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Decomposition of the Gender Wage Gap Using Matching: an Application for Switzerland

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Decomposition of the Gender Wage Gap Using Matching: an Application for Switzerland

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Abstract

In this paper, we investigate the gender wage differentials for Switzerland. Using micro data from the Swiss Labour Force Survey, we apply a matching method to decompose the wage gap in Switzerland. Compared to the traditional Oaxaca-Blinder decomposition, this nonparametric technique does not require any estimation of wage equations and accounts for wage differences that can be due to differences in the support. Our estimation results show that the problem of gender differences in the supports matter in explaining wage differentials. We can interpret these differences as a form of "discrimination" which is reflected in wages because women face "barriers to the entry" in accessing certain individual characteristics that men achieve. As a consequence, accounting for these differences in gender supports may be useful in terms of policy implications in promoting more equality between men and women.

Keywords: discrimination, gender wage gap, matching.
JEL Code: C14, J16, J71

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1 Introduction

In Switzerland, the issue of inequality between women and men has been of policy concern during the last decades. Both progress and stagnation are the special features in terms of gender equality over the period 1970-2000. Some progress has been done in the access to education (see OFS, 2003). Despite this gain, it is important to point that some significant differences remain especially in areas involving the repartition of domestic and work tasks. In Switzerland, the gender specialisation in different areas of life is a strong social norm (see OFS, 2003). Along with occupational segregation, this can be a source of wage inequalities between men and women.[1] Our concern in this paper is to investigate one particular aspect of gender inequalities which is based on wage differentials between men and women.

In the international literature, a growing attention has been paid to this question of gender wage differentials. The way of addressing this issue has typically involved the distinction between the wage differences that can be due to different compositions of personal characteristics (such as age and education) and the wage differences that remain after controlling for these observed differences and that are commonly attributed to discrimination.[2,3]

One way for adjusting these observed differences between men and women involves wage regressions. Although commonly used, this approach has some limitations. First, a particular relationship is assumed between the explained variables and the (log of) wages (with a potential risk of misspecification). Another, perhaps more important problem is the "support" problem in the distribution of the covariates. Men and women may not only differ in age, education and occupation…, but the distributions of these variables can overlap very little. This problem of lack of common support has been ignored in most studies on gender wage gaps. Typically, assumptions are made to extrapolate results: the behaviour of men is projected outside the observed range to form a comparison group for women having the same

[1] Lalive and Stutzer (2004) investigate the importance of social norms in explaining why women do not report a lower job satisfaction while persistent wage gaps are observed in Switzerland. In their study, wage differentials between men and women are attributed to the social norms about appropriate salaries for women. However, we can argue that these social norms can represent a form of barriers to the integration of women to the labour market.

[2] A definition of wage discrimination that is commonly accepted and used in the literature suggests that discrimination against women arises when for seemingly equal work, women earn less than men (see Altonji and Blank, 1999).

characteristics. This can lead to misleading results since individuals are compared though they are not comparable. As an alternative, the attention is restricted to the common support only, thus ignoring a lot of information which can be useful. In addition, the policy conclusions are made for the whole population while the analysis is made only for its part. The importance of the common support problem has been largely addressed in the evaluation literature (for a detailed discussion, see for instance Lechner, 2001).

As an alternative to the parametric approach, nonparametric methods have been proposed. In this paper, we use a nonparametric technique which is based on matching. Matching methods have been widely used in the literature on evaluation in looking at the impact of a treatment on an outcome variable (see for instance Heckman, Lalonde and Smith, 1999). However, matching can be used in the analysis of gender wage differentials as well. In disentangling the explained and the unexplained components of these differentials, we have indeed to compute the counterfactual wage that women would receive if the distribution of their characteristics would be similar to that of men. In this paper, we use the matching procedure and the decomposition of the wage gap along the lines of Nopo (2004). Nopo suggests using exact matching. The advantage of this procedure is that we can simultaneously estimate the common support and the mean counterfactual wage for the women on the common support. In addition, the decomposition of the wage gap explicitly accounts for differences in the supports of the distributions of characteristics. Lastly, this matching method provides useful information on the unexplained wage gap not only at the mean, but also on the distribution of this gap over the entire wage distribution.

However, the flexibility of this method is very costly: in the nonparametric setup, we face the problem of dimensionality which arises when we control for many covariates. The inclusion of many variables will indeed reduce the size of the cells and the number of matches. Hence, this limits the distributional analysis of the unexplained component of the wage gap. This problem is attenuated if a large dataset is available. An alternative approach to exact (multivariate) matching would be propensity score matching which reduces a high-dimensional estimation problem to a *one-dimensional* case (see Rosenbaum and Rubin, 1983). However, in terms of efficiency, it is not clear whether propensity score matching is superior to direct matching (see the efficiency issues discussed in details by Hahn (1998); Heckman, Ichimura and Todd (1998)). As a consequence, we compare the results of the decomposition

[3] This standard decomposition has been extended by Juhn, Murphy and Pierce (1993) into a decomposition that

based on exact matching with the results of decompositions based on more commonly used nearest-neighbour and calliper propensity score matching algorithms.

Besides these methodological issues, taking account of gender differences in supports may also be important for policy implications. Gender differences in supports can indeed reflect a form of pre-labour market discrimination, because women face some "barriers to entry" in reaching certain individual characteristics that men achieve (see Nopo, 2004). Such barriers can for example be attributed to a different access to the education system, but also to the fact that working women still have to carry most of the burden for housework and childcare (see Altonji and Blank, 1999; Waldfogel, 1998).[4] In the latter case, it will take a long time to reduce the gender wage gap, since it involves a change of social norms about men's and women's role on the labour market. As a consequence, measures facilitating the duality between work and family should prove to be useful in reducing gender wage differentials (see for instance Blau and Kahn, 2000 for the US).

The paper is organised as follows. Section 2 gives a brief overview of the existing literature on the decomposition of the wage gap. Section 3 presents some stylised facts about the measures aimed at promoting gender equality in Switzerland. In Section 4, data used for the empirical application are described and some descriptive statistics on gender wage differentials are reported. In section 5, we present the econometrical model. Then, we discuss the results in Section 6. Section 7 concludes.

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accounts for unobserved heterogeneity in addition to the classical "endowment" and "remuneration" effects.

[4] Altonji and Blank (1999) point the importance of "pre-market human capital differences" such as differences in family expectations and in educational choices in explaining gender wage differences in the labour market. Waldfogel (1998) underlines the role of some institutional factors such as the lack of maternity leave in acting as structural barriers to the promotion of women with children in employment that is valuable in terms of work experience and thus in terms of higher pay.

2 Wage gap decomposition: a literature overview

2.1. International overview

A wide strand of empirical literature has focused on the role of discrimination in explaining the observed wage differentials between men and women on the labour market (see Blau and Kahn, 1997 and Altonji and Blank, 1999 for an overview). Typically, the question is to disentangle the part of the gap that can be explained through human capital endowment from the part that may result from discrimination. Human capital endowment (such as education, experience and other characteristics) is distributed differently between men and women.[5] In this case, the wage differentials are explained by some characteristics which men own and which women do not own such that these characteristics are better rewarded on the labour market. As a consequence, if the distribution of the characteristics between men and women were the same, the wage differentials would reduce by the amount that is attributed to differences in human capital endowment. In the literature, this component of the wage gap is often referred to the "explained" part. After controlling for human capital characteristics, the remaining wage gap (or the "unexplained" part of the wage gap) is then due to discrimination.[6] In accounting for this component of the gap, the *counterfactual* wage that women (resp. men) would earn if they had the same characteristics as men (resp. women) has been the key research element of the empirical literature.

Different decomposition methods have been proposed to account for the explained and unexplained components of the wage gap. The most popular method is based on a parametric approach. Following Blinder (1973) and Oaxaca (1973), thereafter BO, separate wage functions are estimated for males $\left(W_{im} = X_{im}{}'\beta_m + U_{im}\right)$ and for females $\left(W_{if} = X_{if}{}'\beta_f + U_{if}\right)$ with X being a vector of human capital characteristics (see Mincer's wage equation, 1974). The difference in average wages between men and women can be decomposed into differences in personal characteristics ("endowment effect") and differences in returns ("remuneration effect") :

[5] For example, in their survey on race and gender differentials in the labour market, Altonji and Blank (1999) provide evidence that differences in personal characteristics that are likely to be related to wages such as education, experience and family status are observed by gender for the US. In our paper, we also find gender differences in these characteristics for Switzerland (see Section 4 for more details).

[6] It is partially attributed to discrimination, since it is possible that some unobserved characteristics that may explain the wage differentials are not controlled for.

$$\bar{W}_m - \bar{W}_f = \underbrace{\left(\bar{X}_m - \bar{X}_f\right)' \hat{\beta}_m}_{\text{endowment effect}} + \underbrace{\bar{X}_f' \left(\hat{\beta}_m - \hat{\beta}_f\right)}_{\text{remuneration effect}}$$

In this decomposition, the term $\bar{X}_f' \hat{\beta}_m$ represents the counterfactual wage for women if they were paid as men (i.e. if their characteristics were rewarded in the same way as for the average man). The second term of the decomposition is often interpreted as wage differences that may result from discrimination. However, the validity of this interpretation has widely been discussed in the empirical literature: omission of observed variables, pre-labour market discrimination, endogeneity issues that can arise in the OLS estimation of the wage regression and the lack of the common support can make it difficult to distinguish between the different components of the wage gap and to assign the true part of the gap that is due to discrimination.

A potential problem inherent to the BO decomposition is the validity of the functional form assumption about the conditional expectation of wages. In constructing the counterfactual wage, it is assumed that it is always possible to find women who are comparable to men in terms of observed characteristics. However, a problem of comparability arises, because some combinations of characteristics that are common among men may not be observed among women. This is particularly true if job characteristics such as job occupations or degree of occupation are accounted for. As a consequence, the BO decomposition assumes that the estimates of the wage equations are valid out of the supports of the distribution of individual characteristics. However, some empirical evidence shows that this specification assumption can lead to misleading results. For instance, Barsky, Bound, Charles and Lupton (2001) account for the differences in earnings in explaining the wealth gap between black and white households. In their study, they provide evidence that a large fraction of black households is not observed over a sizeable portion of the white earnings distribution. With the traditional BO decomposition which fails to account for these differences in the supports of the distributions of the characteristics, Barsky *et al* find that 20% of the average wealth gap is explained by earnings differences. On the contrary, by focusing on comparable white/black households only, the part of the mean wealth gap which is attributed to earnings differences amounts to 64%. In his study about gender wage gap in Peru, Nopo (2004) reports similar empirical evidence about the importance of differences in the supports in explaining the wage gap. First, 30% of working women cannot be matched with any men in the data and thus belong to the out-of-support region. Second, Nopo (2004) finds that the unexplained part of the gender gap is over-estimated using the BO decomposition.

A second disadvantage of the BO decomposition is that it only focuses on the mean unexplained wage differences and does not explore the distribution of these unexplained differences. To overcome this limitation, different approaches have been used to simulate the counterfactual wage distribution. For instance, in their study about the rising wage inequality in the USA, Juhn, Murphy and Pierce (1993) construct the hypothetical wage distributions using a parametric model (based on the OLS estimation of wage equations). In addition, Donald, Green and Paarsch (2000) explore the differences in wage distributions between Canada and the USA by using a parametric proportional hazard model. Other studies use quantile regression methods to construct counterfactual wage distributions (see for instance Poterba and Rueben, 1994 and Melly, 2005 for studies about public-private sector wage differentials for respectively the US and Germany; Garcia *et al*, 2001 and Albrecht *et al*, 2004 investigate the gender wage gap using quantile regressions for respectively Spain and the Netherlands). As an alternative to parametric strategies, the counterfactual wage distribution can also be simulated using nonparametric techniques. For instance, in their study about wage inequality in the USA from 1979 to 1988, DiNardo, Fortin and Lemieux (1996) study the effect of changes in labour market institutions on the distribution of wages. They construct the synthetic wage distribution that would have been observed in 1988 if the labour market institutions of 1979 had remained unchanged using the observed wage distribution in 1988 by applying kernel density methods to re-weighted samples. Similarly, Barsky *et al* (2001) propose a nonparametric alternative to the usual BO decomposition. They simulate the counterfactual wealth distribution by re-weighting white households such that their earnings distribution coincides with the actual earnings distribution of black households. Contrary to the study by DiNardo *et al* (1996), there is only one single explanatory variable in the study by Barsky *et al*. This avoids the problem of dimensionality that arises in the study by DiNardo *et al*. In the nonparametric setup, Nopo (2004) also investigates the distribution of the wage gap but in presence of many explanatory variables. In addition, he proposes a new decomposition technique that accounts for the above mentioned problem of the differences in the supports.

2.2. Swiss studies

In the last decade, the issue of gender wage differences has been the focus of a number of studies in Switzerland. Since the seminal work by Kugler (1988), about ten studies have been published in this area. Table 1 gives an overview of these studies. It indicates that different estimation methods of wage equations and different data sets have been used. This leads not surprisingly to diverse results which do not help in the current public debate on gender wage differences (OFS, 2003). Most studies analysing the gender wage gap in Switzerland are based on parametric methods and use the BO decomposition for wages.

By combining data from the Health Survey, the Income and Wealth Survey and merging them with a supplement survey on labour supply, Kugler (1988) examines the gender wage gap for a sample of about 2500 individuals. Using the traditional BO decomposition, he finds that 93% of the gender wage gap of 43% can be accounted for. Brüderl *et al* (1993) use data from the 1987 International Social Survey Program and find a total wage gap of 81% and an unexplained wage gap of 38%. A range of studies conduct the gender wage gap analysis using the data from the Swiss Labour Force Survey (SLFS). Depending on the estimation techniques and the variables used in these analyses, the studies find a gender wage gap of 20%-40% of which about 10%-20% cannot be explained by the specification used in these studies. The study by Sousa-Poza (2003) is the only study that uses the first 11 waves from the SLFS. After controlling for personal characteristics such as education, foreigner status, experience and for job characteristics such as tenure, firm size and industry sector dummies, between 50% and 60% of the wage gap still remains unexplained. This is rather different from the result obtained in Bonjour (1997) for example. We argue that these differences are due to differences in the specification of the wage equations. In addition, the endogeneity problem associated with variables such as tenure is not accounted for in the study by Sousa-Poza. On the contrary, in Bonjour (1997), different estimation techniques of the wage equations have been proposed to take the endogeneity problem into consideration. However, all these studies are based on the traditional BO decomposition that fails to recognise the problem of gender differences in the supports of the explanatory variables. Since gender occupational segregation is found to be important in the Swiss labour market (see OFS, 2003), assuming that all working women are comparable to working men will lead to misleading results.

Bonjour and Gerfin (2001) is the only Swiss study that uses a distributional analysis: they examine how the unexplained component of the wage gap varies over the wage distribution. To calculate the counterfactual wage distribution, they use the proportional hazard model proposed by Donald *et al* (2000) to estimate density wage functions. Their main finding is that the unexplained component of the wage gap is distributed unequally across the wage distribution. It is actually declining over the range of wages. This indicates that at the lower end of the wage distribution, a large part of wage difference is due to discrimination. On the contrary, at the upper end of the wage distribution, most of the gender gap is explained by differences in human capital endowment. An analysis by specific variables shows that it is a low level of education that explains why the discrimination component of the wage gap is over-proportional at low wages. In their study, the BO decomposition is extended to explore the distribution of the unexplained wage differences. However, this strategy still ignores the problem of gender differences in the supports that we want to address in this paper.

In this paper, we examine the gender wage gap by using a nonparametric econometric method which has been proposed by Nopo (2004). To our knowledge, there is no empirical study for Switzerland that applies matching to investigate the gender wage gap. In this study, we consider that gender is a treatment variable. In order to construct the counterfactual mean wage of women, we then match women to the sample of men having the same observed characteristics. Finally, the counterfactual wage is obtained by taking the average wage over the observations for men providing a matched observation. As argued by Nopo, this matching procedure does not require the estimation of any wage functions. As a consequence, we do not have to face the issue of doing incorrect inferences due to assumptions that are no valid in the out of common support region.

Table 1: Overview of the Swiss studies on the gender wage gap.

Authors	Data	Period	Decomposition	Wage gap in %	Unexplained component in %**
Kugler (1988)	3 datasets merged	1981-1982	Oaxaca-Blinder	43	7
Brüderl, Diekmann and Engelhardt (1993)	ISSP	1987	Oaxaca-Blinder	81	38
Diekmann and Engelhardt (1995)	SLFS	1991	Oaxaca-Blinder	43	16
Bonjour (1997)	SLFS	1991-1993	Oaxaca-Blinder	26	[9-13]
Henneberger and Sousa-Poza (1998)	SLFS	1995	Oaxaca-Blinder	29	[10-16]
Henneberger and Sousa-Poza (1999)	SLFS	1997	Oaxaca-Blinder	24	[8-11]
Flückiger and Ramirez (2000)	SWSS	1994-1996	Oaxaca-Blinder	30	17
Bonjour and Gerfin (2001)	SLFS	1991-1995	Oaxaca-Blinder semiparametric*	21 21	10 8
Sousa-Poza (2002)	SWSS	1998	Oaxaca-Blinder	[18-28]	[14-19]
Sousa-Poza (2003)	SLFS	1991-2001	Oaxaca-Blinder	[23-28]	[50-65]

Notes: SLFS (Swiss Labour Force Survey); SWSS (Swiss Wage Structure Survey); ISSP (International Social Survey Programme); Kugler (Health Survey, Income and Health Survey, supplementary survey on labor supply); * the numbers correspond to the 50% quantile of the wage distribution and ** relative to the raw wage gap.

3 Promotion of gender equality in Switzerland

3.1. Legal framework:

In terms of national legislation in equal pay and equal opportunity, Switzerland is lagging behind the other OECD countries. The Swiss Federal Constitution was amended in 1981 and explicitly stated that women and men must be equally paid for equal work. However, the first federal law on equal wage and equal opportunity came into force only in July 1996. The objective of this law is to promote actually equality between men and women (article 1). As a consequence, direct or indirect sexual discrimination in hiring/firing, in tasks' repartition, in remuneration, in professional training and in job promotion is forbidden. In all cases (except for hiring), it is presumed that discrimination arises when the concerned person can show that discrimination is likely and when the employer cannot prove that there is no discrimination (article 6). According to articles 3 and 4, the disadvantaged person can bring an action for damages. However, the federal law does not stipulate that any office has to be designed to make investigations when cases of discrimination arise and to bring actions for damages in case of violation of the law. It is the responsibility of the victim to attend an action in front of the competent authorities.

Concerning international legislation, Switzerland has ratified in 1997 the UN Convention on the Elimination of all forms of Discrimination Against Women (CEDAW). This ratification should help in promoting the equality between men and women in Switzerland. However, the federal structure of Switzerland implies that the Confederation is responsible for the application of international standards while cantons are the competent authorities which own their own political and juridical institutions. In this case, the principle of equality between men and women is defined on an area for which the same authority has the competence. Even though, it is possible to appeal to the Federal Court in order to have a uniform application of the federal law and the international standards, the Federal Court does not intervene in actions that belong to the cantonal authority. As a consequence, the federal structure of Switzerland poses some issues of policy coherence. This has also been stressed in the reports of the CEDAW in January 2003. These reports underline the necessity of coordinating the application of the Convention between the different administrative levels (federal, cantonal and communal).

3.2. Court practice:

The lack of coordination and transparency is reflected in the small number of actions intended in front of the Federal Court. Since the amendment of the Constitution, only 65 actions regarding equal wage have been observed. Among them, two actions concern employees in the private sector. The small number of suitcases is essentially due to the difficulty of bringing proofs of the existence of discrimination, especially in terms of equal value of the work. In addition, the length and the costs of suits can discourage women of undertaking any action in front of the court. Moreover, some wage differentials can be found to be legitimate. It is indeed possible that some personal and social considerations such as age and family tasks that do not directly influence the work activity are accepted in justifying some observed wage differentials. The differences observed in terms of wages and hours of work are thus more explained by the difficulties which women face in combining work and family than by differences in terms of education and human capital. The CEDAW report on the actual measures struggling against gender discrimination leads to the conclusion that helping the combination between work and family and promoting the repartition of family tasks between men and women should prove to be worthwhile in increasing gender equality in Switzerland. As a consequence, Switzerland has to pursue its efforts in encouraging more equality between men and women.

3.3. Evolution since the last 30 years

In order to evaluate the progress and the pitfalls established in the area of equality, regular detailed surveys by gender have to be undertaken. This is one of the main objectives of the Federal Law of Statistic in 1992. This law explicitly mentions that statistical data have to be systematically elaborated for each of the genders. In addition, a report giving the actual state in the promotion of equality between women and men has to be regularly published. For this purpose, the Federal Statistical Office has published 2 reports on equality between men and women in 1993 and 1996. In addition, two recent OFS reports have appeared in 2003 and 2005: the report of 2003 presents some detailed indicators about gender equality in different areas such as education, working life and wages, social security and poverty, while the report of 2005 gives an overview of the situation in gender equality for the period from 1970 to 2000.

These reports lead to the conclusion that progress and stagnation are observed in measures aimed at promoting equality between women and men over the last 3 decades. Appendix A.1 shows that gender differences with respect to education have narrowed in time. Since 1980, the share of individuals without post-obligatory schooling has reduced by 50%. Nowadays, women are more likely to complete apprenticeship training than two decades ago. In addition, the proportion of women with a tertiary degree has more than doubled over this period. Similarly, female participation rates have continuously increased over the period 1970-2000. Despite this increase, the Swiss labour market remains still segmented. Indeed, full-time positions are primarily occupied by men while women are essentially working part-time (see Appendix A.1). Another indicator of equality is the proportion of men and women in different job positions. Between 1970 and 2000, the fraction of women having a supervisory function has continuously increased (see OFS report, 2005). This evolution is attributed to the progress in educational attendance of women. However, women remain still confined in female dominated sectors such as health care, clerical work and services (see Appendix A.1). The last, but not the least indicator of gender inequality concerns wage differentials. On average, women earn less than men. The gap amounts to 21% in the private sector and to 10% in the public sector. In both sectors, the gender wage gap has decreased between 1994 and 1998, but it has remained at its level thereafter (see Appendix A.2). If wage differentials exist for all economic sectors, these gaps vary a lot across the sector of activity.

4 Data and descriptive statistics

4.1. Some facts about raw gender wage gaps

This section presents some descriptive statistics about the raw gender wage gap using the data from the Swiss Labour Force Survey that have been used in the empirical analysis. The general trend is that the raw gap has narrowed between 1996 and 2003: on average, women earn 32% less than men in 1996 compared to 25% in 2003 (see Table 2).[7] A further look at the different years seems to indicate that over the period 1996-2000, the raw gap decreases: it is the lowest in 2000 when the unemployment rate reaches its lowest level after the recession period of the beginning of the 1990s. There is however an exception for 1997 where the raw gap is low, but the unemployment rate reaches its highest level in Switzerland. Notably, the official statistics from the Swiss Federal Statistical Office tells us that that was the only year from our observation window when unemployment of women was lower than unemployment of men.[8] From 2001, the raw wage gap remains relatively constant. This is in line with the recent recession observed since the beginning of this decade.

Table 2 displays the raw wage gap at some selected quantiles of the total wage distribution and conditional on some observed characteristics. The absolute wage gap at, for example, the 25th quantile is the difference between the wage at the 25th quantile in the male distribution and the wage at the 25th quantile in the female distribution. The relative wage gap at a 25th quantile is the ratio of the absolute wage gap at the 25% quantile to the wage at the 25th quantile in the female distribution in that year. For the period 1996-2003, Table 2 shows that men at the 25th quantile earn about 26.7% (or 4.82 CHF) more than women at the 25th quantile of their wage distribution. The raw gender gap varies considerably across the wage distribution and also by observed characteristics. Over the entire wage distribution, the raw gender wage gap has a convex U-shape. By educational level, the raw gap is higher for low educated individuals, especially at the lower end of their wage distribution. However, at the upper end of the wage distribution, the raw gap is the highest for high educated individuals

[7] The statistics presented in Table 2 are based on the selected samples used in the empirical analysis. The population in a particular year refers to the workers of that corresponding year satisfying the sample selection rules such as being not self-employed, not a student or a worker older than 55 (see Section 4.2).

[8] In Switzerland, two unemployment indicators are used: the statistic of unemployed registered at the regional job placement offices and which is drawn up by the State Secretary for Economic Affairs (Seco) and the statistic recorded by the Swiss Federal Statistical Office (SFSO) which corresponds to the ILO standard unemployment

and the lowest for low educated individuals. This raises the question whether these differentials still remain after controlling for observed characteristics. Table 2 further indicates that the gap is wider in the private sector than in the public sector. Similar behaviour of the raw wage gap is described in Melly (2005). This seems to hold over the entire wage distribution.

Table 2: Absolute and relative raw gender wage gap at mean and selected quantiles.

	mean		at the 10th quantile		at the 25th quantile		at the 50th quantile		at the 75th quantile		at the 90th quantile	
year	in CHF	in %	in CHF	in %	in CHF	in %	in CHF	in %	in CHF	in %	in CHF	in %
1996	7.43	31.7%	4.73	35.6%	5.43	32.9%	5.71	26.9%	7.63	28.1%	12.46	37.1%
1997	5.83	24.2%	4.59	34.1%	5.26	31.5%	5.46	25.3%	7.17	26.2%	10.39	30.0%
1998	6.79	28.7%	4.13	29.6%	4.80	27.7%	4.93	22.3%	7.16	25.9%	10.86	31.5%
1999	6.57	27.1%	4.74	33.8%	4.41	24.9%	4.92	21.9%	7.00	24.9%	10.54	30.1%
2000	5.72	22.4%	4.93	35.3%	4.56	25.6%	4.64	20.2%	7.08	24.6%	11.21	31.8%
2001	6.40	24.6%	4.93	33.5%	4.80	26.4%	5.37	23.0%	8.23	27.8%	11.48	30.5%
2002	7.04	27.5%	4.09	26.6%	4.49	24.4%	5.03	21.4%	8.35	28.2%	12.12	32.4%
2003	6.62	25.0%	3.98	25.6%	4.15	21.9%	4.99	20.7%	8.10	26.6%	12.69	33.1%
1996-2003												
Total	6.65	26.0%	4.80	33.2%	4.82	26.7%	5.13	22.1%	7.81	26.5%	11.63	31.6%
Education												
low	3.70	18.9%	4.22	36.6%	4.35	29.4%	4.66	26.1%	4.00	18.3%	3.23	11.8%
medium	3.73	14.9%	3.99	26.3%	3.74	20.1%	3.29	14.1%	3.99	14.0%	5.72	16.5%
high	7.68	22.6%	4.65	23.9%	4.71	18.8%	6.78	21.9%	9.48	24.7%	12.94	27.2%
Sector												
private	7.56	31.5%	5.19	37.4%	5.50	32.3%	6.12	28.6%	8.73	32.0%	13.02	37.5%
public	6.96	24.7%	3.80	22.8%	4.88	23.3%	6.01	23.0%	8.67	27.1%	10.54	26.6%

Notes: own computations from SLFS data; wages refer to hourly wages; the absolute wage gap is measured in current CHF and the relative wage gap in % of female wages.

4.2. Description of the variables used

This section presents the variables used in the empirical analysis. This study is based on the data of the Swiss Labour Force Survey collected by the Swiss Federal Office since 1991. The Survey is carried out once a year, during the 2nd quarter (April-June). It covers the population of persons aged 15 or more who are permanent residents in Switzerland (at least for one year).[9] The Swiss Labour Force Survey provides important internationally comparable information on the labour market situation in Switzerland. Each year approximately 16'000 persons randomly drawn from the phone register of the Swiss PTT are interviewed.[10] As a

definition. The Swiss data for the OECD statistics are provided by the SFSO and are based on the SLFS data. In this paper, we use the unemployment definition according to the SFSO.

[9] Individuals living in Switzerland during a short period, the cross-border workers and the refugees are excluded.

[10] From 2002, the number of persons randomly chosen increased to about 40’000 persons.

consequence, all persons having no telephone are not covered by the survey. Participation is voluntary. Questions are asked on work activity, professional experience, working times and conditions, job seeking, former occupation, reasons for not being economically active and incomes. The data collected provide information about socio-demographic characteristics of the employed, unemployed and inactive individuals.

This empirical study uses the waves from 1996 to 2003. We choose to not use the first waves from 1991 to 1995, because gender wage gap in Switzerland has been widely studied for this period. In addition, the sample size in each of these years was small making it insufficient for our matching procedure. As mentioned before, approximately 16’000 persons were interviewed each year. This sample size changes to about 40’000 persons from 2002. That is why we prefer to focus on the second part of the decade. The data set consists of a rotating panel: each year, one fifth of the individuals already included in the sample is replaced and the other four fifths are re-interviewed. As a consequence, an individual can stay in the sample for at most 5 consecutive years.

The empirical analysis concentrates on workers who are not self-employed, not in the agricultural sector, not in a training programme (apprenticeship) or completing compulsory military service. We do not take people in agricultural sector, because their earnings are likely to be explained by random factors such as weather conditions. Similarly, we do not include self-employed, because it is difficult to distinguish between returns to human capital from returns to physical capital. In addition, we exclude students and employees older than 55, since they are also involved in the education and retirement decisions which are different from the employment decision. Finally, we drop all observations for which missing values are observed.[11] Hourly wages are calculated using the yearly (net) labour income and the number of normal weekly working hours. In our study, we do not account for holidays, since they are paid. Two points concerning our sample should be discussed briefly. First, the definition of hourly wages is restrictive, since we are implicitly assuming that individuals employed during the reference period are employed during the entire year. With the use of yearly labour income, it is thus not possible to identify persons who were without a job during a part of the year. This implies that hourly wages will be under-estimated. Second, our study concentrates only on wage earners. We are primarily interested in the hourly wage a woman would get if

[11] In 2003, the final data set contains 20’838 individuals (9’958 women and 10’880 men). For other years, see Appendix A.4.

the distribution of her characteristics would be similar to that of men. Selectivity issue that arises in the estimation of women's wage functions is beyond the scope of this paper.[12] As a consequence, our results must be interpreted conditional on the population of employees.

Although our non-parametric approach eliminates the problem of specification of earnings equation, it does not eliminate the problem of choice of variables. Appendix A.3 presents the variables we use for the decomposition of gender wage gap. They include human capital characteristics such as age and education, personal characteristics such as marital status, household composition and foreign citizenship. We further control for job characteristics with variables capturing firm size, job position, industry sector and work experience. Overall, we control for 12 variables that are found to be important in explaining wages in the classical literature on the gender wage gap (see the survey by Altonji and Blank, 1999). Our choice of variables is based on the human capital theory (Becker, 1974, Mincer, 1974). In the simple Mincerian wage equation, the education and experience variables are considered to be the most important determinants of wages. We further include demographic and job characteristics to explain earnings more precisely. Including controls for experience, job position and industry sector may be questionable to the extent they may be an outcome of discrimination. Despite this potential endogeneity problem, we believe that these variables have an important role in explaining the wages and cannot be ignored in our matching procedure. We also control for marital status and presence of young children, because we believe that this influences labour decisions of women in Switzerland. Moreover, Waldfogel (1998) finds evidence of a negative effect of children on women's and men's wages even after controlling for labour market experience.

Table 3 presents some descriptive statistics for male and female employees. Men are over-represented among high educated workers. There are many more married men than married women (this is due to the sample selection of working women). This is also reflected in women's lower number of children. Women also have a lower level of work experience, are more likely to be employed in small firms and less likely to have a responsibility function.

[12] In the literature, it is common to correct the selectivity bias by applying a sample selection model which takes the participation decision of women into account. After using the Heckman's two-stage procedure, "potential" wages of actually non-working women can be imputed from those women who are actually working. In order to be valid, the Heckman correction technique requires the availability of instruments that are related to the propensity to work but not to wages. Since, in practice such exclusion restrictions are hard to find, this highlights the potential weakness of the Heckman approach.

Table 3: Descriptive statistics for 1996 and 2003.

year	1996		2003	
Variables	**Women**	**Men**	**Women**	**Men**
Wages in CHF/hour	23.46	30.88	26.52	33.14
Socio-demographics				
Age				
15-24	53.85	46.15	52.24	47.76
25-29	43.14	56.86	50.32	49.68
30-34	43.74	56.26	44.72	55.28
35-39	41.05	58.95	45.94	54.06
40-44	41.78	58.22	46.08	53.92
45-49	46.53	53.47	45.93	54.07
50-55	44.86	55.14	48.11	51.89
Marital status				
single	46.40	53.60	47.42	52.58
married	39.92	60.08	44.53	55.47
divorced	68.95	31.05	62.60	37.40
widowed	82.26	17.74	79.81	20.19
Level of education				
primary	58.03	41.97	53.09	46.91
secondary	48.34	51.66	52.11	47.89
tertiary	25.34	74.66	34.38	65.62
Foreign citizenship				
Swiss	46.42	53.58	49.46	50.54
Foreign	39.09	60.91	40.31	59.69
Children				
With children under 15	37.25	62.75	44.97	55.03
Without children under 15	48.74	51.26	48.68	51.32
Regional characteristics				
*Region of residence**				
Deutschschweiz	44.01	55.99	47.12	52.88
Westschweiz	46.45	53.55	47.96	52.04
Job characteristics				
Firm size				
less than 20 workers	48.51	51.49	52.78	47.22
between 20 and 99 workers	38.14	61.86	43.47	56.53
more than 99 workers	41.06	58.94	40.78	59.22
Responsibility function				
without	53.52	46.48	56.58	43.42
with	30.39	69.61	33.17	66.83

Notes: own computations, Table 3 continues on the next page.

Table 3: ***(…cont.)***.

year	1996		2003	
Variables	**Women**	**Men**	**Women**	**Men**
Job characteristics				
Occupation				
managers	16.48	83.52	28.59	71.41
academicians	29.80	70.20	36.66	63.34
technicians	53.03	46.97	57.07	42.93
clerical workers	66.40	33.60	69.73	30.27
services	72.27	27.73	67.09	32.91
operators	59.26	40.74	60.63	39.37
handworkers	11.76	88.24	15.23	84.77
assistants	18.13	81.87	14.06	85.94
Work type contract				
non permanent	50.64	49.36	53.82	46.18
permanent	44.29	55.71	46.92	53.08
Public sector				
no	39.09	60.91	40.28	59.72
yes	61.23	38.77	65.53	34.47
Work experience				
less than 6 months	61.52	38.48	59.76	40.24
between 6 and 24 months	60.10	39.90	65.51	34.49
between 2 and 5 years	61.73	38.27	60.79	39.21
more than 5 years	40.23	59.77	43.19	56.81
Observations	2794	3069	9958	10880

Notes: own computations, results for the other years are presented in Appendix A.4.

There is a strong occupational segregation: typically female occupations are clerical and services work, whereas men are more likely to work as operators, handworkers and assistants, but also in higher occupation such as managers and academicians. This occupational segregation is also reflected in women's higher propensity to work in the public sector. Turning to the evolution of personal and job characteristics in time, women are more similar to men in 2003 than in 1996: the share of women with a tertiary education increases from 25.34% in 1996 to 34.38% in 2003.[13] Similarly, women are more likely to occupy a position with a responsibility function or a high qualified position such as manager in 2003 than in 1996. Finally, women are more likely to have a higher work experience in 2003 than in 1996.

[13] In addition, Appendix A.1. shows that the proportion of women with a tertiary degree is 8.3% in 2000 against 2.7% in 1980. For men, this proportion is 13.8% in 2000 against 8% in 1980. More details can be found in the OFS reports (2003 and 2005).

5 Decomposition of the gender wage gap using matching

We begin this section with the description of the matching procedure which we use in the empirical analysis. In the second point, we address some issues related to our matching estimator: in particular, we discuss the limitations of our procedure and the potential biases of the resulting estimates.

5.1. Description of the matching procedure

This section draws on Nopo's study. Nopo (2004) develops a simple matching procedure to construct the counterfactual wage. Based on this procedure, Nopo suggests a new decomposition technique that accounts for gender differences in the distribution of individual characteristics. This approach is a fully nonparametric method, since one does no longer need to estimate a linear wage regression function. Second, the counterfactual mean wage is simulated only for the common support. This implies that no assumption on the out-of-support region is required. In order to construct the counterfactual wage, Nopo (2004) uses a matching procedure that selects two sub-samples of men and women who have the same characteristics.

Let $g^m(x) = E(W|X = x, m)$ denote the average wage for men with characteristics *x*, $F^m(x)$ the cumulative distribution function of individual characteristics *x* among men and S^m the support of the distribution of characteristics for men. Define $g^f(.)$, $F^f(.)$ and S^f similarly for women. The key idea in Nopo's approach is that the supports of the distributions of characteristics for women and men might not completely overlap, so that decomposing the wage gap into two parts, the "endowment" and "remuneration" effects, has to be done for the common support only. For this purpose, let $S = S^m \cap S^f$ be the common support and $p_{S|m} = p(X \in S|m) = \int_S dF^m(x)$ be the probability measure of the set *S* under the distribution $dF^m(.)$. Then, one can divide the male population into two subpopulations composed of individuals having characteristics that belong either to the common support *S* or to the out of the common support $\overline{S}$:

$$E\left(W\left|m\right.\right)=E_S\left(W\left|m\right.\right)p_{S|m}+E_{\bar{S}}\left(W\left|m\right.\right)p_{\bar{S}|m} \quad (1)$$

Since $p_{\bar{S}|m}=p\left(X\in\bar{S}\left|m\right.\right)=1-p_{S|m}$, we can rewrite equation (1) as following:

$$E\left(W\left|m\right.\right)=p_{\bar{S}|m}\left[E_{\bar{S}}\left(W\left|m\right.\right)-E_S\left(W\left|m\right.\right)\right]+E_S\left(W\left|m\right.\right) \quad (1')$$

Similar computations can be done for women and we get the following expression:

$$E\left(W\left|f\right.\right)=p_{\bar{S}|f}\left[E_{\bar{S}}\left(W\left|f\right.\right)-E_S\left(W\left|f\right.\right)\right]+E_S\left(W\left|f\right.\right) \quad (2)$$

Equations (1') and (2) permit to write the total gender wage gap Δ:

$$\Delta\equiv E\left(W\left|m\right.\right)-E\left(W\left|f\right.\right) \quad (3)$$

$$\Delta=\underbrace{\left[E_S\left(W\left|m\right.\right)-E_S\left(W\left|f\right.\right)\right]}_{I}+\underbrace{p_{\bar{S}|m}\left[E_{\bar{S}}\left(W\left|m\right.\right)-E_S\left(W\left|m\right.\right)\right]}_{II}+\underbrace{p_{\bar{S}|f}\left[E_{\bar{S}}\left(W\left|f\right.\right)-E_S\left(W\left|f\right.\right)\right]}_{III}$$

Part I of this expression involves the differences of wages between men and women over the common support only, while part II (resp. III) concerns wage differences between men (resp. women) in and out-of-the support.

Finally, part I in equation (3) can be decomposed as in BO 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 women belonging to the common support.[14] The counterfactual wage represents the average wage of women they would get if they were paid as men possessing the same characteristics. We obtain the following expression:

$$E_S\left(W\left|m\right.\right)-E_S\left(W\left|f\right.\right)\equiv\int_S g^m(x)dF_S^m(x)-\int_S g^f(x)dF_S^f(x)$$

$$E_S\left(W\left|m\right.\right)-E_S\left(W\left|f\right.\right)=\int_S g^m(x)\left[dF_S^m(x)-dF_S^f(x)\right]+\int_S\left[g^m(x)-g^f(x)\right]dF_S^f(x) \quad (4)$$

As in BO decomposition, the first and the second parts of equation (4) represent the "explained" and the "unexplained" parts of the wage gap, but now on the common support only. In the linear model, this corresponds to $\hat{\beta}_m'\left(\bar{X}_m-\bar{X}_f\right)$ and to $\left(\hat{\beta}_m-\hat{\beta}_f\right)'\bar{X}_f$.

As a consequence, the Nopo's decomposition involves 4 components:

$$\Delta = \Delta_m + \Delta_x + \Delta_o + \Delta_f \tag{5}$$

with

$$\Delta_m = p_{\bar{S}|m}\left[E_{\bar{S}}\left(W|m\right) - E_S\left(W|m\right)\right],$$

$$\Delta_x = \int_S g^m\left(x\right)\left[dF_S^m\left(x\right) - dF_S^f\left(x\right)\right]$$

$$\Delta_o = \int_S \left[g^m\left(x\right) - g^f\left(x\right)\right] dF_S^f\left(x\right) \text{ and}$$

$$\Delta_f = p_{\bar{S}|f}\left[E_{\bar{S}}\left(W|f\right) - E_S\left(W|f\right)\right].$$

The component Δ_m stands for the part of the gap that can be explained by differences between men in and men out of the common support, i.e. between those men whose characteristics can be matched to women's characteristics and those who remain unmatched. For instance, it is possible to observe men of 35 years old with a university degree who have been working for more than 8 years at managerial occupations, but it is not possible to find women with a similar combination of characteristics. This component of the gap would drop to zero if there were no man with characteristics *x* such that is it impossible to find a similar woman $\left(p_{\bar{S}|m} = 0\right)$ or if unmatched men and matched men were on average equally paid $E_{\bar{S}}\left(W|m\right) = E_S\left(W|m\right)$. The component Δ_f has a similar interpretation between matched and unmatched women. For this component, we cannot find men who have the same characteristics as women. For instance, it is possible to observe Swiss married women of 45 years old with obligatory schooling and with 2-3 years of work experience, while we cannot find similar men.

As previously mentioned the components Δ_x and Δ_o represent the "endowment" and "remuneration" effects of the gap as in BO decomposition. The component Δ_x represents the part of the wage gap that can be explained by differences in the distribution of human capital variables between men and women (but over the common support). For example, it is possible to observe both men and women with a university degree, but men are more represented in this category than women. As a consequence, Δ_x represents the decrease in the wage gap should the distribution of female characteristics become the same as the distribution of male characteristics over the common support. Lastly, the component Δ_o captures the residual part

[14] $dF_S^f(x) = dF^f(x)/p_{S|m}$ is scaled such that the integral integrates to one.

of the wage gap. The methodological issues that arise in the matching procedure have a direct impact on the interpretation of Δ_o. That is why we discuss this component in more details in Section 5.2.

Contrary to the BO decomposition, we compare unmatched women not to hypothetical (non-existing) men, but rather to observed (existing) matched women. This guarantees that we are comparing comparable individuals. As a consequence, there is no need to make additional assumptions out of the support. In addition, the component Δ_m in equation (5) sheds some light on wage differences that can be attributed to the fact that some characteristics that men typically own are not observed among women and these characteristics are highly rewarded (if this component is positive) in the labour market.

Nopo (2004) proposes a matching procedure in order to estimate the counterfactual wage and the four components of the decomposition. In this procedure, gender is considered to be the treatment variable. The counterfactual wage for women stands for the wage women would earn, had they been men.[15] It is estimated by averaging the observed wage of the men with the same characteristics. This is done under the assumption that the observed characteristics explain the productivity and earnings of individuals. Assumptions underlying the matching procedure are discussed further in Section 5.2. Table 4 presents the matching algorithm.

[15] To build this counterfactual, we take women without replacement and men with replacement. As an alternative, we can take men without replacement and women with replacement in order to simulate the male wages men would earn, had they been women. This is similar to the male and female BO wage decompositions. We did the estimation with these two definitions of the counterfactual and we get the same qualitative results.

Table 4: Matching algorithm for the estimation of the four components

Step1	For each woman in the sample, do steps 2 and 3.
Step2	Select all observations from the sub-sample of men who have the same characteristics as the woman of step 1. Do not remove these selected observations such that they can be used again. Denote these men as matched. If no observations are selected in this step, denote the woman chosen in step 1 as unmatched, otherwise as matched.
Step3	Compute the counterfactual wage of the woman selected in step 1 as the weighted average wage of the men selected in step 2.
Step4	Compute $\Delta_m, \Delta_x, \Delta_o$ and Δ_f using the actual wage variable, the new synthetic wage variable and the "match" dummy variable (which is coded by 1 whenever a woman (resp. a man) is matched to a man (resp. a woman)). $\Delta_m = p_m(unmatched)\left[E_{m,unmatched}(W\mid m) - E_{m,matched}(W\mid m)\right];$ $\Delta_x = E_{m,matched}(W\mid m) - E_{f,matched}(W\mid m);$ $\Delta_o = E_{f,matched}(W\mid m) - E_{f,matched}(W\mid f);$ $\Delta_f = p_f(unmatched)\left[E_{f,matched}(W\mid f) - E_{f,unmatched}(W\mid f)\right],$ where $p_m(unmatched)$ $\left(\text{resp. } p_f(unmatched)\right)$ are the empirical probabilities of being unmatched conditional on being a man (resp. a woman).

Notes: matching is done with replacement (the same man can be used more than once in forming the control group); exact matches are used (see Imbens, 2004 for a detailed survey about the different matching methods for the estimation of treatment effects).[16]

5.2. Methodological issues to our matching estimator

[16] To impute the counterfactual outcomes, matching estimators use outcomes of the nearest neighbours. Given a metric such as Euclidian or Mahalanobis distance and given the fact that matching is with or without replacement, the objective is to choose the number of matches needed to form the control group. In case of matching without replacement, matched pairs are formed and the average treatment effect on the treated is obtained by averaging differences in outcomes within the pairs. In case of matching with replacement, Abadie and Imbens (2004a) implement a matching estimator where a treated observation is matched with a fixed number of control observations (the first M nearest neighbours). In this framework, they show that the matching estimator is subject to a bias, because matching is not exact. The order of the bias is given by the dimension of the continuous variables which are used for the matching procedure. Abadie and Imbens (2004a) provide an estimator that removes this bias and which is $\sqrt{N}$ consistent and asymptotically normal. This estimator is implemented as an ado file in STATA (see Abadie *et al*, 2003).

One of the central statistics of interest in our work is the component Δ_o. It is formally identical to the average treatment effect on the treated (ATET) which has received great attention in the literature about evaluation of ALMP. In our case though, treatment is being a woman as compared to non-treatment – being a man. In order to be able to identify this ATET, the estimation of a counterfactual outcome (wage) is required. In the evaluation literature, the conditional independence assumption (CIA) about the treatment assignment is made (see Lechner, 1999 and Rosenbaum and Rubin, 1983 refer to this assumption as "unconfoundedness"). CIA means that after having controlled for observable characteristics X, there are no variables left out that are both correlated with the potential outcome Y_0 and the treatment D. The plausibility of this assumption has been largely debated in the economic literature. However, the question is not whether we should compare treated and untreated, rather which variables should be controlled for and this determines which individuals would be matched.

In the gender wage gap literature, it is difficult to disentangle the wage differences that arise from unobserved characteristics from the true discrimination. In this context, CIA would imply that after controlling for X, there are no unobserved characteristics which are productivity relevant to explain wages.[17] All remaining wage differences would be thus attributed to discrimination. As we discuss in Section 4, we control for education and experience, variables that are found to be important factors of wages in the human capital theory. In addition, education and experience differ by gender: the probability of being a man is larger when experience is higher, since we can suspect that women will experience more career breaks due to childbearing reasons. Similarly, we expect that men are more educated than women. As previously mentioned, we also control for job characteristics and some personal characteristics which we think they are important factors to determine wages. However, we cannot be sure that we control for all productivity relevant characteristics which are both correlated with wages and with gender. Nevertheless, we can still apply matching to estimate the counterfactual wage. We have only to be careful in the interpretation of Δ_o: the resulting wage differences after controlling for X are only partially attributed to discrimination. The component Δ_o overestimates the true effect of discrimination. Basically, the same issues about the choice of variables arise as in the parametric setup of the BO decomposition.

In addition to this problem of choice of variables, we encounter the problem of potential endogeneity in some variables just as in the parametric case. Occupation and job position may be themselves an outcome of discrimination, and thus they should not be controlled for. As a consequence, the component Δ_o will underestimate the true effect of discrimination. The implications of these methodological considerations is that the interpretation of Δ_o should be done cautiously. Although it is formally identical to the ATET, the interpretation of the statistic Δ_o is somewhat different. We are not interpreting this as a "causal" effect as for the ATET. The maximum we can do is to interpret Δ_o as an estimate of the importance of factors other than human capital factors (discrimination, social norms) that affect gender wage differences. On the other hand Δ_o is a measure of average wage gap between men and women conditional on characteristics *X*.

[17] Formally, CIA means that the expected counterfactual wage of women is equal to the average observed wage of men conditional on *X*.

6 Estimation results

6.1. Differences in the in and out of the common support samples

In this section, we look more precisely at the samples of matched and unmatched individuals. We begin with Table 5 which compares the characteristics of the observations in and out of the common support. Then, we analyse how wages differ in the unmatched and matched samples.

Table 5 shows how the differences between the matched and unmatched individuals in terms of some characteristics have behaved in time. For example, among matched individuals, the share of individuals with a tertiary education increases steadily in time: it has more than doubled from 11.8% in 1996 to 25.3% in 2003. On the contrary, the proportion of high educated individuals remains relatively stable in the unmatched sample. We find similar evidence for the share of individuals with a supervisory function from the year 1997. However, the difference is less striking than that obtained for education. An additional proof is provided by the share of managers and academicians. In the matched sample, the fraction of managers increases steadily from 1.6% in 1996 to 5.2% in 2003 while it has slightly increased among unmatched individuals. This is also confirmed by the fraction of academicians which has almost doubled over the observation period in the matched sample. Note that from 2000, the share of academicians among matched individuals exceeds the one for the unmatched individuals.

As a conclusion, the difference between matched and unmatched samples in terms of high education and high job position has reduced over time. This is in line with the findings from the OFS report (2003) that women have begun to penetrate traditionally male dominated areas. However, the concentration of women in these areas is still lower than that of men as it is indicated by the higher share of individuals with a good education and a good position in the unmatched sample than in the matched sample.

Table 5: Distribution of some characteristics in the in and out the common support populations

year	1996		1997		1998		1999		2000		2001		2002		2003	
sample	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
less than 30 years old	34.30	24.40	38.00	24.20	32.80	24.10	28.60	24.10	28.80	22.80	23.60	22.80	25.30	24.50	23.40	25.00
between 30 and 40 years old	31.60	33.10	30.80	33.20	32.00	34.30	35.60	34.10	35.40	33.50	41.60	33.40	33.50	32.20	34.30	31.50
between 40 and 50 years old	20.80	28.60	19.00	28.70	22.20	28.80	22.00	29.40	21.70	30.40	21.80	30.00	24.90	30.30	27.00	30.00
more than 50 years old	13.30	13.90	12.20	14.00	13.00	12.80	13.90	12.40	13.10	13.20	12.90	13.80	16.30	13.00	15.40	13.40
married	47.60	59.80	44.00	58.70	46.20	57.50	46.80	57.70	46.40	56.90	52.90	56.30	52.20	56.30	54.10	54.30
tertiary level of education	11.80	25.30	12.80	25.30	15.10	26.40	15.00	26.70	19.50	26.00	22.40	27.00	22.80	26.70	25.30	29.00
with children under 15	24.90	38.20	23.90	37.50	24.80	37.20	25.10	37.90	25.40	38.10	31.60	38.00	29.60	39.10	31.30	38.20
with responsibility function	33.90	39.40	30.60	41.10	37.50	41.00	40.50	41.20	38.20	40.50	34.70	40.50	39.20	39.30	36.70	41.90
managers	1.60	6.30	2.60	5.90	2.90	7.20	4.50	6.30	4.50	6.20	3.60	5.80	4.50	7.00	5.20	7.40
academicians	11.80	15.80	11.90	15.90	13.00	16.50	12.60	17.50	17.90	16.30	19.20	16.80	20.10	15.20	20.20	16.50
clerical workers	27.60	14.00	26.70	13.50	23.80	14.20	23.00	13.80	17.90	14.60	19.10	13.80	17.00	13.90	16.70	13.80
services	11.00	14.20	11.90	14.90	13.10	14.10	11.00	14.20	11.60	13.20	11.80	14.20	12.30	16.00	12.90	14.90
more than 5 years of experience	88.50	70.80	87.10	74.80	86.90	75.60	88.90	74.20	87.30	75.50	88.10	75.40	89.70	71.50	88.50	70.80

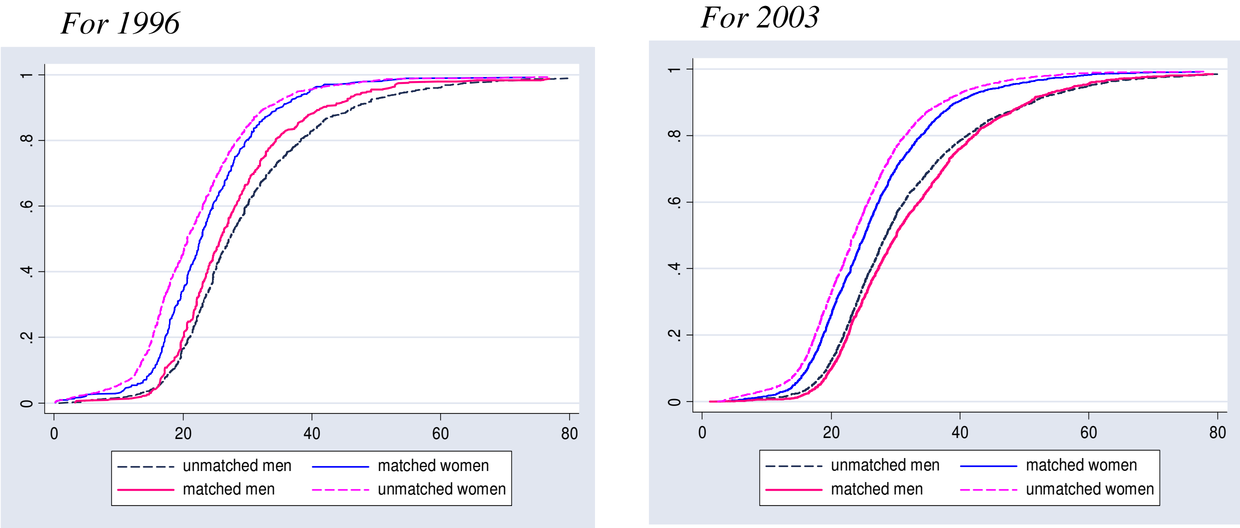
Notes: own computations.

In the rest of this section, we analyse the cumulative distribution functions of hourly wages for the unmatched and matched samples of men and women.[18] Matched individuals refer to individuals on the common support.[19] Figure 1 reports the cumulative distribution functions of wages by gender for the years 1996 and 2003. Over the entire period 1996-2003, matched women earn more than unmatched women and this holds over the whole wage distribution. Compared to 1996, the wage differences between matched women and unmatched women are smaller in 2003, especially at the lower end of the wage distribution. However, this does not seem to hold at the upper end of the wage distribution. For men, we observe a different pattern: unmatched men earn more than matched men in 1996. There is an exception at the lower part of the wage distribution where differences seem to be not significant. In 2003, matched men earn more than unmatched men, except at the upper part of the wage distribution. The observed pattern for men can be related to the fact that the distribution of characteristics of women shifts towards that of men over the period 1996-2003. Indeed, there is evidence that women are more likely to be high educated or to occupy a qualified position in 2003 than in 1996 (see OFS reports, 2003 and 2005).

[18] The software package STATA 8.0 was used to obtain all estimates in the paper. The sub-sampling results were obtained using TurboMatch 1.0 – a computer program specifically developed to perform the decomposition described in this paper. This program shows better performance as compared to a similar STATA routine and works under Microsoft Windows operating system. ("Microsoft Windows" is a registered trademark of Microsoft Corp.) More information is available from the authors upon request.

[19] It is worth noting that the percentage of matches is between 20% and 40% and is higher for the years 2002 and 2003 which provide larger samples. This is explained by the fact that it is easier to find an exact match in larger samples.

Figure 1: Cumulative distribution function of wages for in and out of common support populations



Notes: own computations, hourly wages are in constant 1996 CHF.

6.2. Construction of confidence intervals

In this section, we describe the procedure used to construct the confidence intervals for the mean unexplained gender gap (Δ_o). As argued by Abadie and Imbens (2004), we do not use the bootstrap technique, since it does not provide asymptotically valid confidence intervals in case of matching with replacement. In this context, they suggest to use the sub-sampling variance estimator (see Politis, Romano and Wolff, 1999).[20] Sub-sampling differs from bootstrap in the sense that it does not allow for observations to be included into the sub-sample more than once. The idea of sub-sampling is to draw from the initial sample a certain percentage of individuals and apply the matching procedure for this particular sub-sample. [21] The implementation of the matching procedure produces the four decomposition components for that particular sub-sample. We repeat this sub-sampling procedure a thousand times which appears to be large enough to estimate not only variances but also confidence intervals for each of the parameters of interest.

[20] Alternative estimators have been proposed by Abadie and Imbens (2004b) which are valid together with the sub-sampling bootstrap variance estimator.
[21] We apply the sub-sampling procedure with the following sample sizes: 25%, 50% and 75%. As expected, the "curse of dimensionality" is reinforced in the 25% sub-sampling: the amount of variables on which we match remains the same, but the sample size decreases four times compared to the full sample. Results of 25% and 50% sub-sampling are not reported in the paper, but are available from the authors upon request.

Several points concerning the sub-sampling procedure should be discussed briefly. First, we adopt a proportional sub-sampling procedure: we do not sub-sample from the full sample of initial size *N*, because we could have a different number of women and men in each sub-sample. In our study, we construct a sub-sample with 75% of women and 75% of men by sampling without replacement from the samples of men and women. Second, in the sub-sampling procedure, we do care for the weights of observations when we draw random samples. Finally, because there is no formal proof that the estimators of the parameters of interest are normally distributed, we estimate the bounds empirically from sub-sampling.

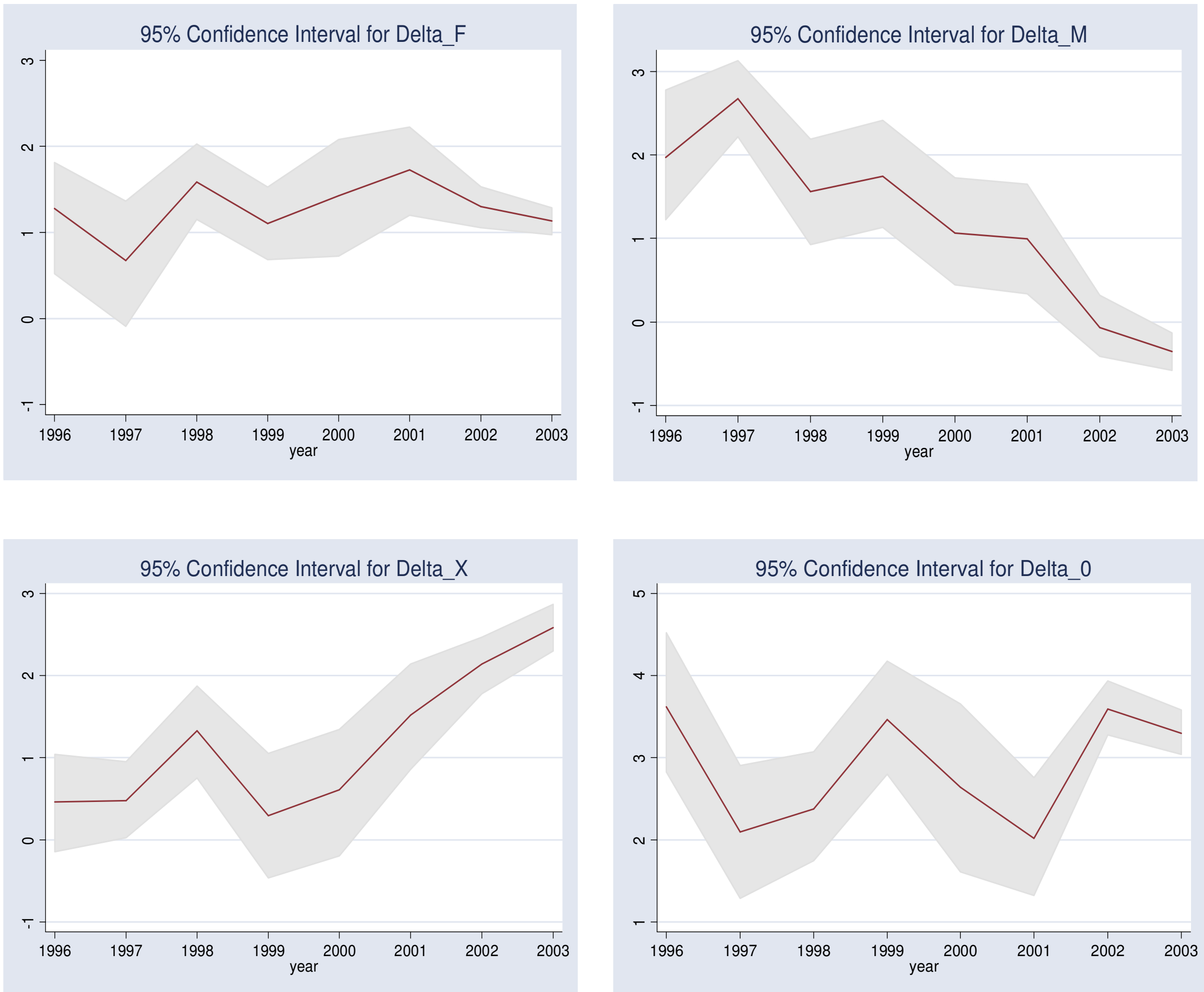
The matching procedure applied in this work is based on exact matching. Since the counterfactual wage is defined for matched women only, it is possible that the four components of the decomposition may be undefined in small samples. As a consequence, the estimates of the standard errors and confidence intervals of the four components will be sensitive to the size of sub-samples. In addition, the means of the parameters of interest obtained using the full sample could be different from those obtained after sub-sampling. Nevertheless, we find that the differences between the mean components of the wage gap using the full sample and the mean components using sub-sampling with 75% are not statistically significant (see Appendix A.5). This provides some evidence on consistency of our matching estimator. Indeed if the estimator depended heavily on the number of observations, our results would have been inconsistent. What we observe is in fact the variability in the estimators due to the differences in the sub-sampled individuals and not due to the differences in the sub-sample size (although the number of matches declines as expected). As a consequence, the graphs plotting the confidence intervals are using the means components obtained after sub-sampling. Concerning the interpretation of the unexplained component by some characteristics, we use the means obtained after matching over the full sample (see Table 6).

6.3. Evolution in time

Using the variables reported in Table 3, we apply the exact matching procedure to estimate the gender wage differential in Switzerland for each year of the period 1996-2003. Figure 2 shows the dynamics of the four components of the wage gap obtained after matching together with the 95% confidence area (shadowed area). As expected, the confidence intervals are much narrower in the years 2002 and 2003 due to the significantly larger amount of observations present in the dataset for these years.

The first graph refers to Δ_f, the part of the wage gap that would have disappeared if the unmatched women had on average the same wages as their matched counterparts. We observe that the variation of this component is rather small over the period of study and it stays in the vicinity of 1 CHF. In addition, Δ_f is statistically significant in almost all years (the exception is for 1997). This suggests that ignoring the problem of differences in gender supports like it is done in some evaluation studies can result in biases since incomparable individuals are compared. In addition, restricting the analysis to the common support only can lead to results that are not applicable to the whole population.

Figure 2: Confidence intervals of the 4 components of the wage gap



Notes: own computations.[22]

[22] Due to the random nature of the subsampling process the results in Figure 2 may vary.

More intriguing evidence comes from the second graph which refers to Δ_m, the part of the wage gap that would have disappeared if the unmatched men had on average the same wages as the matched men. This part steadily declines over the period of study. This indicates that more and more women obtain combinations of characteristics that were exclusively men's before. Hence, the differences between the matched and unmatched men reduce in time and move to zero from the year 2002. The Δ_m component could be a crude measure of the female disadvantage in access to particular combinations of characteristics, which are rewarded on the market. We also find some support for this scenario from Table 3. Over time, the distribution of characteristics of women shifts towards that of men (there are more and more women with higher levels of education, occupying high qualified job positions such as managers, etc.) This increases the chances of women for having the same characteristics as men. Hence, it is less likely to observe significant differences between matched and unmatched men.

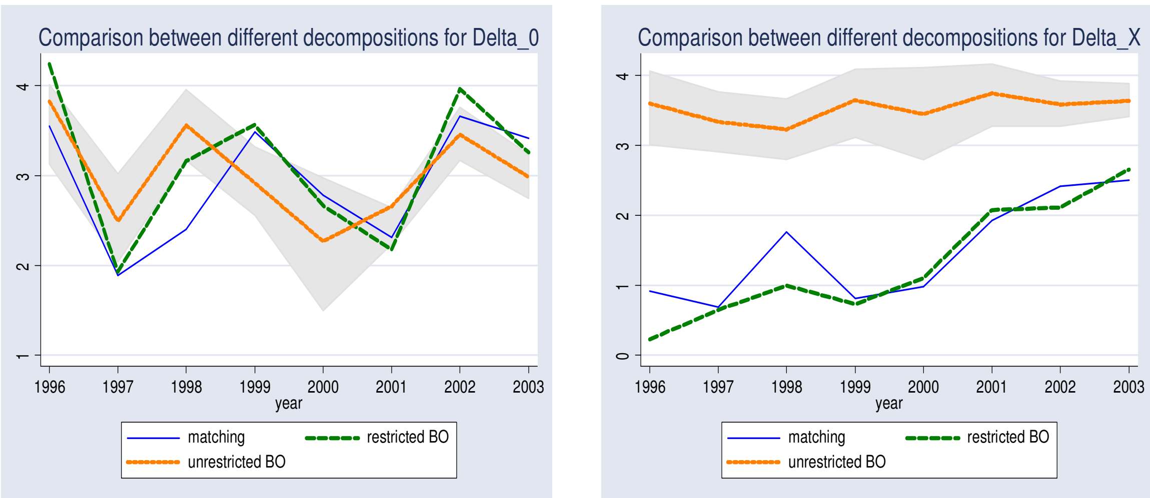
Figure 2 provides further support to the latter scenario. Indeed, the third graph represents, Δ_x, the component of the wage gap that would have disappeared if the distribution of women's characteristics on the common support was the same as the distribution of men's characteristics on the common support. Figure 2 indicates that this component is steadily growing since 1999. This pattern can be interpreted by the fact that although women succeed in entering traditionally males' domains, their concentrations in these areas still differ from men's concentrations. Together with Δ_m and Δ_f, this component stands for the explained part of the wage gap. Since Δ_x is higher than Δ_m and Δ_f, we can conclude that the differences in human capital matter more in explaining the gender wage gap than the differences in the gender supports, although these latter differences are significant.

Finally the fourth graph in Figure 2 shows the dynamics of the unexplained component of the wage gap Δ_o. It is statistically significant in all years of study. However, no systematic pattern is observed. Instead, Δ_o fluctuates around about 3 CHF and repeats the behaviour observed for the raw wage gap (see Appendix A.6). Such volatility in Δ_o raises some doubts about the fact that it can be attributed solely to discrimination. Indeed, if it would be the case, Δ_o would reflect the change in the employers' behaviour (employers' valuation of female workers as compared to male workers), hence it should change only gradually.

6.4. Matching vs BO decomposition

In this section, we are interested in how the results from matching decomposition do differ from those obtained after BO decomposition. As previously mentioned, the main issue with BO decomposition consists in ignoring the gender differences that can arise in the supports. As a consequence, if the linear specification of the wage regression on the common support is correct, then we should have similar results to those obtained after matching.[23] Figure 3 compares the mean effects for the unexplained and explained components of the gap obtained after applying BO without restricting to the common support (called thereafter "unrestricted BO"), BO with restricting to the common support ("restricted BO") and matching. The left (resp. right) graph represents the results for the unexplained (resp. explained) component of the gap. In both graphs, we plot the confidence intervals for the parameters obtained using unrestricted BO.[24] First, Figure 3 provides some evidence on our

Figure 3: Comparing BO and matching decompositions.



Notes: own computations.

expectation that restricting the analysis on the common support will make the results of BO closer to those after matching. Indeed, in both graphs, the solid and broken lines are close one to each other. In addition, the right graph sheds some light on the importance of the gender differences in the supports. Both explained components gap obtained using restricted BO and

[23] Note that in the linear specification, we use the same variables as in the matching procedure. In addition, we use exclusively dummies for all the covariates. For instance, age is not left as a continuous variable.

using matching do not belong to the confidence interval obtained using unrestricted BO. As a consequence, differences in supports account for a significant share of the wage gap. This result is also illustrated in the left graph of Figure 3. Depending on the year of study, it seems that restriction to common support in BO leads to an over or under-estimation of the unexplained component of the gap while the extrapolation assumption (ignorance of the common support) always leads to the overestimation of the explained part of the wage gap. Finally, the similarity of the results between the restricted BO and the matching decompositions indicates that the BO decomposition still provides good results when it is applied on the common support and when the linear regression is correctly specified.[25]

6.5. Comparison with propensity score matching

In our matching procedure of Table 4, the conditioning variables are all discrete and we are using exact matches: a woman is matched whenever we find an identical man in terms of *X*. As argued by Frölich (2003), the exact matching procedure is very conservative, restrictive and is likely to lead to a non-compact common support, where a "36-year old woman and a 38-year old woman are matched while a 37-year old woman is not". In addition, Frölich (2003) shows in a small Monte Carlo analysis that exact matching performs worse than propensity score matching. Since exact matching is not often used in the empirical literature, we compare it with the other more commonly used matching algorithms, namely the nearest neighbour (NN) and calliper matching algorithms based on the propensity score.

Propensity score is estimated using binomial probit model. In the estimation of the propensity score we use the same explanatory variables as in our exact matching procedure. The higher is the propensity score, the higher is the estimated probability that a person with given characteristics is a woman. To determine the closeness of the control and treated units, we use the absolute difference between the propensity scores as a metric. Table 6 reports the sample sizes for women and men and the raw wage gap followed by decompositions based on different matching algorithms. The components of the decompositions are in CHF for the corresponding years.

[24] We apply a 75% sub-sampling procedure to construct the confidence intervals for the parameters obtained using unrestricted BO.
[25] Note that the distances between the restricted BO and the matching decompositions are due to the parametric specification of wage functions in BO decomposition. The effect of applying parametric restrictions is much less important in the restricted BO decomposition than in the unrestricted one.

Table 6: Decompositions based on different matching algorithms.

	1996	1997	1998	1999	2000	2001	2002	2003
Total women	2794	2828	2882	3243	3235	3423	7134	9958
Total men	3069	3107	3169	3439	3311	3381	6958	10880
Raw gap	7.43	5.83	6.79	6.57	5.72	6.40	7.04	6.62
Panel I: Exact matching								
$\Delta 0$	3.55	1.89	2.40	3.49	2.78	2.30	3.66	3.42
ΔX	0.92	0.69	1.76	0.81	0.98	1.94	2.42	2.50
ΔM	1.63	2.22	1.05	1.24	0.88	0.45	-0.38	-0.39
ΔF	1.33	1.04	1.58	1.03	1.07	1.71	1.34	1.09
matched women	697	753	772	895	877	934	2629	3799
matched men	665	720	710	850	838	885	2581	4155
Panel II: Unrestricted Nearest Neighbour matching								
$\Delta 0$	3.50	2.31	4.42	3.72	3.07	2.81	4.05	2.92
ΔX	1.74	1.58	0.89	1.94	1.66	2.63	2.60	3.16
ΔM	2.19	1.94	1.48	0.91	0.98	0.96	0.39	0.55
ΔF	0	0	0	0	0	0	0	0
matched women	2794	2828	2882	3243	3235	3423	7134	9958
matched men	1380	1431	1443	1688	1592	1655	3920	6148
max. distance	0.06	0.01	0.04	0.03	0.01	0.02	0.01	0.02
Panel III: Restricted Nearest neighbour matching								
$\Delta 0$	3.87	2.59	4.83	3.66	3.53	2.92	4.44	3.05
ΔX	1.18	1.13	0.26	1.66	1.19	2.34	2.03	2.81
ΔM	2.16	1.88	1.47	1.00	0.98	0.95	0.36	0.52
ΔF	0.22	0.23	0.23	0.24	0.02	0.20	0.21	0.24
matched women	2511	2532	2582	2932	2931	3062	6432	8955
matched men	1377	1430	1441	1680	1584	1651	3905	6114
epsilon (x 0.0001)	7.65	7.12	8.04	6.40	7.49	6.75	3.43	2.25
Panel IV: Caliper matching 1								
$\Delta 0$	3.67	2.55	3.77	3.35	3.34	2.99	4.22	2.97
ΔX	3.33	2.74	2.64	2.87	1.93	3.20	2.44	3.58
ΔM	0.21	0.30	0.14	0.10	0.43	0.02	0.17	-0.18
ΔF	0.22	0.23	0.23	0.24	0.02	0.20	0.21	0.24
matched women	2511	2532	2582	2932	2931	3062	6432	8955
matched men	2504	2572	2740	2998	2833	2909	6086	9652
epsilon (x 0.0001)	7.65	7.12	8.04	6.40	7.49	6.75	3.43	2.25
Panel V: Caliper matching 2								
$\Delta 0$	3.37	1.88	2.40	3.19	2.65	2.58	3.99	3.27
ΔX	0.67	0.50	1.68	0.94	0.88	1.73	2.10	2.35
ΔM	1.73	2.40	1.11	1.37	1.12	0.57	-0.39	0.06
ΔF	1.66	1.05	1.60	1.06	1.07	1.53	1.33	0.94
matched women	759	819	843	977	949	1029	2890	4421
matched men	730	801	768	923	920	983	2868	4821
epsilon (x 0.0001)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Notes: in CHF current years, "*max. distance*" refers to the maximum distance between the matches, in the unrestricted NN-matching; in the restricted NN-matching "*epsilon*" is the maximum allowed distance a woman and a man to be matched, in the calliper matching "*epsilon*" is the calliper parameter. For the choice of parameters – see text.

Panel I shows the results of the decomposition based on exact matching. Panel II presents the results based on NN-matching. We can note that by construction all women are matched and hence the component Δ_f is zero. It is obvious that these two decompositions yield different results. The validity of the NN-matching can be questioned, though. While in exact matching we are guaranteed to compare similar (comparable) individuals this is not true for the NN-matching algorithm. We use *t*-test to check if the samples of matched men and women are balanced and we find that they are not.[26] One possible explanation to this would be the presence of outliers, i.e. the individuals which have very rare combinations of characteristics and thus positioned remotely on the propensity score scale. Indeed we find that the maximum distance in terms of propensity score between the matched individuals is between one and five percentage points (for different years), which casts doubts about the quality of matches. Hence, we have repeated our NN-matching procedure with the restriction on the distance between the matches (hence the name "restricted nearest neighbour"). We choose as a threshold the 90th percentile of the distribution of the distances between matched men and matched women in the unrestricted NN-matching. The results of restricted NN-matching are presented in the panel III of Table 6. The number of matched women declines by 10% as expected, but the tests show that the samples of matched men and women remain unbalanced. Thus, comparison of results of exact matching with the results of NN-matching might be inadequate.

Next, we present the results of the decompositions based on the calliper matching (also known as radius matching). One of the issues with the calliper matching is the choice of the calliper itself. In fact it is impossible to find a value of calliper which would be universally accepted for all datasets. To determine the calliper, we first run NN-matching and then compute the distances between the matches (see for instance Lechner, Miquel and Wunsch, 2004). Knowing these distances provides us information about how big or how small should the calliper be. We choose as the calliper the 90th percentile of the distribution of the distances between matched men and matched women. This value is reported as epsilon together with the results of decomposition in the panel IV of Table 6. We repeat the tests for these samples of matched men and women and find that they are still unbalanced. They

[26] The balancing property of propensity score is crucial in the matching procedure based on the propensity score. By definition, exact matching on X guarantees that the comparison group is similar to the treated group. When using propensity score matching with the propensity score function being preliminarily estimated, we have to check that the matches obtained after the algorithm are of good quality. In our paper, we apply the test procedure implemented by Sianesi and Leuven (2003) for STATA 8.0 in order to test the balancing property in the calliper and nearest neighbour matching procedures.

remain unbalanced when the calliper is set to 0.00005 and it is only when we decrease the calliper to 0.00001 that all our matched samples become balanced (see panel V of Table 6).[27]

The decompositions in panels I and V of Table 6 are similar but still not identical. As expected, the number of matches is higher for calliper matching than in the exact matching.[28] The differences between the components Δ_f, Δ_0 of these two decompositions do not show any clear pattern, but they are not as large as in the case of NN-matching. The component Δ_m is systematically larger in calliper matching as compared to exact matching, while the component Δ_x is systematically lower (in all but one case). As a consequence, allowing even for small differences in the characteristics of matched men and women may significantly change the estimated components of the wage gap.

6.6. Analysis by some personal characteristics

In this section, we analyse the unexplained part of the gender wage gap for some specific persons. The analysis focuses on the matched sample only. Hence, we are comparing men and women who have the similar characteristics. The upper part of Table 7 indicates the absolute and relative gaps by education level. A look at the mean relative gap shows that it is among individuals with the lowest level of education that wage differences remain after matching. On average, a man with obligatory schooling earns 15% more than his female counterpart. The gap reduces to 12% (resp. 10%) for individuals with a secondary (resp. tertiary) level of education. The lower part of Table 7 shows the gender differences for individuals with specific combinations of age, education level and household composition. Type 0 is the base individual aged between 30 and 40, having a secondary level of education and having no child under 15. Then, we change the characteristics to see how the gap varies across the different types of individuals. Comparing Type 0 with the other types provides useful information on how the unexplained gap is affected by a particular variable. For instance, the comparison between Type 0 and respectively Type 1, Type 2 and Type 3 permits to capture the effect of age.

[27] The results of calliper matching with epsilon equals to 0.00005 are not presented in Table 6 but are available from the authors upon request.

We begin the interpretation of the results by analysing the effect of age. It turns out that the differences between the male and female wage structures strengthen as individuals are older. For instance, a man older than 50 earns 20% more than the similar woman. On the contrary, wage differences between men and women under 30 are less pronounced. Comparing Type 0 and Type 4 provides further light on whether the presence of young children in the household increases the wage penalty for women. Indeed, Table 7 indicates that the unexplained component of the gap is higher in presence of young children.

Table 7: Unexplained component of the gender wage gap by some characteristics.

	in CHF	in % of female wages	Obs
By education level			
obligatory schooling	2.89	15.33	841
secondary level	2.99	11.61	8512
tertiary level	3.69	9.81	2003
By human capital			
Type 0: age 30-40, secondary education level, without children under 15	2.38	8.80	1569
Type 1: age 40-50, secondary education level, without children under 15	2.64	9.07	1209
Type 2: more than 50, secondary education level, without children under 15	5.88	20.32	1205
Type 3: under age 30, secondary education level, without children under 15	1.52	7.11	2284
Type 4: 30-40, secondary education level, with children under 15	3.09	11.31	1363
Type 5: 30-40, tertiary education level, without children under 15	3.12	8.75	634
By job characteristics			
Type 6: without responsibility function, private sector, large firm	2.69	10.30	1926
Type 7: with responsibility function, private sector, large firm	3.80	11.08	768
Type 8: without responsibility function, public sector, large firm	3.08	10.23	690
Type 9: without responsibility function, private sector, small firm	2.72	12.07	3217

Notes: 1996-2003 [29], in constant 1996 CHF.

[28] Notice that in general our exact matching is not the same as radius matching with calliper set to zero, since our exact matching requires all characteristics to be exactly the same, while radius matching with calliper zero requires the estimated propensity scores to be the same.

[29] To obtain the population for the period 1996-2003, we pool the samples (obtained after matching) for the different years. In other words, we do not match individuals across time.

We now turn to the interpretation of the results by some job characteristics. We combine the following variables: responsibility function, firm size and private/public sector. First, the comparison between Type 7 and Type 6 indicates that women with a responsibility function are on average more likely to be “hit by discrimination” than women without any responsibility function. Second, the comparison between Type 6 and Type 8 seems to indicate that at the mean there is no significant difference in the unexplained wage gap between the public sector and the private sector. This would be useful to extend the analysis by accounting the distributional aspects of the wage gap and to compare the results with those obtained in the literature (see for instance Melly, 2005). This extension is left for future work. Lastly, Table 7 indicates that women working in small establishments experience a higher level of “discrimination” than women working in large firms.

To summarise, the results seem to indicate that even after controlling for observable characteristics, significant gender wage differences remain. The analysis of specific persons shows that low educated women are more likely to be disadvantaged. Similarly, older women face considerable “discrimination”. On the contrary, wage differences that remain after controlling for observable characteristics appear to be much less severe for young women. The presence of children exerts an additional wage penalty. Since women with young children are more likely to be less educated, this reinforces the fact that education is a key determinant of “discrimination”.

7 Conclusion

In this paper, we have investigated gender wage differentials over the period of 1996-2003. We take into account that the supports of the distributions of characteristics can be different. This is an important issue since wage comparisons are relevant only when women are compared to "comparable" men. In our paper, we argue that gender differences in supports can be responsible for a substantial part of the wage gap. Indeed, the traditional social norms in Switzerland restrict the role of women on the labour market. Typically, men have priority on the labour market, while women stay at home and raise children. While this gender specialisation in different areas of life has been widely studied in the labour supply discussions, it has its own implications for the wage gap story. High selectivity of women in some jobs and economic sectors makes it difficult to estimate the counterfactual wages and thus to develop public policies aimed at promoting equality between women and men.

To our knowledge, the importance of recognizing the problem of gender differences in the supports has not yet been carefully addressed in any Swiss study about gender wage gap. The focus of the existing Swiss empirical studies is in disentangling the "explained" and "unexplained" components of the wage gap by using the traditional Blinder-Oaxaca (BO) decomposition. In our study, we use a matching method to decompose the wage gap. This method has been proposed by Nopo (2004) and leads to a decomposition into four components: the traditional "explained" and "unexplained" components (that are now defined over the common support only) and two additional components that account for wage differences for men and women in and out-of-the common support. This decomposition into four components sheds some light on the effect of applying parametric restrictions and on the bias which appears when the traditional BO decomposition is applied. For the Swiss data, this bias due to the violation of the common support appears to be large and commonly larger for earlier years of the study. This implies that the estimation of the wage gap in the early 1990s might be not reliable. At the same time, the parametric restriction on the wage function has a much smaller effect, indicating that BO decomposition restricted to the common support, still remains a powerful tool to decompose the wage gap.

Our results show that over the period of study, the unexplained component remains relatively stable. In addition, differences between unmatched and matched women are stable over time. On the contrary, differences between matched and unmatched men narrow in time.

This means that women have begun to penetrate traditionally men's areas. Indeed, the share of women with higher levels of education and occupying high qualified job positions increases over the period of observation. However, the distribution of female characteristics still differs from that of male characteristics even on the common support. This is reflected by the explained component of the wage gap which is steadily increasing since 1999. As a consequence, our results show that compared to the mid 1990s, differences in human capital nowadays matter more in explaining wage differentials than differences in the gender supports. Moreover, these latter differences account for a significant part of the wage gap.

The decomposition of the wage gap into four components has a useful interpretation in terms of policy implications aimed at reducing the male-female wage differentials. Currently, it is recommended to facilitate the access of women to a better education and to particular occupations. However, this policy is difficult to evaluate using the traditional BO decomposition, since it only yields one component of the wage gap which is due to the differences in characteristics, while the second "unexplained" component is the residual wage gap. On the contrary, the four component decomposition applied in this paper allows us to measure the effect of policies more precisely. For example, policies encouraging the combination between family and work would promote women to full-time positions. These women will be more likely to be matched and thus the differences between unmatched and matched women will decline (component Δ_f). Similarly, policies targeted to reduce the barriers for the access to a better education will likely help matched women to reach male characteristics (this will affect the component Δ_x). As a consequence, we can consider two different steps in order to obtain more wage equality between men and women. The first step consists in raising the human capital of those women who are currently unmatched to the level of the matched women. The second step is to remove dissimilarities between the distributions of men and women on the common support. Our analysis shows that these policies should have a larger effect on the total wage gap than struggles against legendary discrimination.

Appendix

Appendix A.1

Education level of the prime age working population, 1980-2000

Women	1980	1990	2000
obligatory schooling	50.0	36.8	27.0
apprenticeship training	37.8	48.4	45.8
general training	6.0	6.1	11.2
post apprenticeship training	3.5	5.0	7.6
university or technical college degree	2.7	3.7	8.3
Men	1980	1990	2000
obligatory schooling	33.9	24.2	17.0
apprenticeship training	44.9	50.3	45.0
general training	2.9	2.6	6.2
post apprenticeship training	10.3	14.3	18.0
university or technical college degree	8.0	8.5	13.8

Source: Census 1980, 1990 and 2000

Occupation degree in % by gender between 1970 and 2000

	Men		**Women**	
year	Full-time	Part-time	Full-time	Part-time
1970	63.1	2.7	24.1	10.1
1980	61.1	2.9	23.5	12.5
1990	57.9	3.1	22.3	16.7
2000	51.3	5.0	21.5	22.3

Source: Census data

Job positions by gender in 2001

	Women	Men
managers, executive employees	3.2	7.5
scientists and academicians	12.0	19.8
technicians	24.1	17.3
administrative personnel	22.1	7.2
personnel in services and retail trade	20.3	6.8
farmers	3.5	5.5
handworkers	4.4	23.7
operators	1.8	7.4
manual workers and assistants	8.0	4.2

Source: OFS report (2003) "Vers l'égalité?"

Appendix A.2

Median gross monthly wage by gender and by sector, 1994-2002

	Private sector			**Public sector**		
year	women	men	gap*	women	men	gap
1994	3 927	5 153	23.8%	5 376	6 181	13.0%
1996	4 086	5 300	22.9%	5 523	6 250	11.6%
1998	4 253	5 417	21.5%	5 568	6 193	10.1%
2000	4 358	5 551	21.5%	5 672	6 316	10.2%
2002	4 586	5 796	20.9%	5 695	6 377	10.7%

Source: OFS report (2003) "Vers l'égalité?"
Note: the wage is calculated on the basis of 4 and 1/3 working weeks at 40 hours worked per week.
(this allows to convert part-time jobs to full-time equivalent jobs), * gap in % of female wages

Median wages by industry sector in 2002 (private sector only)

	Women	Men	Gap*	Share*
Sectors with the lowest wages				
personnel services	3 388	4 593	26.2%	74.7%
restaurants, catering	3 508	3 893	9.9%	55.7%
textiles	3 286	5 482	40.1%	77.6%
Sectors with the highest wages				
real estate	6 320	8 952	29.4%	42.4%
research and development	6 478	8 504	23.8%	36.8%
banking, insurance	6 067	8 808	31.1%	36.8%
Other economic sectors				
construction	5 012	5 361	6.5%	9.9%
trade and repairs	3 864	4 890	21.0%	65.5%

Source: OFS report (2003) "Vers l'égalité?"
Note: the wage is calculated on the basis of 4 and 1/3 working weeks at 40 hours worked per week.
(this allows to convert part-time jobs to full-time equivalent jobs), * gap in % of female wages, and share of women

Appendix A.3: Explanatory variables used in the analysis

Variables	**Descritption**
Socio-demographics	
Age	7 categories: between 15 and 24, between 25 and 29, between 30 and 34, between 35 and 39, between 40 and 44, between 45 and 49 and older than 49.
Marital status	4 categories: single, married, divorced and widowed.
Level of education	3 categories: primary (without education, primary school), secondary (elementary professional training, apprenticeship, full-time professional school, general knowledge school, university entrance qualification), tertiary (professional training with master degree, technical and high professional school, university, high school).
Foreign citizenship	2 categories: non Swiss and Swiss.
Children	2 categories: with and without children under 15.
Regional characteristics	
Region of residence	2 categories: Deutschschweiz (German part) and Westschweiz (Latin part).
Job characteristics	
Firm size	3 categories: less than 50 workers, between 50 and 99 workers and more than 100 workers.
Supervisory	Dummy if supervisory function.
Occupation	8 categories: managers, academicians, technicians, clerical workers, services, handworkers, operators and assistants.
Permanent	Dummy if permanent work contract.
Public	Dummy if job in the public sector.
Work experience	4 categories: less than 6 months, between 6 and 24 months, between 2 and 5 years and more than 5 years.

Notes: SLFS 1996-2003.

Appendix A4: Means of variables (by rows)

	1996		1997		1998		1999		2000		2001		2002		2003	
Variables	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Wages in CHF/hour	23.46	30.88	24.10	29.93	23.67	30.46	24.22	30.79	25.53	31.24	25.98	32.39	25.58	32.62	26.52	33.14
Share	44.68	55.32	45.17	54.83	44.97	55.03	45.83	54.17	46.07	53.93	46.71	53.29	47.29	52.71	47.36	52.64
Socio-demographics																
Age																
15-24	53.85	46.15	54.02	45.98	48.68	51.32	53.23	46.77	52.92	47.08	55.02	44.98	55.89	44.11	52.24	47.76
25-29	43.14	56.86	47.18	52.82	49.25	50.75	51.28	48.72	49.26	50.74	48.64	51.36	48.81	51.19	50.32	49.68
30-34	43.74	56.26	41.86	58.14	40.66	59.34	42.70	57.30	46.69	53.31	48.04	51.96	45.23	54.77	44.72	55.28
35-39	41.05	58.95	43.25	56.75	43.50	56.50	42.79	57.21	42.87	57.13	44.02	55.98	44.21	55.79	45.94	54.06
40-44	41.78	58.22	41.00	59.00	42.91	57.09	42.82	57.18	40.45	59.55	41.30	58.70	45.73	54.27	46.08	53.92
45-49	46.53	53.47	46.12	53.88	44.56	55.44	44.64	55.36	45.58	54.42	46.66	53.34	46.70	53.30	45.93	54.07
50-55	44.86	55.14	44.27	55.73	47.43	52.57	46.34	53.66	47.66	52.34	46.53	53.47	47.12	52.88	48.11	51.89
Marital status																
single	46.40	53.60	46.31	53.69	44.64	55.36	47.96	52.04	47.39	52.61	49.30	50.70	47.99	52.01	47.42	52.58
married	39.92	60.08	41.09	58.91	41.84	58.16	41.56	58.44	42.34	57.66	42.22	57.78	44.43	55.57	44.53	55.47
divorced	68.95	31.05	64.24	35.76	64.25	35.75	61.98	38.02	62.07	37.93	63.45	36.55	61.17	38.83	62.60	37.40
widowed	82.26	17.74	78.13	21.87	77.64	22.36	76.18	23.82	63.92	36.08	71.56	28.44	71.02	28.98	79.81	20.19
Level of education																
primary	58.03	41.97	58.33	41.67	55.44	44.56	53.27	46.73	50.28	49.72	54.19	45.81	53.29	46.71	53.09	46.91
secondary	48.34	51.66	48.53	51.47	49.09	50.91	50.50	49.50	51.44	48.56	51.14	48.86	51.97	48.03	52.11	47.89
tertiary	25.34	74.66	26.98	73.02	28.05	71.95	29.17	70.83	30.17	69.83	32.26	67.74	32.75	67.25	34.38	65.62
Foreign citizenship																
Swiss	46.42	53.58	46.54	53.46	46.13	53.87	46.90	53.10	47.92	52.08	48.42	51.58	49.13	50.87	49.46	50.54
Foreign	39.09	60.91	40.31	59.69	41.02	58.98	42.28	57.72	39.67	60.33	41.17	58.83	41.40	58.60	40.31	59.69
Children																
With children under 15	37.25	62.75	39.09	60.91	39.36	60.64	39.93	60.07	40.26	59.74	41.76	58.24	43.85	56.15	44.97	55.03
Without children under 15	48.74	51.26	48.36	51.64	47.93	52.07	48.98	51.02	49.22	50.78	49.55	50.45	49.20	50.80	48.68	51.32
Regional characteristics																
*Region of residence**																

Notes: own computations; Appendix A4 to be continued

Appendix A4: (*... cont.*)

	1996		1997		1998		1999		2000		2001		2002		2003	
Variables	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**
Deutschschweiz	44.01	55.99	44.67	55.33	44.76	55.24	46.01	53.99	46.19	53.81	46.69	53.31	47.61	52.39	47.12	52.88
Westschweiz	46.45	53.55	46.49	53.51	45.56	54.44	45.37	54.63	45.78	54.22	46.77	53.23	46.48	53.52	47.96	52.04
Job characteristics																
Firm size																
less than 20 workers	48.51	51.49	49.48	50.52	50.48	49.52	50.46	49.54	50.46	49.54	52.36	47.64	52.58	47.42	52.78	47.22
between 20 and 99 workers	38.14	61.86	40.66	59.34	37.62	62.38	40.34	59.66	44.59	55.41	43.57	56.43	44.65	55.35	43.47	56.53
more than 99 workers	41.06	58.94	40.31	59.69	39.66	60.34	40.91	59.09	39.96	60.04	39.38	60.62	40.36	59.64	40.78	59.22
Responsibility function																
without	53.52	46.48	54.12	45.88	53.65	46.35	53.92	46.08	55.06	44.94	55.53	44.47	55.50	44.50	56.58	43.42
with	30.39	69.61	30.99	69.01	32.09	67.91	34.20	65.80	32.56	67.44	32.95	67.05	34.58	65.42	33.17	66.83
Occupation																
managers	16.48	83.52	19.64	80.36	19.18	80.82	19.82	80.18	24.24	75.76	23.81	76.19	26.72	73.28	28.59	71.41
academicians	29.80	70.20	31.78	68.22	34.96	65.04	32.80	67.20	35.68	64.32	36.58	63.42	35.98	64.02	36.66	63.34
technicians	53.03	46.97	54.27	45.73	51.98	48.02	54.02	45.98	54.66	45.34	54.85	45.15	57.27	42.73	57.07	42.93
clerical workers	66.40	33.60	65.74	34.26	69.98	30.02	71.33	28.67	71.82	28.18	69.86	30.14	70.06	29.94	69.73	30.27
services	72.27	27.73	68.90	31.10	67.60	32.40	69.77	30.23	68.79	31.21	69.95	30.05	68.15	31.85	67.09	32.91
operators	59.26	40.74	57.94	42.06	55.58	44.42	58.33	41.67	55.44	44.56	54.80	45.20	56.87	43.13	60.63	39.37
handworkers	11.76	88.24	9.89	90.11	9.93	90.07	13.62	86.38	11.75	88.25	13.99	86.01	15.22	84.78	15.23	84.77
assistants	18.13	81.87	20.05	79.95	15.18	84.82	17.26	82.74	17.49	82.51	15.19	84.81	14.35	85.65	14.06	85.94
Work type contract																
non permanent	50.64	49.36	53.61	46.39	48.84	51.16	49.24	50.76	56.43	43.57	58.75	41.25	57.48	42.52	53.82	46.18
permanent	44.29	55.71	44.71	55.29	44.76	55.24	45.62	54.38	45.44	54.56	45.99	54.01	46.61	53.39	46.92	53.08
Public sector																
no	39.09	60.91	38.76	61.24	38.89	61.11	39.27	60.73	38.90	61.10	39.82	60.18	40.40	59.60	40.28	59.72
yes	61.23	38.77	62.81	37.19	62.07	37.93	63.56	36.44	64.57	35.43	64.38	35.62	65.58	34.42	65.53	34.47
Work experience																
less than 6 months	61.52	38.48	55.31	44.69	44.25	55.75	71.06	28.94	59.57	40.43	64.08	35.92	66.28	33.72	59.76	40.24
between 6 and 24 months	60.10	39.90	68.26	31.74	58.76	41.24	53.19	46.81	61.45	38.55	65.41	34.59	68.12	31.88	65.51	34.49
between 2 and 5 years	61.73	38.27	56.11	43.89	59.81	40.19	62.46	37.54	60.37	39.63	59.00	41.00	59.83	40.17	60.79	39.21
more than 5 years	40.23	59.77	40.90	59.10	41.36	58.64	41.62	58.38	42.06	57.94	42.75	57.25	42.88	57.12	43.19	56.81
Observations	2794	3069	2828	3107	2882	3169	3243	3439	3235	3311	3423	3381	7134	6958	9958	10880

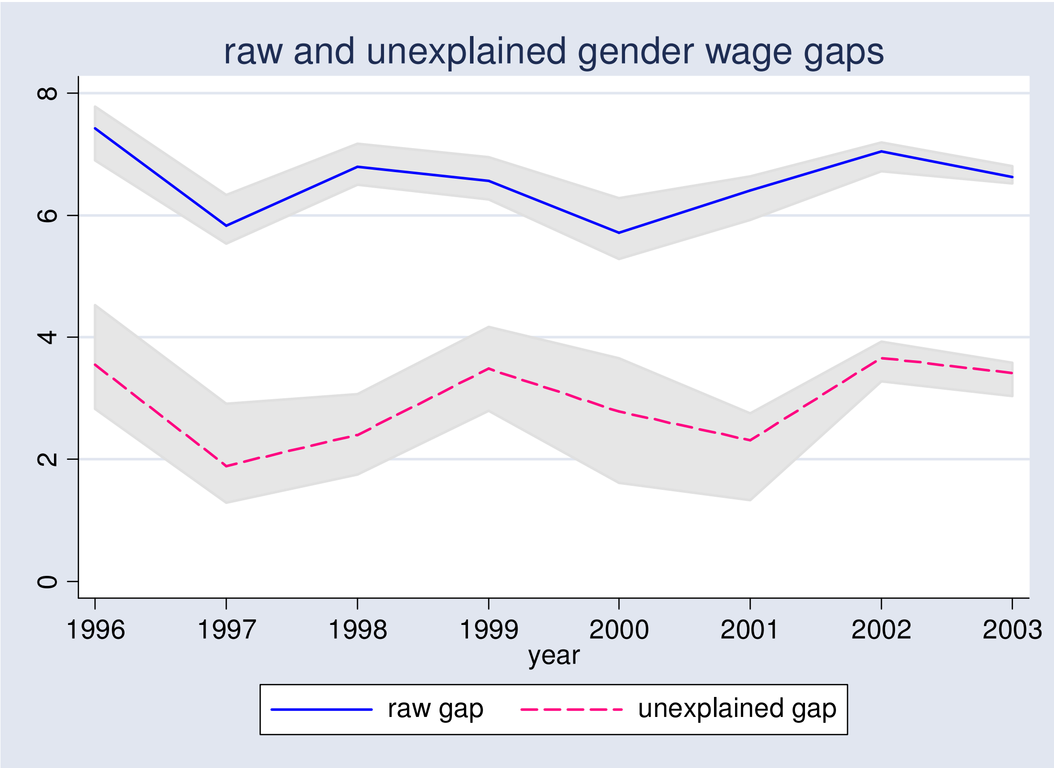
Notes: own computations

Appendix A.5: Differences between full sample size means and 75% sub-sampling means of the corresponding components

95% Confidence Intervals								
year	ΔM		ΔX		Δ0		ΔF	
1996	-0.58	1.36	-1.25	0.28	-0.88	1.25	-1.06	0.59
1997	-0.15	1.05	-0.78	0.37	-0.79	1.23	-1.35	0.56
1998	-0.34	1.34	-1.17	0.25	-0.83	0.85	-0.57	0.55
1999	-0.26	1.32	-1.46	0.43	-0.91	0.85	-0.49	0.60
2000	-0.60	1.04	-1.41	0.55	-1.47	1.16	-0.56	1.14
2001	-0.25	1.30	-1.20	0.34	-1.18	0.63	-0.66	0.67
2002	-0.10	0.79	-0.74	0.13	-0.45	0.36	-0.35	0.23
2003	-0.24	0.32	-0.28	0.43	-0.44	0.23	-0.18	0.24
90% Confidence Intervals								
year	ΔM		ΔX		Δ0		ΔF	
1996	-0.46	1.20	-1.10	0.19	-0.77	1.05	-0.86	0.51
1997	-0.05	0.94	-0.69	0.29	-0.67	1.06	-1.20	0.40
1998	-0.18	1.20	-1.06	0.15	-0.70	0.69	-0.46	0.49
1999	-0.14	1.24	-1.31	0.30	-0.76	0.73	-0.37	0.53
2000	-0.47	0.92	-1.24	0.40	-1.24	0.95	-0.40	1.04
2001	-0.16	1.23	-1.11	0.25	-1.03	0.49	-0.55	0.56
2002	-0.06	0.71	-0.68	0.06	-0.40	0.29	-0.29	0.21
2003	-0.21	0.28	-0.22	0.39	-0.39	0.19	-0.13	0.20
99% Confidence Intervals								
year	ΔM		ΔX		Δ0		ΔF	
1996	-0.80	1.60	-1.58	0.54	-1.16	1.79	-1.30	0.76
1997	-0.32	1.24	-0.98	0.56	-1.18	1.50	-1.61	0.78
1998	-0.58	1.57	-1.41	0.54	-1.01	1.11	-0.74	0.71
1999	-0.46	1.53	-1.67	0.66	-1.15	1.09	-0.61	0.81
2000	-0.80	1.32	-1.70	0.78	-1.79	1.57	-0.83	1.43
2001	-0.46	1.51	-1.44	0.61	-1.44	1.00	-0.98	0.84
2002	-0.19	0.92	-0.85	0.31	-0.57	0.46	-0.43	0.34
2003	-0.31	0.39	-0.37	0.52	-0.53	0.33	-0.27	0.29

Notes: own computations.

Appendix A.6:



Notes: own computations.

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