none (not enough) comparable men, making the parametric estimates economically irrelevant (even if statistically accurate). To address this problem, this paper employs a novel nonparametric estimator of the gender wage gap, as developed by Nöpo (2008). The application of the nonparametric estimation technique is a second novelty of this paper.

The paper is structured as follows. First, we discuss the relevant literature, focusing on the methodological aspect of estimating the adjusted gender wage gap. Second, we describe in the detail the properties of the dataset – Polish Labor Force Survey – and provide the first, pooled estimates of the adjusted gender wage gap, to build the intuition. In the third section we present the detailed results of both the adjusted gender wage gap and the time series properties of this estimate. The conclusions and policy recommendations from this study are discussed in the last section.

2 Literature review

The issues of gender differences in the labor market and gender discrimination have been gaining considerable attention in the last decades. However, as pointed out by Grajek (2003) Poland had a significant delay in having their academic, business, and political elites concentrated on this issue. Polish gender wage gap has been analyzed mostly in the context of transition period as performed by Grajek (2003) as well as Adamchik and Bedi (2003), who underline that the relative economic welfare of women is one of the measures of nation's well-being and they doubted if the economic position of females in Poland has improved along with the positive economic performance of the country. In addition to these two papers, the literature has been scarce. Kotowska and Podogrodzka (1994), Kalinowska-Nawrotek (2005), Zwiech (2005) or Mazur-Łuczak (2010) describe differences in raw gender wage gaps across separate dimensions such as place of residence or educational attainment. Poland was also included in a number of cross-country studies, such as Brainerd (2000), Pailhé

(2000), Blau and Kahn (2001) as well as Newell and Reilly (2001). Without exceptions, all these studies find lower wages for women in Poland along with better characteristics, such as higher educational attainment.

The historically first actual econometric adjustment in the estimates of gender wage gap can be found in Kot, Podolec and Ulman (1999). Subsequent analyses – including Adamchik and Bedi (2003) as well as Brainerd (2000), Pailhé (2000) and Blau and Kahn (2001) all employ parametric decompositions, typically Oaxaca (1973) and Blinder (1973) in the version developed by Neumark (1988)¹. The advantage of the decomposition is to split the difference between the earnings between men and women to a part attributable to differences in endowments and a part attributable only to different pricing of these characteristics across the two genders. The differences in pricing are typically considered to be “unjustified”, i.e. interpreted as an upper boundary of discrimination.

Given the general conclusion that the adjusted gender wage gap in Poland is substantially larger than the raw wage gap, the topic calls for particularly careful and thorough statistical processing. First, the attribution of the estimates of adjusted gender wage gap to discrimination is only as adequate, as comprehensive the information on observables. Second, should the estimation technique be subject to bias of some kind due to the nature of gender differences in observables, parametric estimates are likely to be unreliable. The standard parametric decompositions usually consists of estimating the “determinants” of earnings for females and for a counterfactual – sometimes assumed to be nondiscriminatory – control group². That second group may consist of men, an average for men and women, etc. Depending on the definition of the control group, the standard Oaxaca (1973) and Blinder (1973) decompositions differ in the interpretation³. In addition, since regressions operate at the means, whereas earnings distributions tend to be skewed, the original idea of Oaxaca (1973) and Blinder (1973) have been extended to the moments of distribution⁴.

All parametric estimations rely heavily on the overlap assumption, but this assumption is rarely empirically verified. Nõpo (2008) points out that there are combinations of characteristics for which it is possible to find males but not females in the society, and vice versa. With such distribution of characteristics one cannot compare wages across genders. The problem with comparability is enhanced when job-related variables are included in the explanation of gender gap, as females tend to concentrate in certain occupations that demand particular abilities. In case of violation, parametric estimations are useless, but the decision whether overlap is sufficient in the multivariable context is discretionary. A second severe problem is the endemic endogeneity in how individual, employer and job characteristics affect each other and wages, which implies that many of the parametric estimates may be biased, making any parameter-based inference risky.

¹ Grajek (2003) applied the Juhn, Murphy, and Pierce decomposition to analyze data on Polish employees from Household Budget Survey for the period 1987 – 1996. He also found that explained component is relatively small and rises slowly over the analyzed period. Similar method was employed by Łatuszyński and Woźny (2008), who confirmed the findings of Grajek (2003) using data for 2004.

² Oaxaca (1973) was aiming at estimating the size of actual discrimination in the gender wage gap in the United States according to data for 1967 from Survey of Economic Opportunity. The study took into consideration hourly wage of individuals of age over sixteen, living and employed in urban areas and reporting their race as White or Black. Oaxaca also accounted for human capital characteristics and environmental conditions that impact the distribution of workers across different sectors, positions and occupations. As a result the raw wage difference has been proved to be much larger than adjusted wage gap (understood as part of the raw gap unexplained by differences in characteristics).

³ Decompositions based on different assumed reference wage structures are found in Cotton (1988), Neumark (1988), Oaxaca and Ransom (1994), and Reimers (1983). In Oaxaca and Ransom (1994) vector of coefficients in non-discriminatory wage structure is defined as weighted average of coefficient vectors in male and female wage equations.

⁴ Among those distributional methods there is broadly used decomposition developed by Juhn, Murphy, and Pierce (1991, 1993), quintile regressions methods like in Machado and Mata (2005), inverse propensity reweighing (DiNardo, Fortin, and Lemieux, 1996) or such advanced techniques as recentered influence function regressions (Firpo, Fortin, and Lemieux, 2007). Refer to Fortin *et al.* (2011) and Goraus (2013) for a more detailed review of the parametric methods.

Nöpo (2008) proposed a solution to avoid the problem of overlap by constructing an implicit decomposition based on exact matching. Matching comparisons techniques serve to find matched samples with “similar” observable features except for one particular characteristic, the “treatment”, which is used to group observations into two sets, the treated and the control group. After controlling for these differences in observed characteristics it is possible to measure the impact of treatment alone. Nöpo (2008) went a step further and considered the gender variable as a treatment and used matching to select sub-samples of males and females in such a way, that there are no differences in observable characteristics between “matched” males and “matched” females.

Consequently, Nöpo (2008) decomposition allows to directly measure four components of the overall wage differential: wages of men identical to the women in the sample, wages of women identical to men in the sample, wages of men for whom there are no identical women and wages of women for whom there are no identical men in the sample. While the first two may be considered similar to the standard Oaxaca (1973) and Blinder (1973) decomposition, the other two tackle explicitly the problem of overlap and measure the quantitative effect of overlap on the overall wage differential.

It should be mentioned that the assumption of Rosenbaum and Rubin (1983) about the “ignorability of treatment” required for propensity score matching is not likely to be satisfied in case the gender is perceived as “treatment”. Thus matching individuals in Nöpo is based on characteristics instead of propensity scores. The traditional parametric technique of decomposing gender wage gap developed by Oaxaca (1973) and Blinder (1973), as well as its non-parametric alternative developed by Nöpo (2008) are in fact directly comparable.

2.1 The Oaxaca (1973) and Blinder (1973) parametric case

This decomposition requires the linear regression estimation of earning equation for both groups, in our case, for females and males: $\bar{y}^F = \hat{\beta}^F \bar{x}^F$, and $\bar{y}^M = \hat{\beta}^M \bar{x}^M$, where \bar{y} is an average wage of females or males, \bar{x} is the vector of average characteristics in each group, and $\hat{\beta}$ is a vector of estimated coefficients of characteristics for females or males respectively. With such notations the raw gender wage gap can be expressed as $\bar{y}^M - \bar{y}^F = \hat{\beta}^M \bar{x}^M - \hat{\beta}^F \bar{x}^F$. After adding and subtracting the average counterfactual wage that male workers would have earned under the wage structure of females, $\hat{\beta}^F \bar{x}^M$, the expression becomes $\bar{y}^M - \bar{y}^F = \hat{\beta}^M \bar{x}^M - \hat{\beta}^F \bar{x}^M + \hat{\beta}^F \bar{x}^M - \hat{\beta}^F \bar{x}^F$. Then, after some algebraic manipulations it takes the form $\bar{y}^M - \bar{y}^F = \hat{\beta}^F (\bar{x}^M - \bar{x}^F) + (\hat{\beta}^M - \hat{\beta}^F) \bar{x}^M$.

Alternatively, the added and subtracted term might be the earning for female with average individual characteristics, in the case she is rewarded for her characteristics in the same way as the average male is rewarded, $\hat{\beta}^M \bar{x}^F$. Then the wage gap takes the form $\bar{y}^M - \bar{y}^F = \hat{\beta}^M (\bar{x}^M - \bar{x}^F) + (\hat{\beta}^M - \hat{\beta}^F) \bar{x}^F$. It is worth mentioning that this alternative form is especially important for the purpose of this work, as Nöpo’s decomposition is related precisely to this one.

In both forms of decomposition the first components on the right-hand side, $\hat{\beta}^F (\bar{x}^M - \bar{x}^F)$ or $\hat{\beta}^M (\bar{x}^M - \bar{x}^F)$, are the part of the gap that is due to differences in average characteristics between males and females. In a broader context it is called the composition effect (Fortin, Lemieux, and Firpo, 2010). The second component, $(\hat{\beta}^M - \hat{\beta}^F) \bar{x}^M$ or $(\hat{\beta}^M - \hat{\beta}^F) \bar{x}^F$, is attributed to difference in average rewards to individuals’ characteristics and is called the wage structure effects. The wage structure effect is also called “unexplained” part of the wage differentials, or the part due to “discrimination”, although more precisely it should be perceived as the component containing the effects of both unobservable gender differences in characteristics and discrimination in the labor market.

2.2 The Nöpo (1973) nonparametric case

The traditional Blinder-Oaxaca decomposition fails to recognize gender differences in the supports by estimating earnings equations for all working females and all working males without restricting the comparison only to those individuals with comparable characteristics. In the Blinder-Oaxaca decomposition it is necessary to make “out-of-the-support” assumption that the fitted regression surface can be extended for individual characteristics that have not been found empirically in the data set, using the same estimators computed with the observed data.

The use of matching criterion in Nöpo decomposition does not require any parametric assumptions and is solely based on the modeling assumption that individuals with the same observable characteristics should be paid the same regardless of sex. Nöpo also does account for gender differences in the supports. The traditional interpretation of two components as developed by Blinder and Oaxaca applies, but only over the common support. Additionally, in the Nöpo’s four-element decomposition there are two elements that are attributable to differences in the supports. Based on this partition the raw gender wage gap can be decomposed into four components: $\Delta = \Delta_M + \Delta_X + \Delta_0 + \Delta_F$.

The first of the four additive components, Δ_M , is the part of the gap that can be explained by differences between two groups of males – those whose characteristics can be matched to female characteristics and those who cannot. This component would disappear in two situations: if for each combination of individual characteristics exhibited in the group of males, it would be possible to find comparable females, or if those unmatched males would earn on average as much as the average matched males. This component is computed as the difference between the expected male wages out of the common support minus the expected male wages in the common support, weighted by the probability measure (under the distribution of characteristics of males) of the set of characteristics that females do not reach.

The second component, Δ_X , is the part of the wage gap that can be explained by differences in the distribution of characteristics of males and females over the common support. This part corresponds to the component attributable to characteristics from Blinder-Oaxaca decomposition, namely $\hat{\beta}^M(\bar{x}^M - \bar{x}^F)$, however limited to the common support.

The third component is called by Nöpo the adjusted gender wage gap. It is the part of the raw wage gap that remains unexplained by differences in characteristics of the individuals and is typically attributed to a combination of both the existence of unobservable characteristics that the labor market rewards and the existence of discrimination. This component correspond to the second component from Oaxaca-Blinder decomposition, that is attributable to differences in average rewards to individuals’ characteristics for females and males, $(\hat{\beta}^M - \hat{\beta}^F)\bar{x}^F$, however it is also limited to the common support.

The last component, Δ_F , is the part of the gap that can be explained by the differences in characteristics between two groups of females, those who have characteristics that can be matched to male characteristics and those who cannot. As stated in Nöpo (2008) it is computed as the difference between the expected female wages in the common support minus the expected female wages out of the common support, weighted by the probability measure (under the distribution of characteristics of females) of the set of characteristics that males do not reach.

Three components in Nöpo’s decomposition can be attributed to the existence of differences in individuals’ characteristics that the labor market rewards (Δ_X , Δ_M , Δ_F) and the other (Δ_0) to the existence of a combination of both unobservable characteristics that should be included in the wage equation if would be observed by econometrician, and the discrimination. Thus the wage gap might be expressed as $\Delta = (\Delta_M + \Delta_X + \Delta_F) + \Delta_0$, and interpreted as it is traditionally done in the linear Blinder-Oaxaca decomposition, with two components: one

attributable to differences in observable features of males and females, and the other perceived as an unexplained component. It should also be mentioned that Nõpo's methodology has its limitations. It is burdened by the curse of dimensionality. While the extent to which the raw gender wage gap can be explained depends on the number of explanatory variables, the likelihood of matching decreases with the number of explanatory variables.

To sum up, it can be said that the most important advantage of Nõpo's methodology over Blinder-Oaxaca decomposition is that it accounts for differences in the supports of the distribution. According to Nõpo, it is an empirical regularity that the unmatched males have average wages above the average wages of their matched peers and estimating earnings equations for all males without accounting for this regularity tends to overestimate the unexplained component (Δ_0) in the Blinder-Oaxaca decomposition. However, in cases of countries where females exhibit desirable characteristics that the labor market rewards to a greater extent than males, the unexplained component from the Blinder-Oaxaca decomposition could be actually underestimated.

3 Data

The empirical part of this paper relies on the data from the Labor Force Survey performed by Central Statistical Office in Poland and contains quarterly data from 1995q1 to 2012q4. The data contains demographic, social and labor market indicators. Each quarterly dataset contains between 7 and 40 thou working individuals of both genders. Self-declared information on wages is available for on average 96% of this sample. Thanks to the relatively big data set it is possible to conduct research on gender wage gap and differences in characteristics in each of 72 periods separately and analyze their evolution over time.

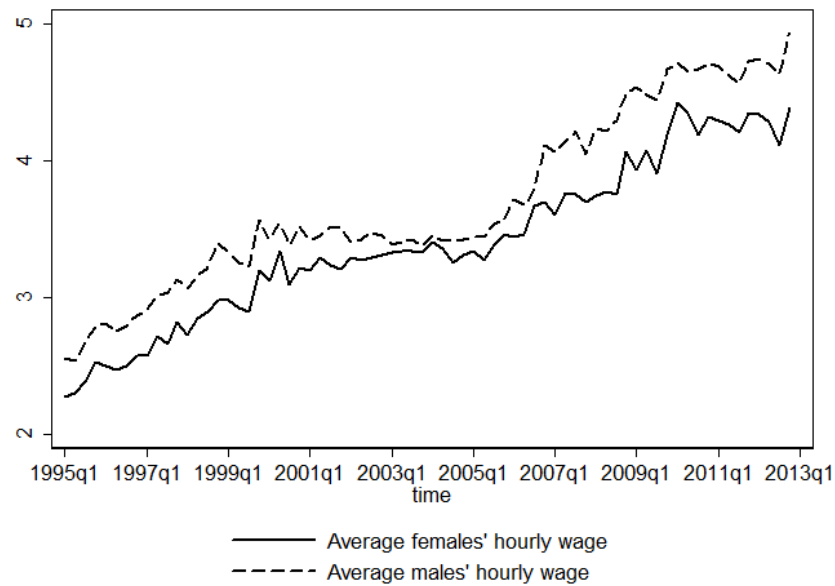
Clearly, variable selection is discretionary, but may drive the results to a large extent. Adamchik and Bedi (2001) argue that the inclusion of job-related variables is indispensable due to self-selection issues, but – as already discussed – there are also important endogeneity concerns. In the original Nõpo (2008) analysis only few simple variables were included: age, marital status, education and urban/rural dummy. This selection of variables was dictated by low data availability, but also has proven sufficient to delineate quantitatively the components of wages differentials across men and women in 63 countries of the world Nõpo *et al.* (2011). On the other hand, Polish LFS is a rich dataset, which implies that more comprehensive set of variables can be included. Yet, multiplicity of variables naturally limits the scope for exact matches between men and women, undermining the universality of the gender wage gap estimates. While conceptually this tradeoff is clear, quantitatively it is ex ante unknown how big the role of variables selection is. To address the problem of variables selection, in the first stage, after deflating the wage data to 1995 constant prices, we have created a one pooled dataset of nearly 800 thou observations and tested various specifications. This pooled dataset permits a general matching with quarter controls. Since Nõpo (2008) involves exact matching, one can be sure that in the nonparametric case similar are compared to the similar. In the case of the parametric decomposition, we assume that estimated coefficients are valid out of the common support, which is unlikely to hold, but on the other hand we do not separate incomparable individuals from the analysis.

3.1 The wage data

Wages are self-reported by the participants of the LFS. Wages are unavailable for persons that are self-employed, unemployed, or inactive, so these individuals have been removed from the original datasets. Wages are reported as monthly compensation. To foster comparability, self-reported number of hours worked is used to impute individually hourly wages for all individuals in the sample. Finally, workers of the mining sector and armed forces have been also removed from the data set. Figure 1 presents the average absolute real hourly wages for females and males in each of analyzed periods. Figure 2 explicitly shows the real wage differentials and presents it in absolute terms and as percentage of average females' hourly wages in every period. Raw wage gap in relative terms was highest in the first and last five years of the analyzed period and amounted to around

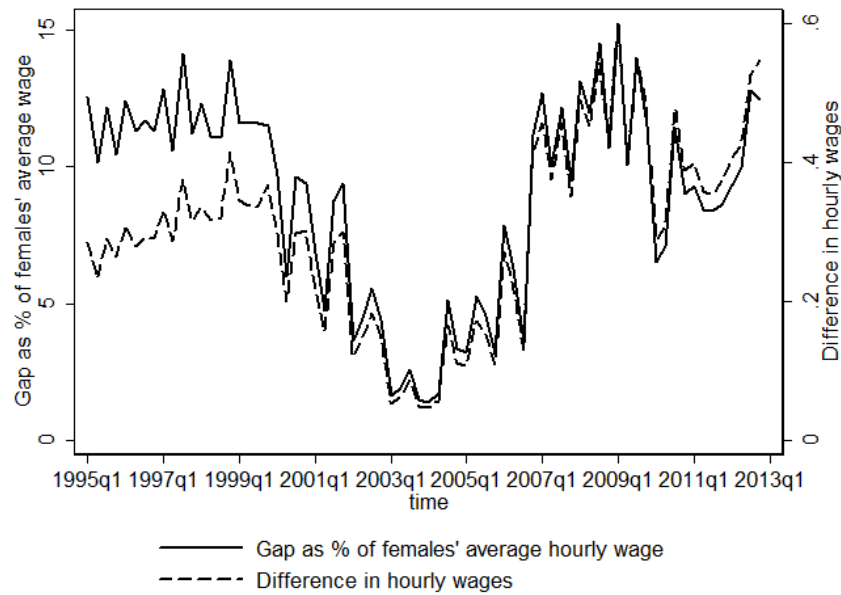
15% of average females' wages. In year 1999 the gap started decreasing and reached the level of around 2% in years 2003 and 2004. Then the gap was increasing until reached its previous level. It is a surprising result that the lowest levels of wage gap were observed after economic downturn in Poland. Explaining the reasons of this results lies beyond the scope of this work, but might be an interesting topic for further analysis.

Figure 1: Females' and males' average hourly wages, 1995-2012 (PLN, 1995 constant prices)



Source: Own computation based on Polish LFS, importance weights included

Figure 2: Absolute (PLN, 1995 constant prices) and relative gender wage gap, 1995-2012



Source: Own computation based on Polish LFS, importance weights included

When performing the two-group mean comparison test in the pooled dataset containing real wages, it was observed that the average hourly wages (PLN, 1995 constant prices) for females over the years 1995-2013 were 3.3PLN, while for males it was 3.6PLN. The difference is highly statistically significant and amounts to around 9 percent of females' average wage.

3.2 The conditioning variables

The Polish Labor Force Survey is relatively scarce in worker and firm specific data. Specifically we dispose of information on age, educational attainment, marital status, occupation category, and tenure with the current employer. In addition, the dataset contains indication of region and the size of residence (rural/urban). There is also quite extensive information on the employer: public or private ownership and the size of the firm (in terms of employment), industry. Unfortunately, in some years data on experience (as opposed to tenure with the current employer) are unavailable and thus is not considered. Share of males in the final data set is 52%. Table 1 contains descriptive statistics of mentioned variables obtained from pooled sample containing all quarters 1995-2012.

Table 1: Descriptive statistics

	Mean			Hourly wages (PLN, 1995 const.prices)			
Continuous variables	Total	Males	Females	Total	Males	Females	Difference
Hourly wage (const. 1995 prices)	3.42	3.56	3.26				9%***
Age	38.39	38.19	38.60				
Tenure with the current employer	10.10	9.72	10.51				
Categorical variables	Percent	Percent	Percent				
Education levels	100	100	100				
Tertiary education	18.50	14.08	23.29	5.57	6.00	5.28	14%***
High school	12.29	6.56	18.51	3.26	3.73	3.07	22%***
High school vocational	27.08	25.70	28.58	3.25	3.62	2.90	25%***
Vocational	33.04	43.43	21.78	2.74	2.96	2.26	31%***
Elementary	9.08	10.24	7.83	2.35	2.53	2.10	20%***
Marital status	100	100	100				
Single	20.72	22.34	18.97	3.04	3.01	3.06	-2%
Married	73.31	75.30	71.15	3.53	3.71	3.31	12%***
Widowed	2.11	0.61	3.75	3.28	3.75	3.20	17%***
Divorced/separated	3.86	1.75	6.13	3.49	3.79	3.39	12%***
Occupation category	100	100	100				
Very high-skilled occupation	19.01	13.98	24.46	5.55	6.07	5.22	16%***
High-skilled occupation	36.16	23.14	50.26	3.09	3.58	2.84	26%***
Middle-skilled occupation	34.54	54.54	12.86	2.96	3.08	2.40	28%***
Low-skilled occupation	10.30	8.34	12.42	2.32	2.49	2.20	14%***
Industry	100	100	100				
Agriculture	2.21	3.19	1.15	2.62	2.63	2.58	2%
Manufacturing	31.16	38.98	22.68	3.23	3.46	2.78	24%***
Construction	7.33	12.98	1.21	3.19	3.17	3.53	-10%***
Market services	30.74	28.67	32.98	3.36	3.66	3.07	19%***

Non-market services	28.57	16.18	41.99	3.82	4.12	3.69	12%***
Residence	100	100	100				
Less than 50 thou inhabitants	57.86	60.31	55.20	3.13	3.23	3.02	7%***
More than 50 thou inhabitants	42.14	39.69	44.80	3.81	4.06	3.57	14%***
Region	100	100	100				
Mazowieckie	14.51	14.25	14.80	3.30	3.44	3.13	10%***
Other	85.49	85.75	85.20	4.13	4.24	4.01	6%***
Type of ownership	100	100	100				
Public	49.25	41.87	57.24	3.61	3.76	3.50	7%***
Private	50.75	58.13	42.76	3.23	3.42	2.96	16%***
Size of the firm	100	100	100				
Small enterprise	20.90	19.59	22.33	2.69	2.77	2.60	7%***
Medium or large enterprise	79.10	80.41	77.67	3.61	3.75	3.45	9%***

Source: Own computation based on Polish LFS, importance weights included, *** p<0.01, ** p<0.05, * p<0.1

There are some significant gender differences in characteristics. If among females more individuals have characteristics which are related to low wage, one may expect that the adjusted gap is explained by these lower endowments. Such situation does not seem to be valid for Poland. In terms of age of working population in years 1995-2012, females are half-year older than males. After checking the difference in age for each quarter separately it might be stated that this difference is stable over time. With such a small difference it is rather impossible that it would cause the differences in wages. Variable reflecting marital status distinguishes persons that are single (first category), married (second category), widowed (third category) or divorced/separated (fourth category). Important observation is that in three marital status categories, namely married, widowed and divorced/separated average wages are similar (between 3.28 PLN and 3.54 PLN), while they are much lower for singles (3.04 PLN). At the same time there are more single males than females in the period 1995-2012 and the difference was deepening over time. Gender differences in marital status are thus not expected to explain gender wage gap.

In the set of demographic characteristics traditionally there is also one describing place of living, precisely indicating if it is rural or urban. We control explicitly for residence in large cities and in Mazowieckie region, where wages are on average approximately 16% higher than elsewhere in the country. In fact, 45% of females live in larger cities, while among males the percentage amounts only to 40%. In Mazowieckie region live 15% of females, and 14% of males. It is also worth mentioning that those differences were stable over time. Similarly to other demographic characteristics, it does not seem that place of residence can be the reason why females earn less than males.

It is an empirical regularity that higher education level translates into higher earnings. This rule applies also for the Polish employees, and education level is highly significant determinant of wages. While it is typically a categorical variable in Polish LFS⁵, there are clear stark differences. There are more females than males with tertiary attainment, whereas the opposite is true for primary education. In addition the educational gap is widening over time.

In addition to individual characteristics, wages differ across job-related characteristics, i.e. occupation, industry, size and ownership form of the firm. In the analyzed dataset occupation categories were at the beginning

⁵ Within this variable the lower is the category the better education (1-"Tertiary", 2-"High school", 3-"High school vocational", 4-"Vocational", 5-"Elementary").

reflecting ISCO-08 classification, there were 9 categories⁶. In order to reach higher likelihood of matching females to males, those occupations were then grouped into 4 categories that still well reflect differences between individuals. First category consists of higher management, policy makers and specialists; second one characterizes technicians, middle management, office workers, sales and personal services; third category consists of farmers, fishermen, artisans, industrial workers and machine operators; and last, fourth category groups low-skilled occupations. As in case of education lower number means higher-skilled occupation. Females are on average more often working in high-skilled occupations than males. However, females are more frequent among low-skilled occupations as well, which makes the extrapolation to wages not that straightforward.

Heterogeneity of productivity is reflected in heterogeneity of wages across industries. Indeed, the same occupation may receive highly dispersed remuneration depending on the industry. We recoded the original variable to comprise agriculture, construction, manufacturing, market services and non-market services. Females are dominating only in the last two categories. In the sector of non-market services there are more than twice as many females as males. At the same time it is sector of an economy where wages are on average highest.

It is not only industry, but also form of ownership that contributes to wage dispersion. Average hourly wages in Poland are approximately 12% higher in the public than in the private sector, and this gap was increasing with time. Common view is that females are more risk averse and prefer more stable and protected jobs in public sector. According to our data set this view is confirmed as over the period 1995-2012 57% of Polish female employees was working in public sector, while for males the percentage was 42%. Thus it can be said that more females are working in the sector where average wages are higher.

Private firms are typically smaller firms, whereas size itself matters for wages. In fact, wages are higher in bigger companies. Average hourly wages in the medium or large enterprises amount to 3.61PLN, and are by 0.92PLN higher than in small companies. It is highly significant result, thus information about size of the firm should be included in further analysis. In small companies share of females and males is almost exactly the same, while in medium or large enterprises there is 2.7pp more males, which is fairly small.

Apart from analyzed individual and job-related characteristics, there are also contract-specific characteristics. These typically include part-time/full-time identification, form of contract (fixed or indefinite duration) and tenure with the current employer. Unfortunately, the availability and definitional coherence of these variables differed in Polish LFS over the analyzed time span. Some periods would be necessarily missing, disabling the trend analysis. Of all these variables, tenure has the least gaps and we use this variable in our analysis in order to test the robustness of the results to its inclusion. Regressing the natural logarithm of hourly wage on number of years worked for the same employer, yields a positive, highly significant coefficient. When it comes to gender differences, average tenure for females is 10.5 years, while for males it is 9.7 years. Again it can be observed that females demonstrate higher level of a characteristic that is positively related to wages⁷.

The above analysis reveals that women are not overrepresented among low earnings groups. Thus, the gender gap in Poland is rather related to differences in wages between males and females within each category. In fact, in almost every group presented in Table 1 males' hourly wages are higher than females' hourly wages.

Although women in Poland are far better educated, this not translated to better wages. In every education category females earn less than males. The gap in relative terms amounts to around 20%-30% of females'

⁶ After previous removal of armed forces

⁷ Nõpo (2008) decomposition requires a categorical variable. The distribution of tenure is highly skewed, so we generate variable indicating tenure quartiles.

average wage in 4 categories of lower education. Among people with tertiary education the gap is smaller and amounts to 14% of females' average wage. The same applies to occupation categories. The wage gap in relative terms was the highest among high- and middle-skilled occupations (26% and 28% of females' average wages in those categories). More variation is observed between industries. The biggest wage gap both in absolute and relative terms is observed in manufacturing sector (24% of females' average wage), gap exceeding 10% is observed within both market and non-market services sectors, and very small and insignificant gap of 2% exists in agricultural sector. In construction sector females earn significantly more – the gap equals -10%. This is not surprising, given that the low earners in construction are mostly male physical workers, while majority of females perform high-skill tasks. When form of ownership is concerned, the wage gap persists in both categories, and it amounts to 8% of female wages in the public sector and 16% in the private one. Similar situation applies to the divisions by size of the firm. Gender wage gap is also observed in every selected category reflecting place of living, and it is higher in Mazowieckie region and in larger cities.

Initial analysis performed above indicates that the overall gender wage gap is rather related to wage differences between males and females with similar characteristics, but the validation of this intuition can only be achieved by applying decomposition methods. Controlling only one characteristic at a time, may lead to misleading results – like in case of the gap in construction sector, where controlling additionally for education level would change the sign of the gender gap. Decomposition methods enable comparing individuals that are similar in all dimensions.

4 Gender wage gap decomposition

We explore the estimates of the adjusted gender wage gap in Poland in three steps. First, we estimate components of gender gap decompositions for the whole period 1995-2012. For the overall gap we are able to transparently present the impact of choosing a particular set of conditioning variables on both parametric and non-parametric decomposition estimates. Second, we present the decompositions for each quarter of the analyzed period. Third, we move to investigating the cyclical properties of the gender wage gaps.

4.1 Components of gender gap over the period 1995-2012

According to Nõpo (2008), the raw wage gap is decomposed into four additive components: first three components of the decomposition, $(\Delta_M + \Delta_X + \Delta_F)$, make up the explained part of the gap, that is due to differences in characteristics between females and males. The last component, Δ_0 , is the unexplained part of the gap, also called the adjusted wage gap, that is due to discrimination, or unobserved differences in characteristics that determine wages. Among explained components:

- Δ_M , can be explained by differences between two groups of males – those who cannot be matched to females and those who can. This component can be also interpreted as expected increase in females' average wage if females achieve those individual characteristics of males that are “unreached” by females.
- Δ_X , is due to differences in distribution of individual characteristics over the common support (for example there are two males and only one female with a particular combination of characteristics). This component expresses how much would average males' wages decrease in a hypothetical situation in which their individual characteristics follow the distribution of females' characteristics (i.e. number of males with particular combinations of characteristics will be equal to the number of females with this combination of characteristics).
- Δ_F , is explained by differences in average wages of females that can be “matched” to males and of those “unmatched”. It measures how the average wage of females would increase if all females achieved the combinations of characteristics that are comparable to those of males.

Consequently, the reliability of Δ_0 as a “true” measure of the gender wage gap depends on how adequate the matching procedure is. Namely, if only few women are matched to the men available in the set, the results loose generality. On the other hand, if only few men are matched, then the gender wage gap is computed with reference to only a segment of the market, i.e. inaccurate. To test actually, how important that is in the case of Poland, we perform a series of decompositions on a pooled set of all observations between 1995 and 2011, in which we manipulate which variables are included in the matching procedure. The results are reported in Table 2. In fact, each separate variable does not affect the estimates of gender wage gap significantly, keeping also the share of matched males and females fairly comparable. However, inclusion of all the variables in one specification reduces the match rate to approximately 50%-60%. At the same time the differences in the estimates of the gender wage gap between specifications differ only by maximum 2 pp.

Table 2: Results of Nōpo (2008) decompositions depending on the conditioning variables

Controls	Raw gap	Unexplained component	Explained component			Share of matched males	Share of matched females
Demographic variables	9%	20%	0%	-1%	-10%	99%	97%
+ Occupation category	9%	20%	0%	0%	-11%	96%	92%
+ Industry category	9%	20%	-1%	-1%	-9%	90%	92%
+ Tenure	9%	21%	0%	-1%	-11%	97%	92%
+ Firm Size	9%	19%	0%	0%	-10%	99%	95%
+ Ownership	9%	20%	0%	-1%	-11%	99%	95%
All variables	9%	19%	-3%	-1%	-7%	52%	59%

Source: Own preparation

In case of Poland, comparing two specifications, basic one controlling only for demographic characteristics, and the one controlling for all available variables, reveals that adding job-related and contract-related characteristics separates low earning males from the common support. However it makes the component related to differences in characteristics within the common support smaller, thus the overall explained component is similar among specifications and amounts to around -11%. This means that if women had the characteristics of males, they would earn 11% less then now. Thus the raw difference in earning between females and males rises from 9% to 20% if we compare similar females and males.

Table 3: Results of Oaxaca (1973) – Blinder (1973) decompositions depending on the conditioning variables

Controls	Raw gap	Unexplained component	Explained component	R2 in male regression	R2 in female regression
Demographic variables	9%	22%	-12%	55%	59%
+ Occupation category	9%	23%	-14%	56%	61%
+ Industry category	9%	22%	-12%	55%	59%
+ Tenure	9%	22%	-13%	57%	60%
+ Ownership	9%	21%	-12%	56%	60%
+Private	9%	22%	-13%	55%	59%
All variables	9%	22%	-13%	59%	62%

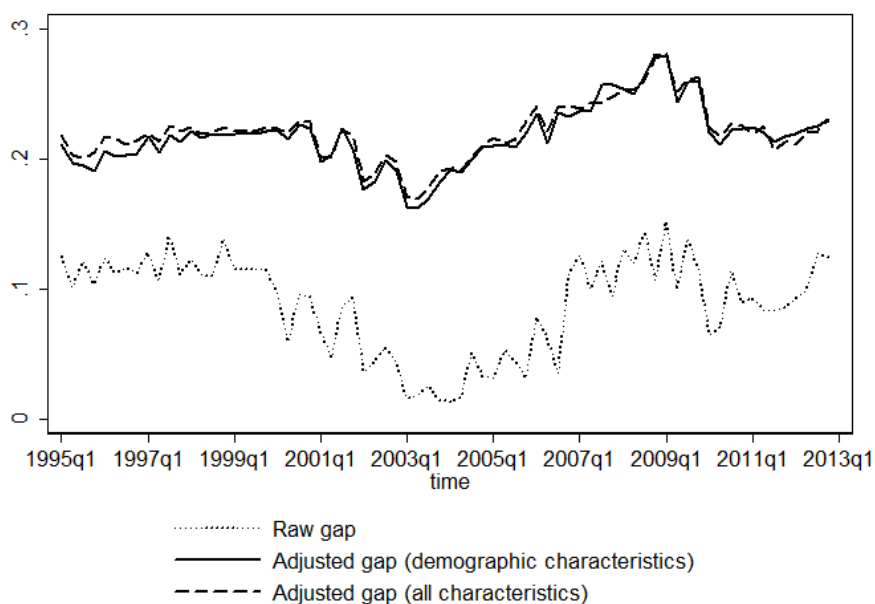
Source: Own preparation, detailed parameter estimates available upon request

We repeated this exercise for the Oaxaca (1973) – Blinder (1973) decomposition. Here too, the inclusion of additional control variables marginally affects the estimation of the adjusted wage gap, which equals around 22%, and the explanatory power of the wage regression models increases only slightly.

4.2 Adjusted gender wage gap over time

Similarly to the result obtained for the pooled sample, in every analyzed quarter the estimation of adjusted wage gap is similar among specifications. Over the whole analyzed period 1995-2012 the adjusted gender wage gap is much larger than the raw gap. Figure 3 presents the raw gap, and two specifications for adjusted gaps – one controller for only demographic characteristics, and the other for all available characteristics, obtained with Oaxaca (1973) and Blinder (1973) method. While there are almost no differences between the latter, the difference between raw gap and adjusted gap amount to around 10pp both at the beginning, and at the end of the analyzed period.

Figure 3: Raw wage gap and adjusted wage gaps over time, Oaxaca (1973) – Blinder (1973) decomposition

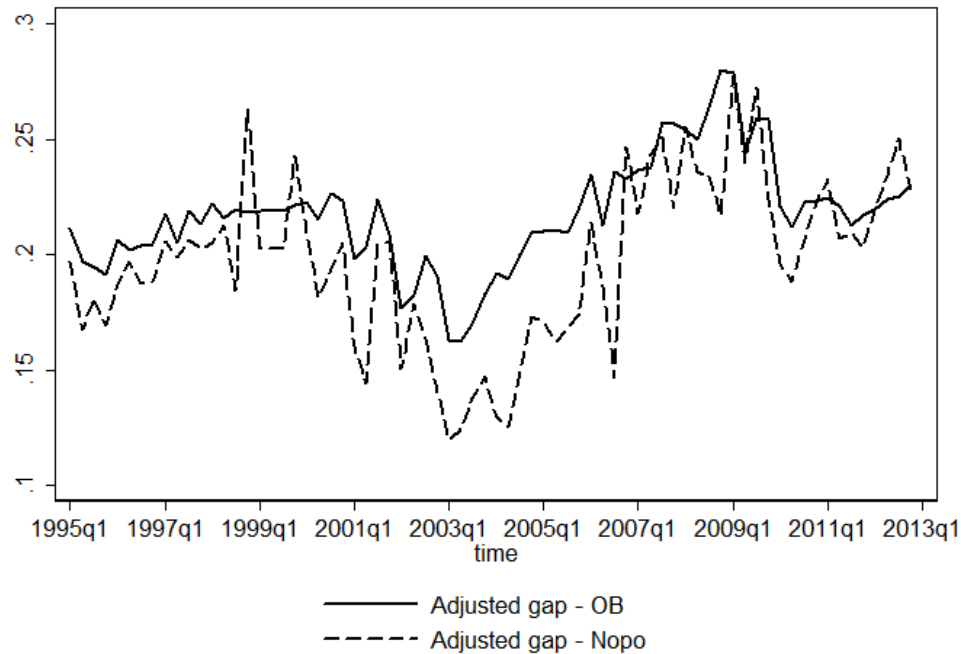


Source: Own preparation, detailed parameter estimates from both male and female equations available upon request

Figure 4 compares the estimates of the gender wage gaps between methods, revealing that also for every quarter separately Nöpo (2008) and Oaxaca (1973) and Blinder (1973) decompositions lead to similar conclusions, although Nöpo (2008) decomposition estimates are characterized by greater variability⁸. We find no decreasing trend in the extent of the adjusted gender wage gap in Polish labor market. While we do not take any stance on the causal interpretation, the lack of the trend is inconsistent with the potential hypotheses which are used to explain the gender wage gap. Namely, it is often argued that family functions asymmetrically distributed across genders provide an unobservable yet rational reason for women to receive lower pay for observationally the same work. However, fertility is systematically decreasing over time, while gender wage gap remains constant. This suggests that although family functions may play a role, they are not likely to capture the time evolution of the extent of unequal pay. Clearly, this topic requires more research.

⁸ Figure 3 shows the adjusted gaps for the most general specification of basic characteristics. Estimates of adjusted gaps for other sets of controlled variables for every quarter are available upon request. The same applies to the estimates from wage regressions for Oaxaca (1973) and Blinder (1973) decompositions, and to estimates of other decomposition components for Nöpo (2008) decomposition.

Figure 4: Adjusted wage gaps (controlled for demographic characteristics) over time – comparison between Nõpo (2008) and Oaxaca (1973) – Blinder (1973) decompositions



Source: Own preparation

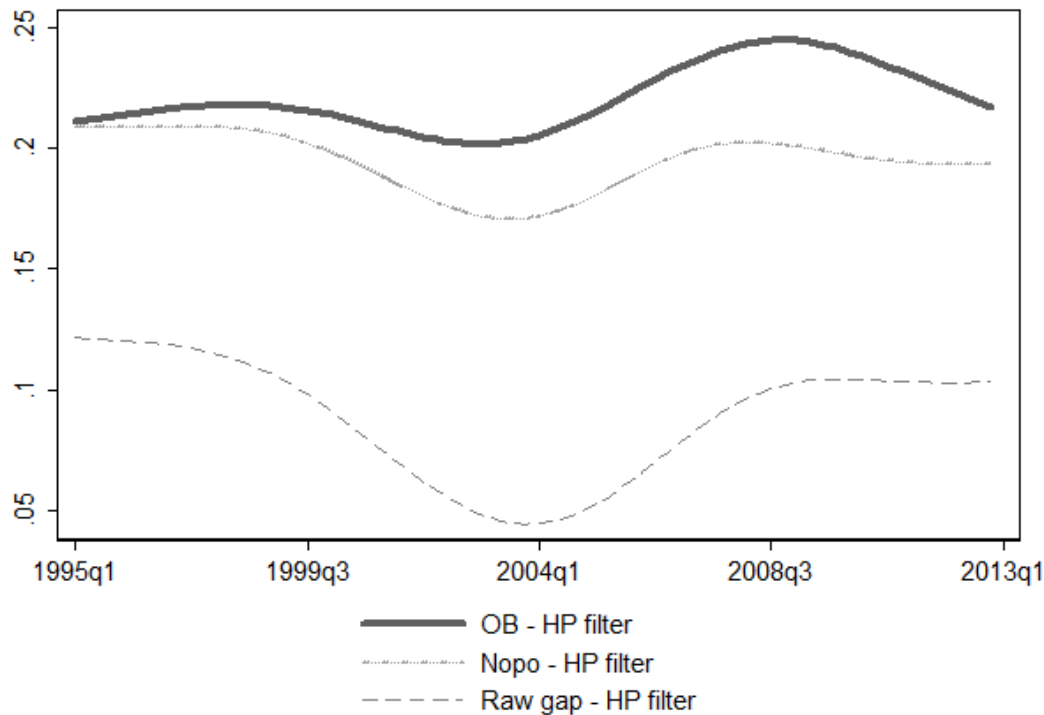
Figure 4 suggests that the adjusted gender wage gap have cyclical properties. There are a number of reasons why one may expect this sort of pattern. First, taste based discrimination is likely to be more sustainable in the periods of lower labor market tension. High unemployment can thus be conducive to more selective hiring. Higher productivity growth could justify less selective hiring, on the other hand. Similar may be true of the unit labor cost – high dynamics are typically consistent with tight labor market and intensive demand for labor. We further explored in detail the cyclical properties of the gender wage gap.

4.3 Cyclical properties of the gender wage gaps

We apply Hodrick & Prescott (1997) filter to eliminate the impact of short-term fluctuations on the quarterly raw and adjusted gender wage gaps. Figure 5 shows smoothed time series of the raw gap, as well as adjusted gaps calculated with Nõpo (2008) and Oaxaca (1973) and Blinder (1973) decomposition methods⁹. While the raw gap is significantly lower in the middle of the analyzed period, the adjusted gaps seem to be more stable over time.

⁹ We use the specification as in figure 4.

Figure 5: Adjusted wage gap, HP filter ($\lambda=1600$)



Source: Own preparation

In order to interpret observed time trend of gender gaps we explore the relation between raw and adjusted gaps and macroeconomic variables. Not surprisingly gender gaps are strongly correlated with each other, and with its lagged values which further corroborates persistency over time.

Correlation coefficients indicate that gender gaps are negatively related to unemployment. This might suggest that during economic downturns when separation rates increase, the employers tend not to differentiate wages due to reasons unrelated to productivity. Another possible explanation is that discriminated groups (in our case: women) have more limited access to employment. If indeed employers become more selective in hiring/firing, those who manage to stay in the labor market may actually receive more equal pay for observationally similar characteristics. In fact the correlation between the unemployment with both raw and adjusted wage gaps has similar strength, which substantiates the latter of the two interpretations.

Both raw and adjusted gaps exhibit also negative correlation with productivity growth rates. This finding further corroborates the interpretation that in the periods of higher labor market tension, employers are less selective towards genders, opening access to the labor market to an otherwise marginalized group. This last claim seems even more grounded if one compares the correlates of raw and adjusted gender wage gaps with the dynamics of unit labor costs. The clear, robust and positive correlation with relatively strong persistence suggests that when productivity falls short of wage growth (the peak and slowdown phase), gender wage gap strengthens. Conversely, drop in ULC typically associated with less tense labor market due to accumulated unemployment and improving demand (the through and recovery), coexists in time with reductions in gender wage gap.

Table 4: Correlations between the gender gaps and macroeconomic variables

	Raw	Oaxaca-Blinder	1 year lag	Nopo (2008)	1 year lag
Oaxaca-Blinder	0.617 (0.000)		0.854 (0.000)		
Nöpo (2008)	0.809 (0.000)	0.785 (0.000)	0.754 (0.000)		0.681 (0.000)
GDP y/y	0.156 (0.204)	0.073 (0.555)	-0.042 (0.733)	0.040 (0.748)	0.021 (0.866)
Productivity y/y	-0.297 (0.014)	-0.565 (0.000)	-0.569 (0.000)	-0.500 (0.000)	-0.422 (0.000)
ULC (SNA)	0.669 (0.000)	0.282 (0.020)	0.235 (0.054)	0.375 (0.002)	0.310 (0.102)
Unemployment	-0.752 (0.000)	-0.731 (0.000)	-0.715 (0.000)	-0.783 (0.000)	-0.750 (0.000)

Source: Own preparation, p-values in the brackets

Productivity growth is far more relevant for the cyclical behavior of the gender wage gap than the overall economic outlook. Actually, correlation between GDP growth and gap measures is insignificant. This finding is quite important because if GDP mimicked the behavior of productivity growth, taste discrimination by the consumers could be an important justification for the male discrimination. However, GDP growth rate does not correlate with the behavior of raw nor adjusted gender wage gaps. It seems that if consumer discrimination exists, it is not particularly strong.

5 Conclusions

Inequalities induced by discrimination pose a serious challenge to both policymakers and society. This rationale underlies equal access legislation in many developing and developed countries. The success of such policies usually consists of opening up many professions to highly skilled individuals previously deprived of the opportunity to adequately use their abilities. Hsieh *et al* (2011) argue that barriers like racial and gender discrimination may have led to a 16% loss in US wealth over 60 just years. In this paper we analyzed the problem of gender wage gap in Poland, trying to reliably measure its size and observe time-related patterns. We inquired if gender wage gap in Poland may be explained by observable characteristics.

In general, it is inadequate to treat the raw gender wage gap as a measure of discrimination. Women may display characteristics that are not valued (or less valued) by the labor market. To account for that possibility, a number of methods has been designed, which all attempt to adequately incorporate the differences in endowments of men and women in comparing their wages. The standard in this literature – the Oaxaca (1973) and Blinder (1973) decomposition – has been already argued to display some weaknesses. In particular, it has been emphasized, that if men and women differ in the *combination* of characteristics, the standard parametric decompositions may estimate gaps in non-existing segments of the labor market. Nöpo (2008) method employs exact matching and decomposes the raw wage gap into the (traditional) unexplained part and the components attributable to specificity of men and women in terms of labor market endowments. Despite considerable differences in activity rates between men and women in Poland, the bias in the estimate of the adjusted gender wage gap due to the lack of overlap does not seem to be large. The estimates from parametric and nonparametric estimation have proven to be fairly similar and relatively well correlated across time. Analysis of gender differences in characteristics demonstrates that females to a greater extent exhibit characteristics that are well rewarded in the labor market. Despite better education, they are less frequently employed in better paying positions. Decomposition analyses confirm this assertion, showing that the discrimination component

quantitatively dominates. In fact, gender wage gap in Poland, understood as the difference in average male and female wages, cannot be explained by gender differences in observable characteristics. Estimators of actual gender gap in hourly wages obtained with both parametric and non-parametric methods indicate that a measure adjusted for differences in characteristics is actually twice as big as the raw wage gap differential and amounts to as much as 20%. Furthermore, neither raw nor the adjusted gender wage gap seems to be decreasing over time.

The key finding of this paper consists of analyzing the cyclical patterns of gender wage gap in Poland. We employed 72 datasets from the Labor Force Survey and obtained the estimates of raw and adjusted gender wage gap for each quarter over 1995-2012 span. We find that in terms of the long term trend, adjusted gender wage gap is far more stable than its raw values. This suggests that even if the simple comparison of means across the two genders shows convergence of compensations, in fact (observationally and unjustifiably) unequal pay for females remains as high as it were in early transition. In fact, if variable at all, the adjusted gender wage gap conforms to the behavior of unit labor costs - the more lax the labor market conditions, the higher the chances for women to be less unequally compensated.

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