https://gospodarkainnowacje.pl
GOSPODARKA I INNOWACJE
Volume: 52 | 2024
Economy and Innovation
ISSN: 2545-0573
For more information contact: editor@gospodarkainnowacje.pl

GENDER WAGE DIFFERENTIALS IN INDIAN LABOUR MARKET

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ARTICLEINFO.

Keywords: gender wage differential, Oaxaca Blinder decomposition, NSS 68th Round.

Abstract

This paper seeks to address the issue of gender discrimination in wages and earnings in India. We use data from the 68th round (2011-12) of National Sample Survey on Employment Unemployment schedule (NSS-EUS) to explore the gender wage gap in the formal sector by setting up a log wage regression model. We introduce a gender dummy along with labour characteristics like education, experience etc. as explanatory variables to estimate gender discrimination when men and women have identical wage structure and further ascertain how returns to productivity characteristics varies for both the genders.

Next, we introduce the classic Oaxaca Blinder decomposition technique to ascertain the factors that contribute to such a wage gap in the labour market: whether it is primarily due to the endowment effect i.e. differences in covariates like education, health, work experience etc. or there is significant presence of the unexplained factor (or simply discrimination) in the market.

Finally, this paper compares and interprets the results of the two aforementioned methodologies while acknowledging its limitations and underlying assumptions and attain a better understanding of the labour market and factors that cause this wage gap. The paper concludes with a discussion as to why gender parity is desirable for sustainable economic growth.

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1. INTRODUCTION

Any country which aims for economic growth and prosperity must realise that such growth can only be sustainable with a strong foundation of social infrastructure and one aspect of this social infrastructure is the principle of equality and inclusivity. While inequalities on the basis of caste, creed, and income have shown much improvement, gender parity took a reverse trend for the first time since 2006 (Global Gender Gap Report, 2017). This trend is primarily driven by declining gender parity under the dimension of Economic participation and opportunity. South Asia is the second lowest scoring region on the report, ahead of Middle East and North

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Africa and behind Sub-Saharan Africa. While it constitutes a good mix of top performers like Bangladesh, Maldives and Sri Lanka, there are also countries which are on the lower rung of this index like Bhutan and Pakistan. The results for India are a mixed bag. It has performed extremely well on the educational front but more efforts are needed in the other three dimensions- Health and Survival, Political Empowerment, Economic opportunity and participation. This study, therefore seeks to analyse the discrimination aspect of the last dimension i.e. economic opportunity and participation by specifically focussing on the labour market. Additionally, the study seeks to understand the hindrances to achieving gender parity. Thus, a gender wage analysis of the Indian labour market can serve the perfect median to all the South Asian countries.

While, there is no dearth of literature on gender wage discrimination in India and abroad, estimating wage differentials through various methodologies. This paper seeks to use the latest round of NSS EUS data to update the estimates of gender wage differentials and gender bias in the labour market for future researches and hence facilitate comparative studies.

2. LITERATURE REVIEW

A cross country analysis shows strong evidence of gender wage gap attributing to discrimination in India where the 'explained' component accounted for only one-fifth of the wage differential (Madheswaran and Khasnobis, 2007). Its South Asian counterparts like Sri Lanka (Gunawardena, 2006), Bhutan (Tobden, 2017) and Pakistan (Sabir and Aftab, 2007) also depict a similar picture with huge gender wage differentials. Interestingly, despite such huge difference in wages due to discrimination, the returns to labour characteristics like education, skill development and experience are increasing and in some cases more than 100 percent for women. Thus, implying that in the absence of such gender wage bias, women may earn more than men. These similarities in the conclusions drawn for the South Asian countries, imply that a more cooperative research and policy effort can improve the gender statistics of all its member paving the way for a more balanced and sustainable growth.

There is now a vast literature measuring and accounting for income or earning differentials between various groups of majority and minority. Oaxaca and Blinder (1973) were the first economists who made an attempt to analyse it quantitatively by developing an equivalent decomposition from human capital theory. They decomposed the wage gaps into two different components: differences in endowments and the residual. Blinder, further identifies two components of the discrimination residual, one due to differences in the coefficients and another due to the 'shift' coefficient or differences between the intercepts. The latter part is termed as the unexplained part of the discrimination. Another extended version of this methodology further decomposes the discrimination component into- (a) underpayment to the minority due to discrimination and (b) overpayment to the majority due to favouritism. This technique brings about more economic insights than the former and even solves much of the problems with Oaxaca Blinder. However, a major operational weakness is the inclusion of unobserved vector which must be estimated if the formulation is to be useful for empirical work. Moreover, its rather strong assumptions which are a restatement of the conclusions required have been a subject of much criticism.

Different aspects of wage discrimination in the labour market have been studied by a number of scholars by applying different methodologies and with data from different parts of the developing world (Oaxaca 1973; Cotton 1988; Oaxaca and Ransom 1994; Banerjee and Knight 1985; Gunewardena 2008). Madheswaran and Attewell (2007) found that occupational discrimination was more pronounced than wage discrimination among workers in scheduled tribe (ST) and scheduled caste (SC) social groups. Sengupta and Das (2014) incorporated religion to gender wage gap using the Heckman's two-step selection model. They found that the discrimination is more in case of Muslim women but overall discrimination trends are on the decline since the post reform periods. Deshpande, Goel and Khanna (2014) used Boserup's proposition and Labour force participation ratios (LFPRs) to determine gender wage gap. By the mid-1990s, newer decomposition methods have come which seek to go beyond the

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mean and know *what happened where* by incorporating quantile regressions. These methodologies also give rise to new and interesting terminologies like Sticky floor effect and Glass ceiling effect (Khanna, 2012).

3. THEORETICAL FRAMEWORK

Economic models of discrimination can be divided into two classes: competitive and collective models. Competitive models study individual maximizing behaviour that may include discrimination. In collective models, groups act collectively against each other. Most models are focussed on competitive models, hence we focus our attention here. Competitive models further are of two types: taste-based (Becker's) and statistical (Arrow's) models of discrimination. For this study, we use Becker's model of economic discrimination.

Gary Becker, in 1950s developed a neoclassical model to study discrimination, wherein he introduced the concept of a 'taste for discrimination' which means there's a disamenity value of minority workers to employers, employees or customers based on the assumptions of perfect competition and utility maximisation. Hence, minority workers may have to 'compensate employers' by being more productive at a given wage or equivalently by accepting a lower wage for identical productivity. He defined discrimination as a phenomenon when members of a minority are treated differently or less favourably than the members of a majority group with identical productive characteristics. Or mathematically, let the wage Y be equal to

$$Y= X\beta + \alpha z + e$$

where X is a vector of exogenous productivity characteristics and Z is an indicator variable for membership in a minority group. Assuming that $X\beta$ fully captures the set of productive characteristics and their returns and/or Z is uncorrelated with e, then discrimination appears as a possibility when $\alpha < 0$.

The result of the model showed that in equilibrium the firms which differentiates on the basis of gender tends to make lower profits than non-discriminating firms. Such loss making firms in the long run will either have to shut down or will be acquired by the profit-making non discriminating firms. Thus, it is assumed that in the long run there will be no discrimination in the labour market at equilibrium.

4. DATA SOURCES

For the purpose of estimation, this paper relies on the data provided by the NSS Employment Unemployment Survey (EUS), Schedule 10, for the year 2011-12, i.e., the 68th round (which is the latest round available). The EUS provides wage information for casual labourers, regular wage workers and self-employed. With respect to the objective of the study, we define a worker in the formal sector as one who works in others' farm or non-farm enterprises, receives a salary or wage on a regular basis and is within the working age set by the labour laws. Hence, the data is restricted to the regular wage/salaried full time workers with age between 15 to 59 years. After making all these arrangements, we are left with a sample of 40,196 workers in the regular wage market which represents a population of 4.56 lakh observations. Reasons to exclude casual workers is that the covariates like education and experience do not explain the variation in the wage rate for casual workers and self-employed as they do for the regular wage workers. Moreover, this paper intends to see if there exists gender wage discrimination in a sector which is governed by the labour laws of equal pay for equal work and if at all there exists discrimination then whether the same factors explain the discrimination in other economies.

5. METHODOLOGY

5.1 Mincerian wage functions

According to human capital theory, accumulation of human capital through education and training enhances worker's skill, productive capacities and their life-cycle earning. The relationship between

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wage and experience, education is well documented in the literature (Mincer 1958, Becker 1964). Based on this logic, it is argued that gender wage gap occurs due to differences in the level of education, experience and other covariates between men and women. Hence, we calculate discrimination using gender as a predictor for ascertaining earnings from characteristics of all workers (a single equation technique).

Mincerian wage function is typically a logarithm of wages modelled as a sum of years of education and a quadratic function of 'years of potential experience'. It is expressed as-

$\ln w = f(s, x) = \ln w_0 + \rho s + \beta_1 x + \beta_2 x^2$

where w is the earnings (intercept $\ln w_0$ is the earnings of someone with no education and experience; s is the years of schooling; x is the years of potential labour market experience while the parameters ρ, β_1, β_2 can be interpreted as the returns to schooling and experience respectively.

To accommodate the objective of our study, we estimate an augmented Mincerian earnings function with a gender dummy in the regular/salaried labour market. The logarithm of the weekly wage is used as the dependent variable, while potential experience, level of education, gender, marital status, sector, union and an interactive dummy of gender and education are taken as the explanatory variables. The general form of this regression equation can be expressed as-

$LnWAGE = \beta_1 + \beta_2 X_i + \beta_3 D_i + \beta_4 X_i D_i + u_i$

where,

X_i's are quadratic functions of productivity coefficients

D_i is gender dummy

$X_i D_i$ are interactive dummies of gender and productivity coefficients

We make the following adjustments to incorporate the NSS data into our study;

(a) *Experience*: Since the years of potential experience in labour market is not easily observed in the NSS data we define age minus 6 as a proxy for experience which has been extensively used by various researchers in the literature.

(b) *Experience square*: Since experience has a twofold impact on the wages, we intend to capture it through a quadratic function of experience drawing on the lines of Mincerian wage function. While an increase in experiences augments the earnings of the workers but as the workers' experience increases, the worker becomes more expensive for the firm. This is because they demand higher wages due to seniority and exhibit lower productivity due to the natural process of aging as compared to their younger compatriots.

(c) *Education dummies*: Instead of number of years of schooling, NSS assigns a unique number to each level of general education. Therefore, we define educational dummies for each level of education i.e. below primary, primary, middle, secondary, higher secondary, graduate and post graduate (with benchmark category as illiterate).

(d) *Gender dummy*: In order to capture the differential returns to wages on the basis of sex, we define a gender dummy with benchmark category of a male worker.

(e) *Interactive dummy of gender and education*: We capture the difference in returns to education to men and women through the simultaneous effect of gender and productivity aspects on wage.

(f) *Marital status*: Effect of marital status on earnings of the worker

(g) *Sector*: Effect of rural/urban sector on wages

(h) *Union*: Effect of union membership on wages

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While the mincer earnings function is one of the most widely used models in empirical economics, serving this methodology as the basis to estimate discrimination in the labour market can give dubious results. This is because it assumes that men and women have identical wage structures. Further, it is unable to distinguish between wage inequality on the basis of gender bias and due to differences in productivity of the two sexes.

5.2 Oaxaca Blinder Decomposition

In his seminal paper on labour market discrimination, Becker (1971) defined a competitive market discrimination coefficient as the difference between their observed wage ratio and the wage ratio that would prevail in the absence of discrimination. Oaxaca (1973) expressed this difference in percentage terms as

$$D = \frac{(Wm/Wf - MPm/MPf)}{MPm/MPf} \quad (1)$$

Where $\frac{Wm}{Wf}$ is the observed male-female average wage ratio, and $\frac{MPm}{MPf}$ is the ratio of the male-female average marginal products, which by assumption is the average wage ratio in the absence of discrimination. Expressed in logarithm form, (1) becomes the male-female average wage differential:

$$lnWm - lnWf = lnMPm - lnMPf + \ln(D+1) \quad (2)$$

The difference between the marginal products is that part of the wage differential that is due to differences in male-female productivity and $\ln(D+1)$ is the treatment, or discrimination component. This decomposition can be further applied within the framework of semi-logarithmic earnings equations (mincer 1974) and estimated via Ordinary Least Squares (OLS) such that:

$\ln \bar{Y}_f = \sum \beta_f \bar{X}_f + e_f$ (female wage equation) (3)

$\ln \bar{Y}_m = \sum \beta_m \bar{X}_m + e_m$ (male wage equation) (4)

$\ln \bar{Y}_m - \ln \bar{Y}_f = \sum \beta_m \bar{X}_m - \sum \beta_f \bar{X}_f$ (subtracting (3) from (4)) (5)

The difference in the earnings function can be taken as the priori evidence of discrimination. If for a given endowment, female individuals are paid according to the male wage structure in the absence of discrimination, then the hypothetical female and male wage function can be given as;

$$lnY_f = \sum \beta_m X_f \quad (6)$$

$$lnY_m = \sum \beta_f X_m \quad (7)$$

Adding and subtracting equation (6) in (5), we get equation (8). With similar manipulations in (5) and (7), we get equation (9).

$$\ln \bar{Y}_m - \ln \bar{Y}_f = \sum \beta_j^m (\bar{X}_j^m - \bar{X}_j^f) + \sum \bar{X}_j^f (\beta_j^m - \beta_j^f) \quad (8)$$

$$\ln \bar{Y}_m - \ln \bar{Y}_f = \sum \beta_j^f (\bar{X}_j^m - \bar{X}_j^f) + \sum \bar{X}_j^m (\beta_j^m - \beta_j^f) \quad (9)$$

where, $\bar{X}$ j's are average productivity determining characteristics and Bj's are least square regression coefficients and superscripts 'm' and 'f' refer to male and female respectively. Referring to the two equations, the left hand side represents the gender log wage differential. While on the right hand, the first term is an estimate of ($\ln MP^m - \ln MP^f$) i.e. difference in marginal products and the second term is an estimate of the discrimination component.

Equation (8) and (9) are the two assumptions of Oaxaca which we use to estimate the male-female wage ratio in the absence of discrimination. If there is no discrimination, then as per (8), the wage structure currently faced by males would also apply to females and as per (9), the wage structure currently faced by females would also apply to males.

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This approach entails the problem of index number. It is assumed that in the long run the wage structure of both the sexes would converge but the path of convergence as stipulated by (8) and (9) does not make any sense in real life. This is because if the males receive the same wage irrespective of the presence of discrimination in the labour market, they would have no economic reason to object resulting in ‘extra-market benevolence’. Similarly, as per (9), the females will get the same wage irrespective of discrimination, while males will get a lower wage than what they got before, hence creating an environment of ‘extra-market-malevolence’. Oaxaca and Blinder treated the issue by obtaining the estimates from both the formulations and using them to establish a range within which the true values of the components presumable would fall or taking weighted means of the two estimates depending on the sample study of the researcher (Cotton, Neumark, Reimers 1988).

However, the principle concern of this methodology has been statistical in nature. Since, we have defined discrimination as the residual term, omission of any variable due to limitations of data or measurement error would be reflected as omission influences on the error term. Thus, for an exact estimation of labour market discrimination all the factors determining the wage must be present and properly accounted for. Or else, it would lead to over- or under-estimation of the discrimination term.

Finally, we compare the results from our basic model to the decomposition results to grab a better understanding of the data. We further take note of the criticisms and implications of each of the methodologies to gain perspective.

6. RESULTS

The data used in this analysis is taken from the 68^{th} round of NSS, Employment and Unemployment Schedule. The data provides information on the weekly wages of casual workers, regular salaried/wage employees and self-employed (with a sample constituting 20% females and 80% males). We restrict ourselves to the weekly wages of the workers in the formal sector and do not indulge in calculating wages per day as it would further complicate the process since the number of working days differs from worker to worker and weighted averages of per day wages does not reflect normality as in the former case.. The average wage per day for men and women is Rs 455.428 and Rs 341.857 respectively. Therefore, in absolute terms, gender wage gap equals Rs 113.57 which is almost 25% less than that of men.

6.1 Mincerian wage function

The estimates of relative wage gap by gender on the basis of observed data provides us with a gross idea about labour market conditions of the economy. Looking at the regression results from Table1.2 we find that all the variables are significant at 5 per cent except the interactive dummies for below primary, primary education and gender. The explanatory variables explain 43 percent of the variation in dependent variable lnwage which in comparison to the results in the literature are quite robust given the limitations of NSS data and multiplicity of factors that affect the earnings of a worker like education, experience, gender, marital status, occupation, industry, caste profile, union membership, contracts and sector among others. On the basis of the regression results, we take note of the following observations.

1) The positive coefficients of experience and education dummies reaffirm the Human Capital Theory that the given factors result in human capital formation and result in higher earnings for the worker. It also reflects the twofold relationship between experience and earnings. The wages increase as the years of potential experience in labour market increases and it increases at a decreasing rate as the workers efficiency falls due to aging. This is reflected from the negative sign of the experience square variable.

The education dummies not only have positive coefficients but also increasing values as we move towards dummies of higher education (0.08 for below primary education to 1.19 for post-graduates) which is in sync with the theory. The benchmark category is of those workers who are illiterate or have

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less than two years of any type of formal education.

2) The gender dummy represents the fall in lnwage due to the *identity* of the workers on the basis of sex. It means that if men and women have identical wage structures then 73.5 per cent of this difference is due to the gender bias prevalent in the labour market.
3) Next, we consider the interactive dummies of gender and education. The coefficients are positive and increasing as we move from below primary schooling to post-graduation and above. This confirms that women have higher returns to education than men and gives a theoretical backing to government initiatives to educate the girl child.
4) Other factors like marital status, union membership and urban sector also play a role in augmenting a worker's earnings. This also means that unmarried workers, non-union members and workers in the rural sector have lesser wages as compared to their respective compatriots.

6.2 Decomposition Results

In order to overcome the limitations of single regression equation, we move on to the next methodology i.e. Oaxaca Blinder Approach where the earnings function of each of the sexes are subjected to decomposition. We consider both threefold and twofold decomposition results for better insights and then construct a range for gender discrimination component in the labour market.

Table 1.4 and Table 1.5 indicate that the unexplained component or simply discrimination is larger than the endowment component. Going back to the two assumptions of Oaxaca, while using female wages as weights, approximately 95 per cent of the gender wage gap is due to discrimination and a meagre 5 per cent due to endowment differences. When male wages are used as weights then approximately 90 per cent of the gender wage gap is due to bias and about 10 per cent due to productivity differences. Therefore, we can define a range from these estimates that discrimination component explains about 90-95 percent of wage differential signifying widespread prevalence of gender bias in the labour market.

Table 6.2: Comparative Analysis of Decomposition Results

lnwage	**Oaxaca Blinder (using female wages as weight)**	**Oaxaca Blinder (using male wages as weight)**
lnwage (men)	7.667948	7.667948
lnwage(female)	7.205305	7.205305
Difference	0.462643	0.462643
Endowment difference	0.0230031 (5%)	0.0478306 (10%)
Discrimination	0.43964 (95%)	0.4148114 (90%)

We now look at the individual contributions of each of the variables to the wage difference. Most of the coefficients are significant at 10 per cent. Table 1.4 and 1.5 indicate that there is unexplained difference in women's wage on the basis of experience and marital status. This means women tend to face a penalty for social requisites like marriage and child rearing in the labour market. This could be due to the fact that women tend to leave the workforce once they're married or have children and devote a greater time to household chores after a certain age which not only results in lesser experience but also creates a bias amongst the firms who prefer continuous flow of labour to optimise profits. However, we also notice significant negative coefficients (especially for higher education dummies and experience square) under the unexplained component. This implies that the bias on the basis of experience is falling leading to reduced gender wage differentials. Moreover, it also throws light on the effects of girl child education in reducing gender wage gaps as it has a significant diminishing effect on gender discrimination.

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Clearly the labour market scenario for uneducated female workers with low productivity is gloomy but there is also an equal (or atleast near equal) set of opportunities for educated women with higher productivities.

7. CONCLUSION

7.1 Comparisons with the literature

To observe the gender dynamics in the labour market, we estimated the average wages of men and women and the extent of wage difference between the two due to their respective gender identities. While the augmented Mincerian earnings function ascertained 73.5 per cent of wage gap due to discrimination for identical wage structures, the Oaxaca Blinder Decomposition revealed that when we drop the assumption of identical wage structures, discrimination accounts for about 90-95 per cent of gender wage gap. These predictions are in sync with the results obtained in the literature where in some cases discrimination has been accounted for more than 100 per cent of gender wage gaps signifying that women would have earned more than men in the absence of discrimination prevalent in the labour market (Khanna, 2012).

Although the gender bias is widespread in the economy, the incidence of burden is higher on women with lower levels of human capital in terms of education, skills, experience and those who belong to a minority community. However, the returns to investment in human capital are higher and rewarding for women in terms of wages earned. Our observations are similar to Sengupta and Das (2014) which analysed the stark discrimination faced by women of religious and tribal-social groups in the job market.

The results of our study are significant and consistent but for a deeper understanding of the gender wage dynamics we must not ignore the limitations of the two methodologies. It is equally important to fully appreciate the underlying theory of discrimination that guides the construction of decomposition and discrimination formulae for a more accurate interpretation of resulting components (Cotton 1988; Madheswaran and Attewell 2007)

7.2 Qualitative Analysis of Gender Wage Differentials

In India and even in South Asia for that matter, traditionally women bear the primary responsibility to take care of the household chores which is further reinforced by societal and religious norms. As a result, women disproportionately face the burden of family duties as compared to men forcing them to drop out of the labour force at an early age. Due to low labour force participation (Deshpande 2015) and higher probability of dropping out of labour force, firms discriminate against women as they foresee future career interruptions. Moving beyond the labour market discrimination, there are various supply side factors that result in decreased productivity levels of women. In the Indian context, a girl child is considered a burden to the family due to the ideological foundations of patriarchy. They are often neglected and given less attention than boys even in terms of basic amenities like healthcare, nutrition and elementary education. This unequal access to healthcare services, educations and various pre-requisites for a normal social functioning result in *depreciation of capabilities*. This along with social malpractices like dowry and female infanticide has led to the phenomenon of 'missing women' in the South Asian Labour Market.

It is important to acknowledge that gender equality is not only a socially desirable outcome for a utopian society but also an essential ingredient to a meaningful and sustainable economic growth. Sen rightly said that Gender inequality is not one homogenous phenomenon but a collection of disparate and interlinked problems which might become a hurdle to the engine of growth if it is not given its due importance (Sen 2001). There are various reasons why *Gender Identity* should not be undermined which include:

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1. We know that labour markets are efficient when the demand equals supply and markets clear. Equilibrium refers to the point where the real wage rate equals the marginal product of labour. However, in real life marginal productivities are hardly observable. As a result, employers hire workers according to their opinion about the productivity of the labour. Interestingly, it was found that the employers' opinion about 'merit' is strongly dependent prevalent rankings of social identities. (Bertrand and Mullainathan 2008). As a consequence, the economy always reaches an equilibrium which is inefficient. (The Economist; Donna Ginther 2017). Therefore, one cannot realise the maximum potential of the economy if there is prevalence of any kind if inequality in the economy.
2. Development analysis cannot be divorced from the gender categories and sex-specific observations. Thus gender inequality plays an integral role in global problems of poverty, malnutrition and illiteracy. Studies have shown that the education of mother has significant impact on the wellbeing of the child. Thus, these problems can be dealt with in a better way by including the gender aspect in the government policies.
3. As per the trends, there is a positive relation between economic growth and gender equality. Countries with lesser disamenity towards diversity on the basis of gender, caste, race etc. are able to use their labour resources to their maximum potential and experience growth which encompasses each and every individual of the economy. Studies have indeed shown that policies of affirmative action has worked well for the economy in the long run.

In a nutshell, India's Achilles' feet is its weak social sector which could hamper its growth in the long run. Taking cue from its neighbours, better gender statistics could be the starting point towards more inclusive growth caters to every strata of the economy.

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APPENDIX

1. Tables

Table 1.1: Explanation of Main Variables in the Wage function

Name of Variable	***Explanation***
lnwage	Log of wage and salary earnings (cash + kind)
exp	Potential years of experience
exp_sqr	Experience squared to capture the effect of change of experience over time
bprim	If the worker has completed below primary education=1; 0 otherwise
prim	If the worker has completed primary school=1; 0 otherwise
middle	If the worker has completed middle school=1; 0 otherwise
sec	If the worker has completed secondary school=1; 0 otherwise
hsec	If the worker has completed higher secondary school=1; 0 otherwise
grad	If the worker has completed graduation=1; 0 otherwise
pgrad	If the worker has completed post-graduation=1; 0 otherwise
gender	If the individual sex is female=1; 0 otherwise
bprim_d	Interactive dummy for gender and below primary education (equals bprim*gender)
prim_d	Interactive dummy for gender and primary education (equals prim*gender)
middle_d	Interactive dummy for gender and middle education (equals middle*gender)
sec_d	Interactive dummy for gender and secondary education (equals sec*gender)
hsec_d	Interactive dummy for gender and higher secondary education (equals hsec*gender)
grad_d	Interactive dummy for gender and graduation, diploma (equals grad*gender)
pgrad_d	Interactive dummy for gender and post-graduation (equals pgrad*gender)
marital_s	If the worker is married=1; 0 otherwise
sector	If the worker belongs to rural sector=1; 0 otherwise
union	If the worker is a member of the union=1; 0 otherwise

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Table 1.2: Descriptive Statistics of Main Variables in the Wage function

Variable	Obs	Mean	Std. Dev.	Min	Max
lnwage	40196	7.576561	.9930515	2.302585	13.46311
exp	40196	31.1992	10.64761	9	53
exp_sqr	40196	1086.759	688.2734	81	2809
bprim	40196	.0407752	.1977715	0	1
prim	40196	.0749328	.2632862	0	1
middle	40196	.142452	.3495175	0	1
sec	40196	.1561847	.3630349	0	1
hsec	40196	.140412	.3474183	0	1
grad	40196	.2742561	.4461442	0	1
pgrad	40196	.1025226	.3033382	0	1
gender	40196	.1975321	.3981421	0	1
bprim_d	40196	.0093044	.0960108	0	1
prim_d	40196	.0131605	.1139633	0	1
middle_d	40196	.0195542	.1384641	0	1
sec_d	40196	.0223903	.147951	0	1
hsec_d	40196	.024082	.1533057	0	1
grad_d	40196	.0569708	.2317898	0	1
pgrad_d	40196	.0273659	.1631492	0	1
marital_s	40196	.7625883	.4255019	0	1
sector	40196	.3941686	.4886775	0	1
union	40196	.38163	.4857926	0	1

Kielce: Laboratorium Wiedzy Artur Borcuch

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Table 1.3 Mincerian regression analysis

Source	SS	df	MS
Model	17058.1652	20	852.908258
Residual	22580.1829	40175	.562045622
Total	39638.348	40195	.986151213

Number of obs =	40196
F(20, 40175) =	1517.51
Prob > F =	0.0000
R-squared =	0.4303
Adj R-squared =	0.4301
Root MSE =	.7497

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
exp	.0324577	.0023741	13.67	0.000	.0278044	.0371109
exp_sqr	-.0001093	.0000352	-3.11	0.002	-.0001783	-.0000403
bprim	.085889	.0258846	3.32	0.001	.0351547	.1366233
prim	.1132355	.0225482	5.02	0.000	.0690405	.1574306
middle	.2236738	.0202239	11.06	0.000	.1840345	.2633131
sec	.4382199	.0200537	21.85	0.000	.3989143	.4775256
hsec	.6570863	.0205205	32.02	0.000	.6168657	.6973068
grad	.9560436	.0194211	49.23	0.000	.9179777	.9941094
pgrad	1.198042	.022501	53.24	0.000	1.15394	1.242145
gender	-.7354206	.032106	-22.91	0.000	-.7983492	-.672492
bprim_d	.0851404	.0553612	1.54	0.124	-.0233688	.1936496
prim_d	.0747327	.0504762	1.48	0.139	-.0242018	.1736672
middle_d	.1454654	.044219	3.29	0.001	.0587952	.2321356
sec_d	.2532779	.0452912	5.59	0.000	.1645061	.3420497
hsec_d	.3877125	.044277	8.76	0.000	.3009285	.4744964
grad_d	.4901805	.0374192	13.10	0.000	.416838	.5635231
pgrad_d	.5205228	.0428139	12.16	0.000	.4366065	.6044391
marital_s	.0608988	.0116234	5.24	0.000	.0381166	.0836809
sector	-.1312648	.0077231	-17.00	0.000	-.1464022	-.1161274
union	.4060556	.0084888	47.83	0.000	.3894173	.4226938
_cons	6.026956	.0371734	162.13	0.000	5.954096	6.099817

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Table 1.4 Threefold Oaxaca Blinder Decomposition (with male wages as weights)

```
Blinder-Oaxaca decomposition                      Number of obs    =      40196
                                                  Model            =     linear
Group 1: gender = 0                               N of obs 1       =      32256
Group 2: gender = 1                               N of obs 2       =       7940
```

lnwage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
overall						
group_1	7.667948	.0052012	1474.28	0.000	7.657754	7.678142
group_2	7.205305	.0126856	567.99	0.000	7.180442	7.230168
difference	.462643	.0137104	33.74	0.000	.4357711	.489515
endowments	.023003	.0107851	2.13	0.033	.0018646	.0441414
coefficients	.4148114	.010944	37.90	0.000	.3933615	.4362612
interaction	.0248286	.0065367	3.80	0.000	.012017	.0376403
endowments						
exp	.0339737	.0094344	3.60	0.000	.0154827	.0524648
exp_sqr	.0048872	.0093638	0.52	0.602	-.0134655	.0232399
bprim	-.0013185	.0005953	-2.22	0.027	-.0024852	-.0001519
prim	.0019006	.0007495	2.54	0.011	.0004317	.0033695
middle	.0197684	.0026342	7.50	0.000	.0146055	.0249313
sec	.0361909	.0035088	10.31	0.000	.0293138	.0430679
hsec	.0234609	.0043339	5.41	0.000	.0149665	.0319553
grad	-.0247877	.0079668	-3.11	0.002	-.0404024	-.0091731
pgrad	-.0749349	.0072252	-10.37	0.000	-.0890961	-.0607737
marital_s	-.0055735	.0039295	-1.42	0.156	-.0132752	.0021283
sector	-.0086663	.0017462	-4.96	0.000	-.0120887	-.0052439
union	.0181022	.0034706	5.22	0.000	.0113001	.0249044
coefficients						
exp	.3079842	.1893253	1.63	0.104	-.0630865	.6790549
exp_sqr	-.1560866	.0979645	-1.59	0.111	-.3480935	.0359203
bprim	-.0037642	.0027299	-1.38	0.168	-.0091147	.0015863
prim	-.0044922	.0033994	-1.32	0.186	-.0111549	.0021705
middle	-.0135744	.0045368	-2.99	0.003	-.0224665	-.0046823
sec	-.0266417	.0051128	-5.21	0.000	-.0366627	-.0166207
hsec	-.0432142	.0055841	-7.74	0.000	-.0541588	-.0322696
grad	-.1262476	.0113462	-11.13	0.000	-.1484858	-.1040095
pgrad	-.063714	.0063745	-10.00	0.000	-.0762077	-.0512203
marital_s	.0854103	.0155047	5.51	0.000	.0550217	.1157989
sector	.0610927	.0080659	7.57	0.000	.0452838	.0769016
union	-.0689441	.0083688	-8.24	0.000	-.0853467	-.0525415
_cons	.4670033	.0959453	4.87	0.000	.278954	.6550525
interaction						
exp	.0161728	.0100316	1.61	0.107	-.0034887	.0358343
exp_sqr	-.016273	.0102937	-1.58	0.114	-.0364483	.0039022
bprim	.0006302	.0005014	1.26	0.209	-.0003526	.0016129
prim	-.0006981	.0005691	-1.23	0.220	-.0018134	.0004172
middle	-.0074264	.0025267	-2.94	0.003	-.0123786	-.0024741
sec	-.012546	.002565	-4.89	0.000	-.0175734	-.0075187
hsec	-.0081707	.0017976	-4.55	0.000	-.0116939	-.0046476
grad	.0077224	.002567	3.01	0.003	.0026912	.0127536
pgrad	.0206412	.002769	7.45	0.000	.0152141	.0260683
marital_s	.025599	.0047133	5.43	0.000	.0163611	.0348369
sector	.0053836	.0012292	4.38	0.000	.0029744	.0077927
union	-.0062063	.0013851	-4.48	0.000	-.008921	-.0034916

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Table 1.5 Oaxaca Blinder Decomposition (with female wages as weights)

```
Blinder-Oaxaca decomposition                    Number of obs     =      40196
                                                Model             =     linear
Group 1: gender = 0                             N of obs 1        =      32256
Group 2: gender = 1                             N of obs 2        =       7940
```

lnwage	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
overall						
group_1	7.667948	.0052012	1474.28	0.000	7.657754	7.678142
group_2	7.205305	.0126856	567.99	0.000	7.180442	7.230168
difference	.462643	.0137104	33.74	0.000	.4357711	.489515
endowments	.0478317	.0076955	6.22	0.000	.0327487	.0629146
coefficients	.43964	.0115882	37.94	0.000	.4169276	.4623524
interaction	-.0248286	.0065367	-3.80	0.000	-.0376403	-.012017
endowments						
exp	.0501465	.0059188	8.47	0.000	.0385459	.0617471
exp_sqr	-.0113859	.004193	-2.72	0.007	-.019604	-.0031678
bprim	-.0006884	.0003102	-2.22	0.026	-.0012964	-.0000803
prim	.0012025	.000436	2.76	0.006	.000348	.002057
middle	.012342	.0014083	8.76	0.000	.0095818	.0151023
sec	.0236448	.0021116	11.20	0.000	.0195061	.0277836
hsec	.0152902	.0028007	5.46	0.000	.0098009	.0207795
grad	-.0170654	.0054801	-3.11	0.002	-.0278061	-.0063246
pgrad	-.0542937	.0051786	-10.48	0.000	-.0644435	-.0441438
marital_s	.0200256	.0025583	7.83	0.000	.0150113	.0250398
sector	-.0032827	.0006696	-4.90	0.000	-.0045951	-.0019704
union	.011896	.0022532	5.28	0.000	.0074797	.0163123
coefficients						
exp	.324157	.1992641	1.63	0.104	-.0663934	.7147074
exp_sqr	-.1723597	.1081723	-1.59	0.111	-.3843735	.0396541
bprim	-.003134	.002269	-1.38	0.167	-.0075812	.0013132
prim	-.0051903	.0039229	-1.32	0.186	-.012879	.0024984
middle	-.0210008	.0069882	-3.01	0.003	-.0346974	-.0073042
sec	-.0391877	.0074353	-5.27	0.000	-.0537606	-.0246148
hsec	-.0513849	.0064943	-7.91	0.000	-.0641134	-.0386564
grad	-.1185253	.0105012	-11.29	0.000	-.1391073	-.0979432
pgrad	-.0430728	.004204	-10.25	0.000	-.0513126	-.034833
marital_s	.1110093	.0201299	5.51	0.000	.0715554	.1504633
sector	.0664763	.0087338	7.61	0.000	.0493582	.0835943
union	-.0751504	.0090666	-8.29	0.000	-.0929206	-.0573801
_cons	.4670033	.0959453	4.87	0.000	.278954	.6550525
interaction						
exp	-.0161728	.0100316	-1.61	0.107	-.0358343	.0034887
exp_sqr	.016273	.0102937	1.58	0.114	-.0039022	.0364483
bprim	-.0006302	.0005014	-1.26	0.209	-.0016129	.0003526
prim	.0006981	.0005691	1.23	0.220	-.0004172	.0018134
middle	.0074264	.0025267	2.94	0.003	.0024741	.0123786
sec	.012546	.002565	4.89	0.000	.0075187	.0175734
hsec	.0081707	.0017976	4.55	0.000	.0046476	.0116939
grad	-.0077224	.002567	-3.01	0.003	-.0127536	-.0026912
pgrad	-.0206412	.002769	-7.45	0.000	-.0260683	-.0152141
marital_s	-.025599	.0047133	-5.43	0.000	-.0348369	-.0163611
sector	-.0053836	.0012292	-4.38	0.000	-.0077927	-.0029744
union	.0062063	.0013851	4.48	0.000	.0034916	.008921

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