Empirical Assessment of the Gender Wage Gap:

An Application for East Germany During Transition (1990-1994)

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ABSTRACT

This thesis revolves around the estimation of the gender wage gap in East Germany during the transition from socialism to market economy (1990-1994). The analysis' main goal is to provide evidence on the question of how the relative position of women changed by the introduction of market reforms. For this purpose I use different decomposition methods, starting with the Blinder-Oaxaca method and continuing with the extended version of it after assessing the issue of sample selection through applying Heckman's two-step method. To overcome the limitations of the Blinder-Oaxaca method, I use the reweighting method of DiNardo, Fortin and Lemieux (1996) and Ñopo's (2004) matching-based method. The main results of the thesis show that the large fall in the gender gap observed during the transition is almost solely due to the fall in the unexplained part of the gender gap. Results from Heckman's correction procedure suggest that for female workers there exists substantial selection bias in the labor market which affects moderately the gender pay gap. Findings from using the DiNardo-Fortin-Lemieux reweighting method and Ñopo's method indicate that the decrease in the gender gap is larger in relative terms for female workers at higher points of the distribution than at lower points.

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1. INTRODUCTION

Since its re-unification with West Germany, East Germany (former German Democratic Republic) has experienced a course of profound economic and political changes during its transition from socialism to a market economy, changes that have had great influence on women's relative position. During socialism, a political system that (at least in principal) heavily emphasized the idea of bringing men and women into equal positions in the labor market had prevailed, leading to high labor force participation rates among women thanks to labor market institutions such as maternity leave and (relatively) high minimum wages and social entitlements such as day care benefits and housing (Brainerd, 2000). Over the years of transition that followed, East Germany, just like all other formerly socialist countries, has experienced a dramatic widening of the wage structure as well as a significant increase in its wage level as a result of intensive collective bargaining to reach parity with levels of wages in West Germany in 1994 (Brainerd, 2000).

As formerly socialist countries shared a similar economic environment before the transition and implemented market reforms during the transition that had many common aspects, one would expect similar changes in the male-female wage differentials to be present. Nevertheless, countries of the former Soviet Union seem to have experienced a substantial increase in the gender gap compared to East Germany and other Eastern European countries. Hence, questions were raised concering the underlying reasons of the favorable change in womens' relative positions in these countries. The observed narrowing of the gender pay gaps may have been a result of improvement in gender-specific factors that include women's relative level of measured and unmeasured labor market skills as well as potential decrease in discrimination against female workers (Blau and Kahn, 1997 and 2000).¹ Findings of Hunt (2002) for East Germany seem to support this hypothesis, since according to Hunt's results

¹Discrimination in wages is defined as follow: It occurs if workers of two different groups with equal marginal productivity receive different wages.

the gender-specific factors dominated in the change of the gender wage differential and worked in favor of women during the years of transition.

The aim of this thesis is to examine the gender wage gap in East Germany right before and after the transformation from central planning to a market economy, providing evidence on the question of how the relative position of women changed by the introduction of market reforms, that is, whether the male-female wage differential truly decreased or increased during the transition from 1990 to 1994. I am interested in how much of the wage gaps between the two genders are due to observed factors or unobserved factors, possibly including discrimination. For this purpose, I use various decomposition methods on a data set that was assembled from the German Socio-Economic Panel spanning four years (from 1990 to 1994). Since observed changes can have different effects at different points of the wage distributions of female and male workers respectively, the decomposition analysis I implement in this thesis goes beyond the mean and allows for decomposition of the gender gap at different quantiles of the wage density functions. Finally, an important aspect of the analysis is that it takes into account the validity of the implemented decomposition methods because of nonrandom sample selection and lack of common support (as discussed later) are carefully considered.

Due to the usefulness of the decomposition techniques in quantifying the contribution of multiple factors to differences in outcomes, I first use the widely utilized and known decomposition method based on the seminal works of Blinder (1973) and Oaxaca (1973). While this technique is widely used in the literature of gender wage gap and its simplicity makes it appealing, it suffers from many limitations. Firstly, the Blinder-Oaxaca method cannot be extended to the case of other general distributional statistics beyond the mean. This is a very important limitation since decompositions at mean provide very little information concerning what happens at other points of the wage distribution which could be very

important in identifying the sources of the gender gap e.g. "glass ceiling" effect. Secondly, this method is based on very restrictive assumptions such as linear relationship between the outcome variable and the covariates. This condition can be easily violated, for example in case there are non-linearities in the returns to education, e.g. "sheepskin effect". Thirdly, in presence of nonrandom sample selection, which I assume to be true and substantial for East Germany over the considered period (Hunt, 2002, p.148), this method will give inconsistent estimates. Finally, implementation of the Blinder-Oaxaca method might face problems when there is lack of common support in the distribution of covariates (Fortin, Lemieux and Firpo, 2010).

To address the above discussed limitations of the Blinder-Oaxaca method, first I apply Heckman's method to correct for potential sample selection bias (Heckman, 1979), then I use the extended Blinder-Oaxaca decomposition to quantify the contribution of sample selection to the overall gender gap. The question of selectivity bias is of particular concern in the present case as the employment rate of female workers declined significantly more during the transitional years than the male labor force participation rates (Bonin and Euwals, 2001). The underlying reason could be higher unemployment risk for low wage earners who were disproportionately women (Hunt, 2002) or increased discrimination against working women that can be a result of lower state control over firms that might have allowed employers to take such actions more openly (Brainerd, 2000).² Therefore, concerning the direction of the bias, I expect female workers to be a positively selected group in terms of their unobserved characteristics, meaning that working women earn more on average than non-working women would if they would decide to participate in the labor force.

Next, I utilize two methods: one is a regression-based (semi-parametric) reweighting method as in DiNardo, Fortin and Lemieux (1996); the other is a matching-based

²I would like to note that the effect of transition on discrimination against women might have been positive if discrimination became too costly to maintain in a competitive market economy (Becker, 1957).

nonparametric decomposition approach introduced by Ñopo (2008). These methods, in comparison with the Blinder-Oaxaca decomposition, both can be extended to other distributional statistics and they do not impose the restrictive assumption of linear functional form of conditional wage expectations that could be a source of potential misspecification. Additionally, the two methods in question do not require the zero conditional mean assumption to hold; instead, it can be replaced by the weaker unconfoundedness condition (or ignorability) that only requires the unobservables' conditional distribution given covariates X to be the same for both working men and women as opposed to the unobservables' (mean) independency of covariates X.

The advantage of matching over the reweighting method is related to the common support problem, under which, as Frölich (2004) noted, reweighting procedure in particular performs quite poorly. Thus, I utilize Ñopo's matching-based decomposition technique that accounts for this problem to see how the results from traditional regression-based decomposition techniques, the Blinder-Oaxaca and DiNardo-Fortin-Lemieux methods in particular, compare. On the other hand, it is important to emphasize that Ñopo's decomposition method might face the problem of high dimensionality whereas in case of the reweighting method this problem is reduced, therefore the usage of the latter remains relevant.

However, decomposition techniques in general are not without limitations. Firstly, according to Fortin, Lemieux and Firpo (2010), decomposition methods follow a partial equilibrium approach which inherently assumes that in the construction of counterfactuals for one group, observed outcomes for the other can be utilized. Secondly, decompositions might not aid the unveiling of mechanisms describing relationship between the outcome variable (the wage in present case) and various factors.

The results show that there was a significant decrease in the observed gender wage gap during the transition and the traditional Blinder-Oaxaca method reveals that this decrease is almost solely due to the significant fall in the "Renumeration" effect or unexplained part of the gender pay gap which largely dominates the determination of the male-female wage differentials in both years leaving nearly no role for human capital measures like education or work experience. The results from Heckman's selection correction method suggest that for female workers there exists substantial selection bias in the labor market, while for male workers no evidence on sample selection can be obtained. By applying the extended Blinder-Oaxaca method I show that selectivity bias affects moderately the determination of the gender pay gap. Findings from implementing the DiNardo-Fortin-Lemieux reweighting method indicate that in both years the gender wage gap is significantly larger for working women at the lower quantiles of the wage distribution than at the higher ones. Furthermore, the decrease in the gender gap occuring at all points of the wage distribution is larger in relative terms for female workers at higher points of the distribution than at lower points. Finally, by using Ñopo's procedure I show support for the results of the reweighting method as well as find (moderate) evidence on the presence of such highly rewarded individual labor market skills that are obtained solely by working men.

The rest of the paper is organized as follows. Chapter 2 describes the data set constructed for the analysis as well as the utilized variables in detail, and presents the descriptive statistics. Chapter 3 provides the methodological framework applied to examine the gender wage gap, while the results of the empirical analysis are presented in Chapter 4. The paper ends with the conclusion where I sum up the results and outline some possibilities to extend the present analysis.

2. DATA DESCRIPTION AND DESCRIPTIVE STATISTICS

This chapter describes the data set utilized in this analysis assembled from the German Socio-Economic Panel for East Germany.³ I used data from 1990 when individuals from East Germany were surveyed just before the re-unification and from 1994. I chose these years because this way the observed period is short enough to ensure that the observed changes reflect the effects of market reforms associated with the transition from socialism to market economy. The reason I chose this data set is because it provides a large set of harmonized variables on household and personal level making it very appealing for the present analysis. The sample was restricted to workers with nonzero working hours and a valid wage who are not self-employed, not in a training program (apprenticeship), not in the agricultural sector, nor completing compulsory military service. I do not include self-employed individuals, because it is difficult to distinguish between returns to human capital from returns to physical capital. Similarly, I do not take individuals in the agricultural sector since their earnings are likely to be explained also by random factors like weather conditions. The sample was trimmed at the bottom and the top 1% of wage observations in order to get rid of implausibly low and high wages. In addition, the sample was restricted to individuals aged 18 to 60 since individuals younger than 18 or older than 60 are most probably also involved in decisions concerning education and (early) retirement that are different from the employment decision. Following the work of Fortin and Lemieux (1998) part-time workers are not excluded from the sample along full-time workers, but each observation in the sample is weighted by the number of weekly hours worked. This way more weight is put on workers who provide relatively more hours of work to the labor market, thus through this procedure each worker's contribution is better reflected. Finally, missing values observed account for less than 1% of the final sample and they were generated with the simple procedure of unconditional mean

³ By East Germany I mean the former German Democratic Republic which ceased to exist in 1990 after its unification with West Germany (former Federal Republic of Germany).

imputation. The idea of this method is to simply replace the missing values observed in the data set with the arithmethic average of the observed values on the same variable over the other observations (Little and Rubin 1987). This imputation method provides unbiased, consistent estimators if missing values are missing either completely at random or at random, but it underestimates variability/variance.

The set of variables used for the present analysis includes wages, gender, level of education, and years of actual work experience. The wage variable (W_t , which denotes the logarithm of the worker's wage for time period t) is a measure of the monthly, gross amount (not adjusted for end of year bonuses) earned by the workers. The gender variable (*female*) is a dummy, which takes the value of one if the individual is female, and zero otherwise. The highest level of education attained by the workers was captured by using a set of four dummy variables (*general schooling*, *vocational training*, *apprenticeship* and *university*) that corresponds to only general classroom education, classroom vocational training, participation in the dual-system that stands for classroom education and work in a firm, and to the completion of university, respectively. The actual working experience variable (*experience*) gives a measure of the entire period of employment in the respondent's working career up to the point when the survey was taken. It gives the length of time in years with months in decimal form.

Furthermore, I used the following set of instrumental variables for Heckman's two-step correction model: marital status, presence of young children, an indicator for the head of household and nonlabor household financial variables (child allowance and income from interests/dividends). The marital status variable (*married*) is a dummy, which takes the value of one if the individual is married, and zero otherwise. I used a set of two variables to capture the presence of young children in the household (*child0*_5 and *child6*_16): the number of children under the age of five as well as the number of children between six and sixteen. In

addition, I included interaction terms between number of children and number of adults in the household. The indicator for the head of household is a dummy variable (*hhead*) that takes the value of one if it is true for the individual, and zero otherwise. The contents of the two nonlabor household income variables are as follows: the child allowance variable (*lnchcare*) measures the logarithm of monthly, gross amount of child allowance while the *divid* dummy variable takes the value of one if the individual had nonzero amount of income from interests and dividends in the last year, and zero otherwise.

Following Oaxaca's study (1973) I do not include occupational or job position dummies in the model, as they may already be the result of discrimination ("pre-labor market discrimination"). Hence, controlling for occupational differences between female and male workers would result in the underestimation of the effects of discrimination by eliminating "some of the effects of occupational barriers as sources of discrimination" (Oaxaca, 1973, p.699). For similar reasons I also do not include industry dummy variables in the analysis. I would like to note that unionization which is expected to contribute to the evolvement of the gender pay gap as suggested by many studies (Blau and Kahn, 1997 and DiNardo, Fortin and Lemieux, 1996) is not included in this analysis due to lack of data.

The descriptive statistics of the variables used in the analysis (Table 1 in the Appendix) reveal several differences between female and male workers as well as various changes during the examined period that are different across gender. First of all, it is easy to see from the table that men and women in the sample have experienced some different changes in educational attainment over the period. The proportion of women in the sample with an apprenticeship or with general schooling as the highest level of education declined more than the same proportion of men in the sample (which remained quite stable during 1990-1994) which - since we can assume that few individuals change their education - can indicate that women with lower level of education disproportionately left employment. This seems to

support the hypothesis that there might be a strong selection effect in the sample of female workers⁴ which could result in such change in the composition of educational attainment. In addition, this is in line with the findings of Hunt (2002) who notes an even more drastic fall among working women with apprenticeship during transition. Secondly, Table 1 shows that in both years women in the sample have lower level of actual experience on average than men as well as they are slightly younger on average.

Finally, concerning the monthly wages of workers in the sample, Figure 1 shows the (Epanechnikov) kernel density estimates of monthly real wages (left panel) and of log monthly wages (right panel) by gender in 1990 and 1994. For both years the real wages are expressed in 1994 DEMs and the Consumer Price Index (CPI) was obtained from the German Statistical Office.



Figure 1. Kernel Density Estimates in East Germany (1990-1994)

The left panel shows the increase in both means and dispersion of monthly real wages for both genders. It is important to note that the mean of the female wage distribution is significantly below the mean of the male wage distribution even in 1990 which is in contrast

⁴ Labor force participation rate of women declined substantially more after unification in 1990 than employment rate of men. (See for example Bonin and Euwals (2001)

with the "equal pay for equal work" idea that was heavily emphasized during socialism. The right panel shows that there is substantial difference between the average log wages (indicated by the dashed vertical lines) of men and women in the sample – the raw gender wage gap – and that this difference shrank during the considered period. In addition, the panels of Figure 1 show that the unadjusted male-female wage differential declined at all quantiles of the wage distribution from 1990 to 1994 and that both wage densities became less skewed to the left.

Table 2 (in the Appendix) presents the descriptive statistics of the instrumental variables from which I would only like to emphasize the fact that while proportion of married men and women in the sample on average remained quite stable during transition, the average number of children in the household under the age of five declined for both genders and increased for children between six and sixteen.

3. METHODOLOGY

In this chapter, following the presentation of the data set used, I describe the methodology implemented in the thesis. First, I start with estimating the gender wage gap unconditional and conditional on selected human capital characteristics. Next, I decompose the gender wage gap with the Blinder-Oaxaca technique followed by the implementation of Heckman's correction method to adjust for sample selection. Then, I use DiNardo-Fortin-Lemieux reweighting method to decompose the gender differences in wages at all points of the wage distribution. Finally, I use Ñopo's matching-based procedure to overcome the limitations of the DiNardo-Fortin-Lemieux reweighting method and Blinder-Oaxaca method related to the "support problem".

3.1 Gender Wage Gap: Unconditional and Conditional on Human Capital Measures

The starting point of this paper is to simply calculate the unconditional male-female pay gap at means for each year in order to attain an overall picture of the actual gender wage gap:

$$(1) \quad W_{M,t} - W_{F,t}$$

where $W_{M,t}$ is the logarithm of male wages, while $W_{F,t}$ is the logarithm of female wages. Since this measure does not reveal too much information, for example about the sources of the male-female wage differentials, I continue with estimating the gender wage gap for time period t conditional on a set of human capital measures. The estimation of the conditional gender wage gap is based on the traditional Mincer earnings equation (Bosworth et al. 1996):

(2)
$$W_t = \alpha + \beta * X_t + \delta * female + u_t$$

where W_t is the logarithm of monthly wages, X_t denotes an array of control variables including the schooling dummy variables (where the omitted or reference category is *vocational training*), the experience and the square of experience divided by 100, *female* is the gender dummy variable, and u_t is the error term. The variable of interest is the coefficient on the gender dummy variable, δ , which indicates the gender gap in pay conditional on the above described control variables. I use OLS estimation method and White Heteroskedasticity-Consistent Standard Errors to take into account possible heteroskedasticity in the error term. Following the works of Heckman, Lochner and Todd (2003) and Lemieux (2006), in addition to the above described specification, I also estimate a model that includes an interaction term between schooling dummies and experience as well as one in which a linear and a quadratic term of years of education are included instead of schooling dummies. However, while these wage regression models contribute to the better understanding of the evolution of the gender wage gap, the simple OLS estimation method described above suffers from several drawbacks and for consistent estimation of the parameters a set of restrictive assumptions are required. These assumptions include exogeneity of explanatory variables, random sample selection and no misspecification may arise due to omitted right-hand side variables. It is important to note that thorough discussion and assessment of these assumptions is beyond the scope of this paper and thus it will not be dealt with in depth. To gain a better view into the composition and development of gender gap in pay, as a next step, I turn to different aggregate decomposition methods. In this thesis I only focus on aggregate decomposition methods, techniques that decompose the total gap into "Endowment" and "Renumeration" effects, and will not include detailed decompositions which involves subdivision of these two effects into respective contributions of included covariates.

3.2 The Blinder-Oaxaca Decomposition of Mean Gender Pay Gap

The most common approach used to identify and quantify the causes of male-female wage differential is the Blinder-Oaxaca decomposition method suggested by Blinder (1973) and Oaxaca (1973) in their seminal work. This technique, replacing traditional linear regression methods incorporating a gender dummy variable, have the advantage that it allows for the separation of observable and unobservable effects (in the latter, discrimination being included); however, it suffers from several deficiencies. Following the standard approach in

econometrics, first I discuss the aim of the method applied and the assumptions required to interpret the obtained estimates, and then I show the estimation procedure itself.

Assumptions

The aim of the Blinder-Oaxaca method is to divide the overall gender wage gap at means into two parts, into a term that is attributable to differences in female and male wage structures, and a part attributable to differences in female and male workers' observed characteristics. The Blinder-Oaxaca method is based on the standard assumption of linear relation of the outcome variable (Y) to the covariates (X) in the underlying wage setting model (I) and on the restrictive assumption of zero conditional mean (II):

(3)
$$Y_{ji} = \beta_{g0} + \sum_{k=1}^{K} X_{ik} \beta_{jk} + u_{gi}$$
 where $j = M, F$ and $E(u_{ji}|X_i) = 0$

Additionally, this decomposition builds on the assumption of "overlapping support" (III) that requires an overlap in observable characteristics across gender, meaning that provided the assumption holds, there is no such value of the covariates (X = x) or of the error term (u = e) that could serve as an identifier of membership into one of the genders.

Procedure

The Blinder-Oaxaca decomposition of the gender gap for period *t* can be estimated as:

(4)
$$\Delta_t = \overline{W}_{M,t} - \overline{W}_{F,t} = \left(\overline{X}_{M,t} - \overline{X}_{F,t}\right) * \hat{\beta}_{M,t} + \overline{X}_{F,t} * \left(\hat{\beta}_{M,t} - \hat{\beta}_{F,t}\right)$$

This method decomposes the differences in female and male wages at the mean into two components: "Endowment" effect (also called "Composition" or "Explained" effect) and "Renumeration" effect (also called "Wage Structure" or "Unexplained" effect). The "Endowment" effect - the first term on the right-hand side of equation (4) - measures the part of the gender gap due to differences in the average human capital characteristics, while the "Renumeration" component - the second term on the right-hand side of equation (4) - captures the effects due to differences in estimated coefficients. The latter component has also

been called as the measure of discrimination. For simplicity I adopt the male wage structure as the nondiscriminatory norm, as it is done in most studies. Alternative choices for nondiscriminatory wage standard can be the female wage structure or one estimated from pooled sample of the two genders.

Limitations

While the Blinder-Oaxaca procedure is very simple to implement and widely used in the gender pay gap literature, it suffers from many drawbacks. First of all, the Blinder-Oaxaca decomposition cannot be extended to the case of general distributional statistics other than the mean. This limitation is noteworthy since decomposing gender wage differences at mean do not provide information regarding other points of the wage distribution even though that can be very important in identifying the underlying reasons of the gender differential e.g. "glass ceiling" effect. Secondly, this method is based on very restrictive assumptions (as discussed previously), thus it might not provide consistent estimates when the conditional mean is a non-linear function or when the problem of endogeneity arises. The simplest example is the case of omitted unobserved ability: individuals with higher innate ability will attain higher level of education as well as higher wages, thus estimated returns to education will be biased ("ability bias") when unobserved ability is not included in the wage setting model. Thirdly, in presence of nonrandom sample selection, which I assume to be true and substantial for East Germany over the considered period (Hunt, 2002, p.148), this method will give inconsistent estimates. Finally, lack of common support can impose problems (referred to as "support" problem in the literature) when applying the Blinder-Oaxaca method (Fortin, Lemieux and Firpo, 2010). The "support" problem relates to the fact that male and female workers may not only differ in human capital characteristics, but also the distributions of these variables can overlap very little. The issue of the lack of common support is mostly neglected in the literature of gender wage gap, even though it can be important from a policy point of view as

well, since gender differences in the distribution of covariates can reflect pre-labor market discrimination as female workers might face barriers in reaching certain individual charateristics that male workers achieve.

3.3 The Heckman Correction Method and the Extended Blinder-Oaxaca Decomposition

As the next step I use Heckman's two-step sample correction procedure to correct for non-random sample selection (Heckman, 1979). Selectivity bias might be found at two stages of the employment process: at the stage of entering the labor market or when an occupation is chosen, but in the present thesis only the first case is going to be considered. Selectivity in participation exists if the working individuals do not form a random subgroup of the sampled population, but differ systematically from those who are not employed. In other words, if the determinants of the participation decisions are uncorrelated with the determinants of individual wages, the fact that not employed individuals and their wages are not observed could be simply ignored. However, such an assumption is unlikely to hold in practice. Sample selection bias are particularly important in case of East Germany during the transition as the employment rate of working women declined substantially more over this period than the employment rate of their male counterparts. Thus, regarding the direction of the selectivity bias, I expect female workers to be positively selected into employment, meaning that female workers earn more on average than women who are currently not working would if they would decide to become employed. Concerning male workers I expect to find no evidence on significant sample selection. I would like to emphasize that while its ease of implementation makes the Heckman's correction method appealing, it has a rather limited structure, it is highly parameterized and the identification conditions that are required to successfully perform the method are potentially serious (Vella, 1998).

I chose the two-step model over the maximum likelihood model since the latter relies more heavily on normality assumptions.⁵ Bias stemming from self-selection can be characterized in the following way: consider a two equation model (equation (5a) and (5b)) and a random sample of *I* observations:

(5a)
$$Y_{1i}^* = X_{1i}\beta_1 + u_{1i}$$
 (5c) $Y_{1i} = Y_{1i}^*$ if $Y_{2i}^* > 0$
(5b) $Y_{2i}^* = X_{2i}\beta_2 + u_{2i}$ (5d) $Y_{1i} = 0$ if $Y_{2i}^* \le 0$

Suppose that (5a) is the wage equation and (5b) is a probit-type of selection model that describes the individuals' propensity to work or to have an observed wage. In principal, Y_1^* and Y_2^* are unobserved for certain observations (no wage is observed for people not working), while Y_1 is observed and the sample selection rule is expressed in equation (5c) and (5d). It is commonly assumed that u_1 and u_2 *i.i.d.* error terms have a bivariate normal distribution. For the subsample with positive Y_1^* , the conditional expectation of Y_1^* can be written as follows:

(6)
$$E(Y_{1i}^*|X_{1i}Y_{2i}^*>0) = X_{1i}\beta_1 + E(u_{1i}|u_2>-X_{2i}\beta_2)$$

If the conditional expectation of u_1 is zero, the regression model is the same for the subsample and the sample. Given that the distributional assumptions on the error terms hold, the conditional expectation of Y_1^* can be rewritten as:

(7)
$$E(Y_{1i}^*|X_{1i}Y_{2i}^*>0) = X_{1i}\beta_1 + \frac{\sigma_{12}}{\sigma_2} \frac{\phi(-\left(\frac{X_{2i}\beta_2}{\sigma_2}\right))}{1 - \Phi(-\left(\frac{X_{2i}\beta_2}{\sigma_2}\right))}$$

where $\phi(.)$ and $\Phi(.)$ denote the density and cumulative density functions of the standard normal distribution. Heckman's proposed two-step method is to first estimate the inverse Mills ratio $\left[\lambda\left(\frac{X_{2i}\beta_2}{\sigma_2}\right)\right]$ by way of a probit model on the whole random sample, then in the

⁵There are several examples in the literature of gender gap, see for example Oaxaca and Neuman (2001) or Dolton and Makepeace (1986), where first Heckman's two-step method was used to correct for selection bias and then the extended Blinder-Oaxaca method adjusted for selectivity bias was used to decompose the gender wage gap.

second step estimate equation (8) on the subsample with positive Y_1^* by using OLS estimation method:

(8)
$$Y_{1i} = X_{1i}\beta_1 + \frac{\sigma_{12}}{\sigma_2}\hat{\lambda}\left(\frac{X_{2i}\beta_2}{\sigma_2}\right) + \varepsilon_i$$

It is important to note that as long as u_2 has a normal distribution and ε_1 is independent of λ , the Heckman's two-step estimator is consistent, but it is not efficient. Heckman proposes to test for selectivity bias by way of a t-test on the coefficient of λ . While this method has been widely used in the literature, it relies on restrictive assumptions, and its implementation involves several problematic issues, therefore it needs very careful consideration and caution when interpreting the results. (For further details see for example Puhani, 2000)

One of the most important problems is that the inclusion of the inverse Mills ratio often results in multicollinearity. Since the inverse Mills ratio is estimated by a non-linear probit model, the correction term λ and X_1 will never be perfectly correlated. However, the probit model will be linear for the mid-range values of X_1 ; therefore, in the absence of exclusion restrictions the wage equation will suffer from inflated standard errors due to strong multicollinearity. The best solution is to incorporate exclusion restrictions,⁶ since with valid instruments, the inverse Mills ratio and the set of controls included in the wage equation (X_1) will be less correlated, reducing the collinearity as well as facilitating model identification. Therefore, I use a set of exclusion restrictions in the analysis, namely marital status, presence of young children in the household, interaction term between number of adults and number of young children in the household, indicator of the head of household and nonlabor household financial variables. I expect that marriage lowers the probability to work for females and increases it for males. While both the presence of young children in the household (with stronger effect expected if they are younger than five rather than between six and sixteen) and

⁶ Exclusion restrictions are variables that affect the selection process as they contribute to the determination of the propensity to work, but they do not affect the wage equation.

higher nonlabor income are expected to lower the probability to work (especially for women), being the head of household and the interaction term are expected to increase this probability. I test for collinearity by regressing the inverse Mills ratio on X_1 , where a large R^2 indicates strong multicollinearity.

Finally, since I am interested in the male-female wage differential and its evolvement, I integrate the selection correction into the Blinder-Oaxaca decomposition method. The consequences of sample selection correction are twofold. On the one hand, the estimated rates of return differ, on the other hand, a selection correction term adds to the "Endowment" and "Renumeration" components. There are several proposed ways in the literature on how to handle the selection correction term within the decomposition of the wage gap. See for instance Neuman and Oaxaca (2004) or Dolton and Makepeace (1986). I chose to treat the gender differences in selectivity as a third separate component of the wage decomposition:

(9) $\Delta_t = \overline{W}_{M,t} - \overline{W}_{F,t} = (\overline{X}_{M,t} - \overline{X}_{F,t}) * \hat{\beta}_{M,t} + \overline{X}_{F,t} * (\hat{\beta}_{M,t} - \hat{\beta}_{F,t}) + (\hat{\theta}_{M,t}\hat{\lambda}_{M,t} - \hat{\theta}_{F,t}\hat{\lambda}_{F,t})$ where $\hat{\theta}$ is an estimate of (σ_{12}/σ_2) and $\hat{\lambda}$ is an estimate of the Inverse Mills Ratio. I chose this specification as I am interested in the overall contribution of selection effects to the wage gap.

3.4 The DiNardo-Fortin-Lemieux (1996) Reweighting Method

Next, I apply the inverse probability reweighting decomposition method introduced by DiNardo, Fortin and Lemieux (1996). The goal of this method is to go beyond summary measures such as the mean or variance and establish decomposition of the gender wage gap into unexplained and explained parts at all points of the wage distribution by construction of counterfactual wage density function. The method is based on the assumptions of ignorability, overlapping support and invariance of conditional distributions. The invariance assumption requires that the conditional wage distribution $f_M(w|x, u)$ (where *M* takes value of one when individual is male, zero otherwise) can be extrapolated for $x \in X$ (Fortin, Lemieux and Firpo, 2010).

The density of log wages ($f_M(w)$ for men and $f_F(w)$ for women, respectively) can be written as follows:

(10a)
$$f_M(w) = \int f_M(w|x, u)g(x|M = 1)dx$$

(10b) $f_F(w) = \int f_F(w|x, u)g(x|F = 1)dx$

where $f_j(w|x, u)$ is the conditional wage distribution given gender status (j = M, F) and observed individual characteristics (X); g(x|j = 1) denotes the distribution of covariates conditional upon gender; M and F are variables indicating gender status⁷; and the vector of observed individual characteristics is denoted by $x \in X$ while u is the unobserved term. The counterfactual density function – which is a function of counterfactual wage distribution that can be referred to as the distribution of wages that would prevail for female workers if they were paid like their male counterparts – is constructed in the following way in the spirit of DiNardo, Fortin and Lemieux's work (1996):

(10c)
$$f_C(w) = \int f_M(w|x, u)\psi(x)g(x|M=1)dx$$

where $\psi(x)$ is the reweighting function defined as $\psi(x) = g(x|F = 1)/g(x|M = 1)$ which expression can be reformulated by using Bayes' rules in the following way:

(11)
$$\psi(x) = \frac{\Pr(F=1|x) / \Pr(F=1)}{\Pr(M=1|x) / \Pr(M=1)}$$

It is important to note the construction of the counterfactual relies on the assumption of invariance and that I chose to estimate it using the male wage structure as the nondiscriminatory norm. In general, it can be stated that the male wage structure is closer to a nondiscriminatory norm than the female one and I assumed that relative changes in the female workers' wage position does not influence the male wage structure. Also, I chose the male wage structure as nondiscriminatory norm for ease of comparability since most studies do the

 $^{^{7}}$ *M* takes value of one when individual is male, zero otherwise, and *F* takes value of one when individual is female, zero otherwise.

same. However, there are other alternative solutions used, e.g. choice of pooled wage structure.

The estimation procedure can be implemented in as follows. First, estimating the probability model for Pr(M = 1|x) using probit model on the pooled sample of both genders:

(12)
$$\Pr(M = 1|x) = \Pr(u > z(x)\beta) = 1 - \Phi(-z(x)\beta)$$

where Pr(M = 1|x) is the probability of being male given x; $\Phi(.)$ is the cumulative normal distribution and z(x) is vector of covariates that includes schooling and experience. Next, computing the value of the reweighting factor utilizing the predicted probabilities:

(13)
$$\hat{\psi}(x) = \frac{\widehat{\Pr}(F=1|x) / \widehat{\Pr}(F=1)}{\widehat{\Pr}(M=1|x) / \widehat{\Pr}(M=1)}$$

Lastly, estimating the wage densities for both genders and the counterfactual density (with the help of $\hat{\psi}(x)$) by utilizing kernel density methods (equations (14a) - (14c)):

$$(14a) \quad \hat{f}_{M}(w) = \sum_{i \in M} \frac{\theta_{i}}{h} K\left(\frac{w - W_{i}}{h}\right)$$

$$(14b) \quad \hat{f}_{F}(w) = \sum_{i \in F} \frac{\theta_{i}}{h} K\left(\frac{w - W_{i}}{h}\right)$$

$$(14c) \quad \hat{f}_{C}(w) = \sum_{i \in M} \frac{\theta_{i}}{h} \hat{\psi}(x_{i}) K\left(\frac{w - W_{i}}{h}\right)$$

where $\hat{f}_{j}(w)$ is the estimated wage density; θ_{i} is the weight adjusting for hours worked; K(.) is the kernel function; h is the bandwidth and W_{i} is observation of wage in the sample. The Gaussian kernel function was chosen for the estimation and for the bandwidth I chose the default setting in Stata statistical software package which is based on Silverman's (1986) rule of thumb optimal bandwidth. Once the estimates of wage densities are obtained, they can be utilized to construct the decomposition of the gender wage gap that allows the examination of differences at different quantiles of the wage distribution:

(15)
$$\Delta^{f(w)} = \left(\hat{f}_M(w) - \hat{f}_C(w)\right) + \left(\hat{f}_C(w) - \hat{f}_F(w)\right)$$

where the first term of the right-hand side of equation (15) captures the "Endowment" effect and the second term stands for the "Renumeration" effect.

3.5 Ñopo's Matching-based Nonparametric Decomposition Method

As a final step I use Nopo's nonparametric decomposition procedure which is based on exact matching (Nopo, 2004). This method aims at providing a decomposition of the overall gender gap that accounts for the "support" problem and relies on the key assumption of ignorability. The advantage of this technique is that it can be extended to other distributional statistics and does not impose the restrictive assumption of linear functional form in contrast with the Blinder-Oaxaca decomposition. Moreover, it relies on the weaker unconfoundedness condition and does not require the unobservables' (mean) independency of covariates X as the Blinder-Oaxaca decomposition does. Finally, Nopo's matching-based method accounts for the "support" problem, under which the implementation of Blinder-Oaxaca procedure and the DiNardo-Fortin-Lemieux method might face severe problems. The main disadvantage of Nopo's method is that it might suffer from the problem of high dimensionality, but using propensity score matching instead of exact matching could reduce this problem.

Let $S = (S^M \cap S^F)$ be the common support and $p_{S|M} = p(X \in S|M) = \int_S dF^M(x)$ the probability measure of the set *S* under the distribution $dF^M(.)$. Then, the male population (and similarly the female population) can be divided into two subpopulations composed of individuals that belong either to the common support *S* or are out of the common support \overline{S} :

(16)
$$E(W|M) = E_S(W|M)p_{S|M} + E_{\overline{S}}(W|M)p_{\overline{S}|M}$$

$$= p_{\overline{S}|M} [E_{\overline{S}}(W|M) - E_S(W|M)] + E_S(W|M)$$

(17) $E(W|F) = p_{\overline{S}|F} [E_{\overline{S}}(W|F) - E_S(W|F)] + E_S(W|F)$

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Using equation (16) and (17), the total gender wage differential $[\Delta \equiv E(W|M) - E(W|F)]$ can be written in the following form:

$$(18) \Delta = [E_S(W|M) - E_S(W|F)] + p_{\overline{S}|M} [E_{\overline{S}}(W|M) - E_S(W|M)]$$
$$+ p_{\overline{S}|F} [E_{\overline{S}}(W|F) - E_S(W|F)]$$

The first term of this expression concerns the differences of wages between male and female workers over the common support only, while second term (third term) involves wage differences between male (female) workers in and out-of-the support. Furthermore, the first term of equation (18) can be decomposed as in the Blinder-Oaxaca decomposition by adding and subtracting the counterfactual mean wage $(\int_{S} g^{M}(x) dF_{S}^{F}(x))$ with $dF_{S}^{F}(x)$ being the density of characteristics in the subpopulation of female workers belonging to the common support \overline{S}).

(19)
$$E_S(W|M) - E_S(W|F) = \int_S g^M(x) [dF_S^M(x) - dF_S^F(x)] + \int_S [g^M(x) - g^F(x)] dF_S^F(x)$$

The first and second term of the right-hand side of equation (19) correspond to the "Endowment" and "Renumeration" effects in the Blinder-Oaxaca decomposition, but now only on the common support. Finally, Ñopo's four component decomposition can be given as follows:

$$(20) \quad \Delta = \Delta_x + \Delta_o + \Delta_M + \Delta_F$$

with
$$\Delta_x = \int_S g^M(x) [dF_S^M(x) - dF_S^F(x)] \qquad \Delta_0 = \int_S [g^M(x) - g^F(x)] dF_S^F(x)$$
$$\Delta_M = p_{\overline{S}|M} [E_{\overline{S}}(W|M) - E_S(W|M)] \qquad \Delta_F = p_{\overline{S}|F} [E_{\overline{S}}(W|F) - E_S(W|F)]$$

Component Δ_X captures the part of the gender gap that can be explained by differences in the distribution of characteristics of female and male workers over the common support. The term Δ_o captures the residual part of the wage differential, the part which is typically attributed to both unobservable characteristics and discrimination. Component Δ_M measures the part of the gender wage differential that can be explained by differences between men in the common support and men out of the common support. This term accounts for the part of the wage gap that can be attributed to the fact that some characteristics that male workers own are not observed among female workers and if this term is positive, it means that these characteristics are highly rewarded in the labor market. Component Δ_F can be defined in a similar way for female workers in and out of common support. The exact matching algorithm can be summarized as follows. First, for each female worker all male workers with same characteristics are selected, that is, matching is done with replacement meaning that the same man can be selected more than once (One-to-many matching). Second, the counterfactual wage for each female workers is computed as an average of all the matched male workers' wage. Finally, the previously described four components are calculated.

4. ESTIMATION RESULTS

4.1 Gender Wage Gap: Unconditional and Conditional on Human Capital Measures

The unconditional male-female wage differential at means, calculated as described previously in equation (1), fell from 29.579 log points in 1990 to 18.643 log points in 1994. This nearly 11 log points decrease indicates that over the considered period, the female wages notably improved relative to male wages among workers.

The gender wage gap adjusted for years of actual labor market experience and highest level of education attained, estimated as specified in equation (2), fell from about 27 log points in 1990 to 17 log points in 1994, keeping other variables fixed, as shown in Table 3.

Left-hand side variable: Log(Wage)							
Method: Least Squares							
Coefficients							
Right-hand side variables	(t-stat	tistics)					
	1990	1994					
	(1)	(2)					
C	7.187***	7.851***					
C	(0.022)	(0.034)					
Fomala	-0.269***	-0.170***					
remaie	(0.012)	(0.017)					
Constal schooling	-0.458***	-0.225***					
General schooling	(0.309)	(0.071)					
Appropriate	-0.192***	-0.104***					
Apprenticeship	(0.014)	(0.021)					
University	0.160***	0.273***					
University	(0.023)	(0.031)					
Experience	0.013***	0.023***					
Experience	(0.002)	(0.003)					
Experience squared	-0.025***	-0.048***					
Experience squared	(0.005)	(0.009)					
Adjusted R-squared	0.366	0.228					
Total observations	2405	1685					

Table 3. OLS estimation results of conditional gender wage differences by year

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

All estimates are statistically significant on any conventional significance level (1%, 5% and 10%). This 10 log points decline in the conditional wage gap, is very similar to what I obtained above when estimating the change in the unadjusted gender gap. Estimates for the

schooling dummies show that with respect to the omitted category (vocational school), workers with university degree earned more on average in both years, while workers with general schooling or apprenticeship earned less on average over the period, holding all other variables fixed. The return to education (represented by coefficient estimates on schooling dummies) increased for all level of highest educational attainment from 1990 to 1994. As for estimates on experience, for both years the more experienced workers earn more than the less experienced ones until they reach a certain number of years of experience (26 and 24, respectively), keeping all other variables fixed. The return to labor market experience increased from 1990 to 1994, but also its rate of decrease was higher in 1994. According to the adjusted R-squared, 36.6% of the sample variation in log wages was explained by schooling and experience in 1990, which decreased to 22.8% in 1994, meaning that during transition the explanatory power of the included human capital measures with respect to log wages decreased. I also estimated two alternative versions⁸ of the model presented in equation (2), but both specifications resulted in coefficient estimates very similar to the ones presented in Table 3, thus they are not reported here. Nevertheless, the estimation of these wage regression models does not allow one to identify and quantify the different sources of the gender gap, hence, to gain a better understanding of the composition and of the evolvement of male-female wage differential, I continue my analysis with various aggregate decomposition techniques.

4.2 Blinder-Oaxaca Decomposition of Mean Gender Pay Gap

The estimation results from the Blinder-Oaxaca decomposition estimated on the whole sample as specified in equation (4) show that the "Renumeration" effect's contribution

⁸One of them included an interaction term between schooling dummies and experience while in the other one a linear and a quadratic term of years of education were included instead of schooling dummies.

dominates in the determination of the gender wage gap, while the "Endowment" effect plays a very insubstantial role in both years (see Table 4).

Year	Gender wage gap	"Endowment" effect	"Renumeration" effect	Obs
	(1+2)	(1)	(2)	
1990	0.296	0.020	0.276	2405
1994	0.186	0.014	0.172	1685

Table 4. The Blinder-Oaxaca decomposition of the gender wage gap

The sharp decline observed in the male-female wage differential is solely a consequence of the decrease in "Renumeration" effect, meaning that the wage gain women would experience, given their mean individual characteristics if they were renumerated like men, substantially decreased from 1990 to 1994. This can be a result of improvement in women's relative level of unmeasured labor market skills, a potential decline in discrimination against females, as well as a consequence of the disproportionate quits of low-skilled female workers from the labor market. Some support for the last factor can be observed in the descriptive statistics (as noted in Chapter 2) as proportion of women in the sample with apprenticehip or general schooling declined more than the same proportion of men sampled. Concerning the "Endowment" effect, from the results it is obvious that the existing differential between male and female workers' wages cannot be explained by gender differences in actual experience and educational attainment. While the magnitude of obtained estimates for the explained gap might seem too low, they are in line with estimates obtained for other formerly socialist countries during the period of transition, see for example Oglobin (1999) for Russia or Adamchik and Bedi (2001) for Poland. In addition, in case of countries undergoing transition, labor market experience is expected to play a much smaller role in the evolution of the gender wage gap, as general human capital acquired before the change of regime became obsolete afterwards (Orlowski and Riphahn, 2009).

4.3 The Heckman Correction Method and the Extended Blinder-Oaxaca Decomposition

As the next step I use Heckman's two-step sample correction method to correct for potential sample selection bias that seems to be particularly important for women in the present case. The results from Heckman's procedure in Table 5 include estimates for the wage equation and the participation equation for women. Results of the correction method obtained for men are not reported in the thesis since – according to the t-test for selectivity bias on the coefficients of the inverse Mills ratio – no evidence of selectivity bias can be found for men during the examined period. The estimated coefficients on the inverse Mills ratio for men were negative, but very close to zero. On the other hand, the estimated coefficients of the inverse Mills ratio are positive (and strongly significant in 1994) for women, suggesting the presence of sample selection. The found positive selectivity bias for women indicates that women selected into employment earn more on average than non-working women would if they would decide to participate in the labor force.

It is important to note that in the participation equation, along the exclusion restrictions earlier mentioned, the right-hand side variables of the wage equation (schooling dummies and experience) are also included. The coefficient estimates on these variables correspond to what one would expect – education has strong positive effect on participation, while experience has parabolic effects – but they are not reported in the thesis.

Concerning the exclusion restrictions, results in Table 5 show that while some of the variables chosen as instruments are highly significant and have a strong effect on participation in the labor market (namely the number of children in the household under five and their interaction with number of adults in the household), most of them are either insignificant or the magnitude of their coefficients is very small. According to the results, the higher the number of children in the household under five, the lower the probability of participation will be, while the estimated coefficients on their interaction with number of adults in the household under five and the probability of participation will

household suggest that keeping all other variables fixed, probability of participation for women increases with higher the number of adults in households where there is at least one child under five.

	Coefficients				
Right-hand side variables	(std. e	errors)			
	1990	1994			
Wage equation					
C	6.912***	7.690***			
C	(0.027)	(0.043)			
Conoral schooling	-0.535***	-0.412***			
General schooling	(0.039)	(0.111)			
Apprenticeship	-0.238***	-0.168***			
Apprenticeship	(0.019)	(0.030)			
University	0.213***	0.270***			
Olliversity	(0.031)	(0.046)			
Experience	0.016***	0.029***			
Experience	(0.003)	(0.005)			
Experience squared	-0.029***	-0.058***			
	(0.007)	(0.013)			
Selection equation ¹⁾					
C	1.503***	1.533***			
C	(0.234)	(0.274)			
Marital status	-0.007	-0.163			
Iviai Ital Status	(0.174)	(0.222)			
# of shildren (under 5)	-0.717***	-0.695**			
# of children (under 5)	(0.270)	(0.288)			
# of children (between 6 and 16)	-0.142	-0.070			
	(0.244)	(0.287)			
(# of adults in HH) *	0.286***	0.235**			
(# of children under 5)	(0.100)	(0.099)			
(# of adults in HH) *	0.012	0.123			
(# of children between 6 and 16)	(0.104)	(0.126)			
Head of household	0.181	-0.079			
field of household	(0.132)	(0.163)			
Log(child allowance)	-0.052	-0.035			
Log(clinic anowalice)	(0.033)	(0.050)			
Income from interest/dividend	-0.132	-0.136			
	(0.132)	(0.262)			
Mills ratio (lambda)	0.197	0.355***			
	(0.117)	(0.022)			
Total observations	1223	830			
-Censored	69	29			
-Uncensored	1154	801			
Adj. R — squared ²⁾	0.289	0.649			

Table 5. Estimation results from Heckman's method for female workers by year

* p-value<0.1; ** p-value<0.05; *** p-value<0.01

1) Right-hand side variables of the wage equation are included, but not reported.

2) Adjusted R-squared from regressing the inverse Mills ratio on controls of the wage equation.

Concerning the problem of collinearity, the adjusted R-squared from regressing the inverse Mills ratio on the control variables of the wage equation shows that in year 1990 multicollinearity most probably does not arise as a problem since the R-squared is very low. In contrast, the adjusted R-squared for year 1994 is much higher, indicating that collinearity might be a problem. It is worth mentioning that the number of censored observations are very small as a result of a series of restrictions imposed on the sample (for example only individuals between 18 and 60 are considered), thus the grounds for considering selection in the sample are questionable.

To see the effects of the existing sample selection bias on the decomposition of the gender wage gap I used the Blinder-Oaxaca decomposition with a correction term for gender differences in selectivity included, as indicated in equation (9). The results provided in Table 6 show that the sample selection bias present in the labor market affects the determination of the gender pay gap in a moderate degree.

Year	Observed Gender wage gap	Wage gap corrected for selection bias	"Endowment" effect	"Renumeration" effect	"Selection" effect	Obs
	(1+2+3)	(1+2-3)	(1)	(2)	(3)	
1990	0.296	0.347	0.022	0.274	-0.051	2156
1994	0.186	0.223	0.014	0.172	-0.037	1674

Table 6. The Extended Blinder-Oaxaca decomposition of the gender wage gap^{1}

1) As described in equation (9)

According to the obtained results, the observed male-female wage differential $(\overline{W}_{M,t} - \overline{W}_{F,t})$ underestimates the differences in the selection corrected (or offered) earnings between the two genders $([\overline{W}_{M,t} - \overline{W}_{F,t}] - [\hat{\theta}_{M,t}\hat{\lambda}_{M,t} - \hat{\theta}_{F,t}\hat{\lambda}_{F,t}])$, meaning that the estimated wage for working women in the traditional Blinder-Oaxaca decomposition was upward biased. The selection effect is greater proportionally for 1994 indicating a stronger selection in later years which is in line with the expectations discussed in previous chapters. Additionally, it is worth noting that correcting for selectivity bias does not have any effect on the estimates of "Renumeration" effect. Comparing these results with the findings of Hunt (2002), I arrive to a different conclusion regarding the role of sample selection in the change of the gender gap during transition. While I found evidence on strong positive selection effect in the sample of working women, I did not find evidence supporting Hunt's statement that almost half of the closing of the gap between 1990 and 1994 is a result of the disproportionate exits of low-skilled and low-paid women from the labor force. According to the results presented in Table 6, the male-female wage gap corrected for selection bias decreased by 12 log points during the transition from socialism to market economy.

4.4 The DiNardo-Fortin-Lemieux (1996) Reweighting Method

Since the traditional Blinder-Oaxaca decomposition technique cannot be extended to the case of other general distributional statistics besides the mean and it imposes the restrictive assumption of linear functional form, I continue the analysis with the reweighting decomposition method introduced in the work of DiNardo, Fortin and Lemieux (1996) which solves both of the above mentioned limitations. The fact that the reweighting method allows for going beyond summary statistics like the mean or the variance is a very important advantage since decompositions at mean provide very little information concerning the sources of the gender gap at other points of the wage distribution which could be very important e.g. "glass ceiling" effect. Similarly for the relaxation of the linearity assumption it can be said that since the outcome variable (log wage) can be related non-linearly to covariates, for example one can think of the "sheepskin effect", the usage of the reweighting method is highly advantageous. Additionally, this method does not require the zero conditional mean assumption to hold in contrast with the Blinder-Oaxaca method.

Figure 2 shows the (Epanechnikov) kernel density estimates of log monthly wages by gender in 1990 and 1994 and the constructed counterfactual density function of female wages.





a) 1990



CEU eTD Collection

b) 1994

From the constructed counterfactual wage density function which is the density function of wages that would have prevailed for female workers if they were paid like their male counterparts, it can be seen that the "Endowment" effect (in line with all previously obtained results in the thesis) was very small at all quantiles, playing close to zero role in the determining of the male-female pay gap and suggesting that differences between female and male workers' measured labor market skills were really small. From Figure 2a) it can be inferred that there was a considerable unadjusted gender gap at all quantiles of the wage distribution in 1990 and that the wage differential was substantially larger for the lower quantiles than the upper ones. Figure 2b) shows that the gender wage gap decreased greatly at each point of the wage distribution from 1990 to 1994. In addition, it can be stated that similarly to 1990, the contribution of "Renumeration" effect determined mainly the gender gap, although its magnitude decreased significantly during the transition.

With the usage of the obtained wage densities I estimated the decomposition of the gender wage gap into "Renumeration" and "Endowment" effects at different quantiles of the wage distribution as described in equation (15). The results of the decomposition by using the reweighting method are provided in Table 7.

				1990					
Percentiles	10^{th}	20^{th}	30 th	40^{th}	50^{th}	60^{th}	70^{th}	80^{th}	90 th
Explained Gap	0.0270	0.0186	0.0272	0.0186	0.0280	0.0278	0.0180	0.0190	0.0278
Unexplained Gap	0.3803	0.3061	0.2690	0.2597	0.2412	0.2319	0.2134	0.2041	0.2134
Total Observed Gender Gap	0.4082	0.3247	0.2968	0.2783	0.2690	0.2597	0.2319	0.2226	0.2412
				1994					
Percentiles	10 th	20 th	30 th	1994 40 th	50 th	60 th	70 th	80 th	90 th
Percentiles Explained Gap	10 th	20 th	30 th	1994 40 th 0.0211	50 th 0.0106	60 th 0.0103	70 th 0.0210	80 th 0.0317	90 th 0.0211
Percentiles Explained Gap Unexplained Gap	10 th 0.0001 0.3062	20 th 0.0106 0.2323	30 th 0.0100 0.2006	1994 40 th 0.0211 0.1584	50 th 0.0106 0.1373	60 th 0.0103 0.0950	70 th 0.0210 0.0845	80 th 0.0317 0.0845	90 th 0.0211 0.1056

Table 7. The DiNardo-Fortin-Lemieux Reweighting decomposition of the gender gap

Naturally, the estimation results presented in Table 7 are in support of the earlier examination of Figure 2, but they provide some additional important details. The gender gap declined at all quantiles with approximately 10 log points, meaning that female workers' wages relative to male workers' wages improved much more proportionally at the higher quantiles of the wage distribution than at the lower quantiles. Furthermore, it can be observed that the explained part of the gender gap was relatively uniform across the wage distribution in both years. Finally, the "Endowment" effect declined in all, but one decile (the 8th decile) where it even increased from 1990 to 1994.

4.5 Ñopo's Matching-based Nonparametric Decomposition Method

Finally, as the last step in the thesis I implemented the decomposition of the male-female wage differentials based on Ñopo's proposed nonparametric technique. The advantages of this method over the traditional Blinder-Oaxaca decomposition are similar to the previously applied DiNardo-Fortin-Lemieux reweighting method. Namely, Ñopo's method also can be extended to general distributional statistics other than the mean, it does not impose the assumption of linear functional form of conditional wage expectations and it does not require the unobservables' (mean) independency of covariates X. However, Ñopo's technique has an additional advantage over the other two methods, that is, it accounts for the so-called "support" problem. Moreover, it allows direct comparison with the Blinder-Oaxaca decomposition when estimated at the means. The disadvantage of Ñopo's method is that it might face the problem of high dimensionality, a problem reduced in the previously applied reweighting technique. Table 8 presents the estimated results of Ñopo's decomposition method where the matching was based on educational dummies and experience.⁹

⁹ Experience and experience squared were replaced by a set of five dummies: under ten; between ten and twenty; between twenty and thirty; between thirty and forty; and between forty and fifty years. No individual in the sample had more than fifty years of experience.

Ñopo's matching-based decomposition										
Year	Year $\Delta \qquad \Delta_X \qquad \Delta_O \qquad \Delta_M \qquad \Delta_F$ Matched men Matched wome									
	(1+2+3+4)	(1)	(2)	(3)	(4)					
1990	0.320	0.003	0.309	0.028	-0.020	660	649			
1994	0.204	0.012	0.240	0.036	-0.084	439	406			

Table 8. Ñopo's decomposition of the gender wage gap

First of all, it can be noted that the gender wage differentials indicated by this method are close in magnitude to the estimates of from the extended Blinder-Oaxaca method. Secondly, similarly to previously obtained results, again, the component representing the "Renumeration" effect (Δ_0 ,) dominates in explaining the existing gender pay gap over the considered period. Components Δ_F , Δ_M and Δ_X play very little role in the explanation of the gender wage differential, however their closer examination reveals some interesting facts.

Term Δ_M takes a positive value in both years that might signal pre-labor market discrimination and can be interpreted as follows. There are some characteristics that male workers have which are not observed among female workers and these characteristics are highly rewarded in the labor market. The small increase observed in the term Δ_M during the analyzed time period could indicate that in 1994 even less women in the sample obtained combinations of characteristics that were exclusively men's before, thus widening the existing gender gap.

Component Δ_F can be interpreted in a similar way, that is, its negative value indicates that there are some characteristics that female workers have which are not observed among male workers and these characteristics are unfavorably rewarded in the labor market. Thirdly, while the estimates of components Δ_F and Δ_M are much smaller in magnitude than term Δ_O that denotes the unexplained part of the male-female wage differential, they might convey important information concerning the potential existence of pre-market discrimination against women. Comparison with the Blinder-Oaxaca decomposition estimated on the whole sample shows that proportions of the component "Renumeration" effect in the gender gap is quite similar in case of both estimation methods (around 80-90%). To allow for more direct comparison, the Blinder-Oaxaca decomposition was estimated only on the common support as well (Table 9). These estimates are now much closer to those obtained by the extended Blinder-Oaxaca method than those provided by the traditional Blinder-Oaxaca technique.

Blinder-Oaxaca decomposition Year Δ Δ_0 Matched men Matched women Δ_X (1+2)(1)(2) 1990 0.312 0.002 0.310 660 649 1994 0.231 0.006 0.225 439 406

Table 9. Blinder-Oaxaca decomposition on the common support

Finally, to analyse the gender differences in wages at different quantiles of the wage distribution I plotted the cumulative distribution functions for the matched samples of working women and men and I also estimated the unexplained part of the gender wage differentials in each year at different quantiles, the results are shown in Figure 3 and Table 10.

Unexplained Gap by percentile									
Percentiles	10th	20th	30th	40th	50th	60th	70th	80th	90th
1990	0.379	0.337	0.316	0.296	0.253	0.263	0.275	0.301	0.374
1994	0.371	0.306	0.268	0.252	0.197	0.174	0.144	0.176	0.112

Table 10. Ñopo's matching-based decomposition of the gender wage gap

By examining Figure 3a) and 3b), it can be easily noticed that from 1990 to 1994 the unexplained part of the gender gap shrunk at all points of the wage distribution, but the decrease in the unexplained component is substantially larger for female workers at the higher quantiles than for female workers at the lower quantiles. This is consistent with results previously obtained by the DiNardo-Fortin-Lemieux reweighting method. Not surprisingly, estimates shown in Table 10 give support to this statement, the male-female wage gap

decreased by 0.8 log points for those at the 1st decile, while it fell by 26.2 log points for those at the 9th decile.



Figure 3. Cumulative Distribution Functions by gender in East Germany (1990-1994)

a) 1990



b) 1994

5. CONCLUSION

In this thesis I showed that the relative position of women improved during the economic transition from socialism to market economy in East Germany between 1990 and 1994, meaning that the observed gender wage differential substantially decreased over the considered period. I examined the underlying reasons behind the gender gap and its change in order to see whether there was a true decline in the male-female wage differential, meaning either an improvement in women's relative level of measured and unmeasured labor market characteristics or a potential decrease in discrimination against female workers, or the narrowing of the gender gap is simply a result of disproportionate quits of low-skilled and low-earner women from employment.

For this purpose, after briefly exploring the existing gender gap and its constituting components, I first implemented Heckman's two-step correction method to adjust for potential selection bias. While I found no evidence for selectivity bias for men, I found positive selection for women into employment during the observed period in line with findings of Hunt (2002). This result could suggest that the transition to market economy influenced low-skilled and low-earner female workers unfavorably, if it does not reflect voluntary withdrawal from participating in the labor force, for instance if it is due to discriminatory actions of employers against women or it is a consequence of reduction in maternity leave, child care and other social entitlements. From the extended Blinder-Oaxaca decomposition adjusted for sample selection one can see that the observed wage gap underestimates the offered wage gap in each year. However, after correcting for the found sample selection bias in the estimation of the change in the offered wage gaps from 1990 to 1994, I still found a decline in the male-female wage differential that is of the same magnitude as previously. This indicates that the substantial fall observed in the gender gap cannot be

accounted for solely (or in a large part) by the exits of low-skilled workers from labor force participation who were disproportionately women.

Next, I continued with decomposition methods escaping the limitations involved with the restrictive assumptions of the traditional Blinder-Oaxaca procedure. First, I implemented a reweighting method suggested by DiNardo, Fortin and Lemieux (1996). This technique allows for the decomposition of the gender gap at different quantiles of the wage distribution while relying on weaker assumptions than the Blinder-Oaxaca decomposition. Using the reweighting procedure. I found that the existing wage gap is significantly larger for female workers at the lower quantiles of the wage distribution than for female workers at the higher quantiles in both years. Furthermore, the obtained results also showed that while the malefemale pay gap decreased at each quantile of the distribution over the period, the estimated fall was larger in relative terms for working women at higher points of the distribution than at lower points. These results indicate that while working women all enjoyed a relative wage growth during the transition, low-skilled and low-earner female workers experienced these favorable changes only at a much smaller degree. Moreover, the decomposition of the total gender gap into unexplained and explained components ("Renumeration" and "Endowment" effects) revealed that only a very small fraction of the male-female wage differential can be accounted for by differences in the human capital measures (educational attainment and labor market experience) included in the analysis. This is important also from a policy point of view, since present analysis suggests that to achieve substantial improvement in female workers' relative situation, more research needs to be done concerning the possible sources of the dominating unexplained part of the gender wage gap.

Then, I applied an exact matching-based decomposition technique introduced by Nopo (2004) that not only incorporates all the advantages of the previously described reweighting method, but also accounts for the "support" problem in the distribution of human capital

characteristics included in the analysis as opposed to the Blinder-Oaxaca and the DiNardo-Fortin-Lemieux methods that both perform poorly in case of lack common support. The obtained results are consistent with the findings of the reweighting method. The estimates indicate that the unexplained part of the male-female wage gap fell at all points of the wage distribution during the transition and that this decrease was substantially larger for female workers at the higher quantiles than for female workers at the lower quantiles. Furthermore, I found evidence that there are such highly rewarded individual characteristics on the labor market that are attained exclusively by male workers. It is important to note that this method is also subject to some limitations, since it is based on exact matching it might suffer from the problem of high dimensionality.

Finally, there are a couple of possible extensions to the study done so far that could be conducted in future research. Firstly, since Heckman's two-step sample selection correction method is highly sensitive to the distributional assumptions placed on the error terms and the specification of both the wage and the participation models (see Puhani, 2000), I would suggest to depart from this method and use available semi-parametric or nonparametric methods that relax the restrictive assumptions imposed by Heckman's method (see Vella, 1998). Additionally, a natural extension would be to use propensity score matching instead of exact matching in the case of Ñopo's decomposition technique so as to avoid the problem of high dimensionality.

APPENDIX

Variables	Μ	en	Women		
variables	1990	1994	1990	1994	
		Me	ean		
Log(Wage)	7.172	8.004	6.852	7.801	
Age					
under 25	0.104	0.065	0.094	0.078	
between 25 and 35	0.290	0.290	0.299	0.273	
between 35 and 45	0.264	0.323	0.285	0.348	
between 46 and 50	0.156	0.138	0.144	0.147	
between 51 and 55	0.117	0.138	0.121	0.120	
between 56 and 60	0.069	0.045	0.056	0.035	
General schooling	0.024	0.020	0.061	0.030	
Apprenticeship	0.702	0.695	0.688	0.637	
Vocational training	0.147	0.154	0.163	0.222	
University	0.127	0.131	0.087	0.111	
Experience					
under 10	0.275	0.275	0.367	0.377	
between 11 and 20	0.337	0.296	0.356	0.310	
between 21 and 30	0.182	0.210	0.148	0.180	
between 31 and 40	0.122	0.124	0.080	0.083	
between 41 and 50	0.014	0.001	0.004	0.000	
		Std de	viation		
Log(Wage)	0.282	0.324	0.360	0.411	
Observations	1199	908	1206	777	

Table 1. Descriptive statistics of variables included in the analysis

Variables	Μ	en	Women		
v al lables	1990	1994	1990	1994	
		Me	ean		
Head of household	0.529	0.539	0.483	0.497	
Marital status	0.779	0.759	0.764	0.770	
Number of children in HH					
under the age of 5	0.155	0.137	0.155	0.106	
between 6 and 16	0.570	0.679	0.619	0.716	
Number of adults in HH	2.415	2.422	2.347	2.366	
Log(child allowance)	1.396	3.090	1.449	3.144	
Income from interest/dividend	0.262	0.262	0.256	0.241	
		Std de	viation		
Number of children in HH					
under the age of 5	0.391	0.363	0.395	0.324	
between 6 and 16	0.769	0.863	0.779	0.832	
Number of adults in HH	0.796	0.846	0.799	0.819	
Log(child allowance)	2.326	2.428	2.333	2.366	
Observations	1199	908	1206	777	

Table 2. Descriptive statistics of instruments included in the analysis

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